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Predicting the Moisture Ratio of Dried Tomato Slices Uusing Artificial Neural Network and Genetic Aalgorithm Modeling

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Abstract

Nowadays, mathemathical simulation and modeling of drying curves are useful instruments in order to improve control systems for final product quality under various conditions. These approaches are usually applied for studying the factors present in the process, optimization of the conditions and working factors as well as predicting the drying kinetics of products. Two intelligent tools including artificial neural network (ANN) and genetic algorithm (GA) were used in the current paper for predicting tomato drying kinetics. For this purpose, four mathematical models were taken from the literatures, then they were matched with the empirical data. Final step was choosing the best fitting model for tomato drying curves. According to the results, the model proposed by Aghbashlo et al (Agh-m) showed great performance in predicting the moisture ratio of the dried tomato slices. Moreover, the genetic algorithm was utilized for optimization of the best empirical model. Ultimately, the results were compared with the findings observed in ANN and GA models. The comparison indicated that the GA model offers higher accuracy for predicting the moisture ratio of dried tomato with the correlation coefficient (R^2) of 0.9987.

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Keywords

Artificial neural network
Genetic algorithm
Thin-layer drying
Tomato slice

Introduction

Tomato (*Lycopersicone sculantum*L.) is a species of the *Solanaceae* family that commonly consumed as fresh in world (Badaoui, Hanini, Djebli, Haddad, & Benhamou, 2019; Mozumder, Rahman, Kamal, Mustafa, & Rahman, 2012). It is also used in forms of paste, canned, dried, juice and sauces (Akanbi, Adeyemi, & Ojo, 2006). As it contains high levels of polyphenols (10-50 mg/kg), lycopene (60-90 mg/kg), vitamin C and some amount of vitamin E (5-20 mg/kg), it is assumed as a good source of antioxidants (Demiray, Tulek, & Yilmaz, 2013; Mozumder *et al.*, 2012). Thus, it is necessary to select appropriate approaches to keep its properties and decrease losses after harvest (Shakouri, Ziaolhagh, Sharifi-Rad, Heydari-Majd, Tajali, Nezarat, & Da Silva, 2015). Drying is one of these method to maintain the quality. Mathematical simulation and modeling of drying curves under various conditions could improve quality control systems (Ajani, Curcio, Dejchanchaiwong, & Tekasakul, 2019; Mokhtarian, Heydari Majd, Koushki, Bakhshabadi, Daraei Garmakhany, & Rashidzadeh, 2014a). These approaches are usually applied for studying the variables present in the process, optimization of the conditions and working parameters as well as predicting the drying kinetics of product (Garau, Simal, Femenia, & Rosselló, 2006). Several researchers have worked on modeling of drying kinetic for different products. For instance, Tavakolipour & Mokhtarian (2012) studied pistachio nut's drying kinetic and stated that the Modified Page model showed the best results for predicting the moisture ratio (MR). Taheri-Garavand, Rafiee, & Keyhani (2011) investigated the monolayer drying kinetics of tomato slice under air drying condition. Their findings showed that Midilli model provided acceptable correlation in predicting tomato drying curve. In a study by Guiné, Pinho, & Barroca (2011), behavior of pumpkin was observed during drying. According to the results, the drying process can be strongly accelerated by the increase in temperature. It was in such a way that the process was taken for 8 h at 30 ^{o}C, while the process of drying ended after only 2 h at 70 °C. The empirical data fitting to the various models for prediction of moisture ratio was done, and Page and modified Page were identified as the best fitted models. Diamante, Ihns, Savage, & Vanhanen (2010) proposed a new mathematical relationship for mono-layer drying to be used on the fruits. According to their findings, this equation presented the largest coefficient of determination for apricot & kiwi, closely followed by Page equation. Furthermore, their results showed that the suggested equation provides the best curve fitting for kiwi and apricot.

Recently, more accurate and newer predictive tools like the genetic algorithm (GA) and neural network (ANN) are applied for predicting and optimization of various processes in different products. Tavakolipour & Mokhtarian (2012) used the ANN model for predicting the pistachio nut's moisture ratio. According to the results, the multilayer perceptron (MLP) with 7 neurons in the 1st and 2nd hidden layers predicted MR ratio with R^2 value as to 0.994. In addition, Kerdpiboon, Kerr, & Devahastin (2006) employed ANN analysis for prediction of rehydration and shrinkage in the dried carrots on the basis of employed inputs of normalized fractal dimension analysis of the cell-wall structure and moisture content. Mousavi & Javan (2009) employed neuro-Taguchi's approach and ANN method for simulation of drying process of apple. Abbaszadeh, Motevali, Khoshtaghaza, & Kazemi (2011) compared the thin layer drying equations and neural networks so as to predict the drying behavior of *Elaeagnus angustifolia*. To achieve online predictions of moisture kinetics during sweet potato drying, a predictive model was developed by the use of the artificial neural network (Singh, 2011). Erenturk & Erenturk (2007) also compared the thin-layer drying process of carrot by using ANN and GA approaches. They found that the neural network showed better drying properties in comparison to other techniques (i.e., empirical model and GA) (Erenturk & Erenturk, 2007). Also, Aghajani, Kashaninejad, Dehghani, & Daraei Garmakhany (2012) and Kashiri, Daraei Garmakhany, & Dehghani (2012) studied the ability of ANN model for predicting green malt moisture ratio and sorghum soaking modeling, respectively. They showed that the ANN model with higher R^2 was selected as the best model for process modeling compared to classical models The goals of current study include: (1) determining the drying properties of tomato under various drying air conditions, (2) feasibility evaluation of neural network application for predicting tomato moisture ratio for momentarily monitoring the drying properties; and (3) optimizing the suitability of the mathematical model, which describes drying properties using genetic algorithm in order to increase the model accuracy.

Materials and methods

Preparation of raw material

Fresh tomato was prepared from local

market. The raw fruits were washed and kept in a refrigerator temperature at 5 °C. The tomatoes had three locular in their structure. Fresh tomato was cut in 5±0.1 mm thickness for experiment. By direct heating in a hot oven (Memmert, model UNE 400 PA, Scheabach, Germany) at 105 °C for 48 h based on AOAC (1990) method 931.04, the primary moisture content (MC) was determined. Average primary MC of tomatoes was obtained as 92.37±1 (%wet basis). Some physical features of fresh tomatoes including true density (ρ_P), geometric mean diameter (D_g), surface area (S), mean diameter (D_a), volume (V) and sphericity (Φ) were specified and indicated in Table (1) (Mpotokwane, Gaditlhatlhelwe, Sebaka, & Jideani, 2008). The following equations were used to calculate physical properties of fresh tomato.

$$D_a = \frac{L+W+T}{3} \tag{1}$$

$$D_g = (LWT)^{0.333} \tag{2}$$

$$\Phi = \frac{(L\,W\,T)^{0.333}}{L} \tag{3}$$

$$S = \pi D_g^2 \tag{4}$$

$$V = \frac{\pi W T L^2}{6(2L-\sqrt{WT})} \tag{5}$$

In the above equations, L, W and T are Length (cm), Width (cm) and Thickness (cm) respectively.

Table 1. Physical properties of fresh tomato

Physical properties	Present study	Previous study (Li, Li, & Liu, 2011)
Moisture (% dry basis)	12.47±0.526	-
Length (cm)	6.29±0.384	6.07±0.43
Width (cm)	5.44±0.372	7.38±0.44
Thickness (cm)	5.14±0.404	7.29±0.56
Surface area (cm^2)	98.80±11.99	148.20±16.62
Arithmetic mean diameter (cm)	5.62±0.329	6.89±0.39
Geometric mean diameter (cm)	5.60±0.335	6.86±0.38
Unit mass (g)	103.70±19.90	159.60±28.94
Volume (cm^3)	80.61±16.50	168.90±29.89
Sphericity Φ (%)	89.07±4.18	92.99±2.04
True density (g/cm^3)	1.29±0.112	1.05±0.07

Data represent means, standard deviations and values are the average of three replications.

Drying experiments

A tray dryer was used as the hot-air dryer in the tests. The tests were done at two temperatures (60 and 70 °C). The air velocity over drying samples was constant. The dryer was fitted to an optimal temperature and before experiment initiation, it was stabilized for 1 h and half. A fan with a steady speed was used in the tray to induce air convection inside the chamber. A digital balance was used for capturing the weight loss readings (AND, FX-300 CT, Japan), with interval of 15 min, with an accuracy of ±0.01 g during drying. As when as MC of the samples was reached ~0.5±0.12 (d.b.), drying process was ended.

Mathematical modeling of drying process

In order to mathematically model drying curves of the tomato slice samples, thin layer drying approaches were applied. The results of drying curves was fitted with four different MR approaches (Table 2). New model was selected according to previous article (Tavakolipour & Mokhtarian, 2012).

The correlation coefficient (R^2) is one of the main statistical criteria for selecting the best equation. Moreover, the effectiveness of fitting was also specified by different statistical parameters like mean relative deviation modulus P (%), root mean square error (RMSE), and reduced chi-square (χ^2). The R^2-value must be higher for better fitting, and RMSE & χ^2, P (%) values must be lower. These parameters were calculated as follow:

$$\chi^2 = \frac{\sum_{i=1}^{N}(MR_{e,i}-MR_{p,i})^2}{N-z} \tag{6}$$

$$\frac{100}{N}\sum_{i=1}^{N}\left|MR_{p,i} - MR_{e,i}\right| \tag{7}$$

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(MR_{p,i} - MR_{e,i})\right]^{\frac{1}{2}} \tag{8}$$

Where $MR_{p,i}$ denotes anticipated MR, $MR_{e,i}$ denotes experimental MR, z is the number of model parameters and N denotes the number of observations.

Table 2. Results of statistical analysis based on drying kinetic models on thin layer drying of tomato slice and constant coefficients of the models during different drying conditions

Equation	Name	Temperature (°C)	χ^2	RMSE	R^2
Modified Page	MR=exp(-(kt)n)	60	0.00074	0.02609	0.9922
		70	0.00021	0.01366	0.9979
Agh-m	MR=exp(-kt/1+k1t)	60	0.00020	0.01382	0.9978
		70	0.00011	0.00996	0.9988
Thomson	MR=exp(t/(a+blnMR)	60	0.00312	0.05365	0.9671
		70	0.00217	0.04398	0.9781
New model	ln(-ln MR)=a+b(ln t)+c(ln t)2	60	0.02344	0.14362	0.7645
		70	0.03474	0.17014	0.6732

Model	Temp. (°C)	k (min^{-1})	k_1	n	a	b	c
Modified Page	60	0.007021	-	1.21883	-	-	-
	70	0.013566	-	1.11068	-	-	-
Agh-m	60	0.005424	-0.00134	-	-	-	-
	70	0.012042	-0.00125	-	-	-	-
Thomson	60	-	-	-	-0.00223	-0.0000261	-
	70	-	-	-	-0.00713	-0.0000544	-
New model	60	-	-	-	-0.06433	-1.41010	0.2829
	70	-	-	-	-0.06998	-1.22732	0.2800

Calculation of effective diffusion coefficient

The empirical drying data was collected in order to determine diffusivity coefficients using Fick's second diffusion equation. The analytical solution presented by Fick's second law implies an unsteady state diffusion in an infinite slab by the drying process, which is observed in the equation (9):

(9)

$$MR = \frac{X_t - X_e}{X_t - X_e} = \frac{8}{\pi^2}\sum_{n=0}^{\infty}\frac{1}{(2n+1)^2}\exp(-(2n+1)^2\frac{-\pi^2 D_{eff} t}{4L^2}$$

Where X_t, MR, X_0, and X_e denote moisture content at t, the moisture ratio (dimensionless), primary MC, and equilibrium MC (d.b.), respectively. Also, L denotes the sample's half-thickness (m), D_{eff}, denotes the effective diffusion coefficient (m^2/s) and t denotes the drying time (min) (Mewa, Okoth, Kunyanga, & Rugiri, 2019).

In case of good approximation, it is possible to use the first term equation (9). Hence, if n=1 is substituted and taking logarithm from both sides of the equation (10):

(10)

$$\ln MR = \ln\frac{X_t - X_e}{X_t - X_e} = \ln\frac{8}{\pi^2} - \frac{\pi^2 D_{eff} t}{4L^2}$$

Thus, by plotting lnMR versus time (min), effective diffusion coefficient (D_{eff}) can be gained. Acording to the equation (10), a plot of lnMR vs. time showed a straight line with a (α) slope, where:

(11)

$$\alpha = \frac{\pi^2 D_{eff}}{4L^2}$$

Color changes

In order to determine the browning index, a modified version of Cernîşev (2010) method was used. Using UV–Vis spectrophotometer, the extent of browning was considered as color change, which was measured as absorbance at 420 nm (Shimadzo, Model UV-120-02, Japan). For the purpose of determining the color, firstly, the dried tomatoes were ground into powder. Afterward, small amount of tomato powder was weighed and mixed with a specific amount of distilled water so that a uniform sample was obtained. The brix of prepared suspension was equal to 5°. Following the adjustment of the suspension, 0.45 μm filter membrane was used for filtering the samples, and 4 mL of the extract mixed with 10 mL of acetone was used and the samples were filtered again. Then, some amount of the clear extracts was put in the spectrophotometer cell, and the absorbance read at 420 nm.

Shrinkage

For determining the shrinkage of dried sample, the equation given below was used.

$$\%SKG = \frac{V}{V_0} \tag{12}$$

Where, V denotes the dried tomato volume (cm^3), and V_0 denotes the fresh tomato volume (cm^3). Using a slide caliper, the thickness and diameter of fresh and dried samples were measured for calculating the sample volume (Vertex model, M502, with 0.01 mm accuracy) (Figiel, 2010).

Rehydration ratio

Rehydration test was conducted based on the instruction given by Mozumder *et al.* (2012). For this purpose, almost ten grams of dried products were weighted and soaked in 100 mL distilled water at 25 °C. Afterward, the weight of sample was red in intervals between 1 to 8 h. The sample was put on the filter paper so that the excessive water was absorbed and then the rehydrated sample was weighed. This procedure was continued until a fix weight was achieved. The following equation was used for calculating rehydration ratio:

$$RR = \frac{W}{W_0} \tag{13}$$

Where, W_0 denotes dried weight of the sample (g) and W denotes the weight of rehydrated sample (g).

Artificial neural network (ANN)

Multilayer perceptron network (MLP) with varying architectures was used and trained using the empirical data for obtaining the best prediction by the neural network (Mokhtarian *et al.*, 2014a). For training ANN, the back-propagation algorithm was utilized. The supervised training technique is used by the algorithm where the network biases and weights are randomly initialized at the start of the training stage. Using a gradient descent rule, the error in minimization process is obtained. The arrangement of the network was based on 1 output on 2 inputs. Drying time and temperature (x_1 and x_2) were the input factors, and MR (y) was chosen as the output (Fig. 1). For output and input layers, Logarithmic sigmoid (logsig) function was selected. This threshold function is employed in the engineering modeling and problems providing satisfactory results.

$$\mathrm{logsig}(\beta) = (1 + e^{-\beta})^{-1} \tag{14}$$

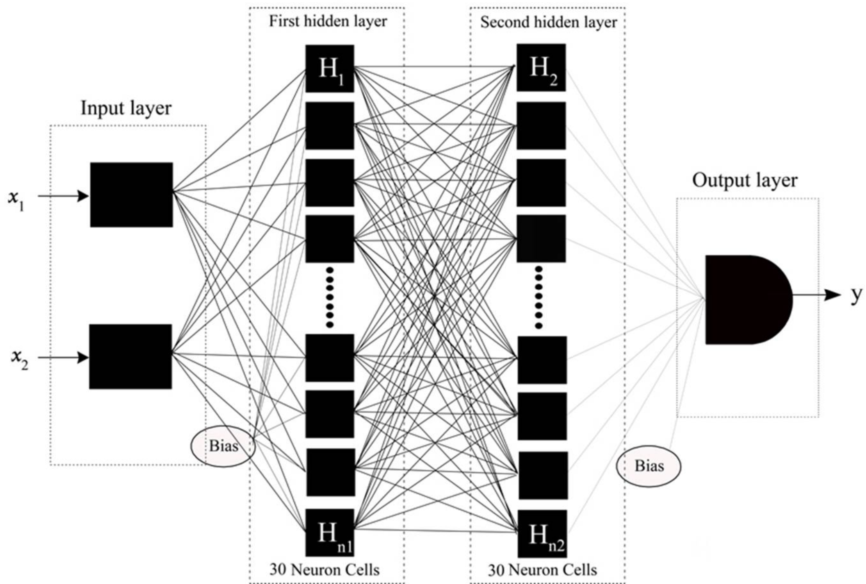

Fig. 1. A neural network scheme, x_1, drying time, x_2, drying temperature and y, moisture ratio (MR)

Two criteria of root mean square error (RMSE) and R^2-value were used for evaluating the performance of the network and the selection of the best topology. The computer program SPSS version 17 (2011) was used for designing the neural network.

Genetic algorithm

Genetic algorithm is known as a complex optimization approach, which achieves an optimal level of a different character set through the biological evolution processes based on integration and mutation, similar to what happens in the genetic. It has a successful application in analyzing different problems (Katoch, Chauhan, & Kumar, 2020). Generally, various parameters like number of data, population size, and number of generations influence the optimization approaches. Through trial and error, it is possible to obtain the optimal values of these parameters. These properties were used for optimization of the following empirical data: population size was 30, number of generations were between 8 to 300, survivors per generation were 15 considered, and the number of mutations was 2. In order to select the best model for optimizing the model coefficients, generations 8, 15, 29, 34, 42, 100, and 300 were considered and their impact on the correlation coefficient (R^2) was studied.

Statistical analysis

In order to do empirical data analysis, a completely randomized design (CRD) was used. One-way ANOVA analysis was used for determining impact of drying temperature using SAS software version 9.1. The mean-values differences were compared using Duncan's multiple range tests at a confidence level of 99% (P<0.01) (Abdolshahi, Heydari Majd, Abdollahi, Fatemizadeh, & Monjazeb Marvdashti, 2020; Heydari-Majd, Ghanbarzadeh, Shahidi-Noghabi, Abdolshahi, Dahmardeh, & Mohammadi, 2020; Salarbashi, Tafaghodi, & Heydari-Majd, 2020). The experiments were all conducted in triplicate.

Results and discussion

Data fitting

In the current study, the drying kinetic curves of tomato at two temperatures including 60 and 70 °C were fitted in terms of statistical parameters: R^2, χ^2, and RMSE by four mono-layer drying models given in Table (2).

Table (2), also indicates the modeling results. As observed, the model developed by Agh-m showed a higher R^2-value and the lower RMSE and χ^2 values. Therefore, according to R^2, RMSE, and χ^2 values, it can be found that the model suggested by Agh-m provided the best results compared to other models, which indicate the thin-layer drying properties of tomato slices. Moreover, Table (2) represents the parameters used in different applied models.

The predicted and empirical data of mono-layer drying of tomato for the Agh-m was compared in Fig. (2a). As observed in the model, MR-values were banded along a straight line, suggesting the fitness of this model for explaining the drying properties of tomato sample. Many other authors have also reported similar results (Tavakolipour & Mokhtarian, 2012; Zarein, Samadi, & Ghobadian, 2015).

The variation of the drying rate vs. time at the various temperatures were showed in Fig. (2b). As observed, the drying rate was raised by increasing air temperature that was in agreement with the results of (Mokhtarian *et al.*, 2014a; Mokhtarian, Koushki, Bakhshabadi, Askari, Garmakhany, & Rashidzadeh, 2014b).

Table (3) gives the effective moisture diffusivity values of tomato sample (current work) and other products at various temperatures. It is evident that the range of effective moisture diffusion is between 1.5793E-10 and 1.2829E-09 m^2/s. In addition, by increasing air-drying temperature, moisture diffusivity showed an accelerating trend significantly.

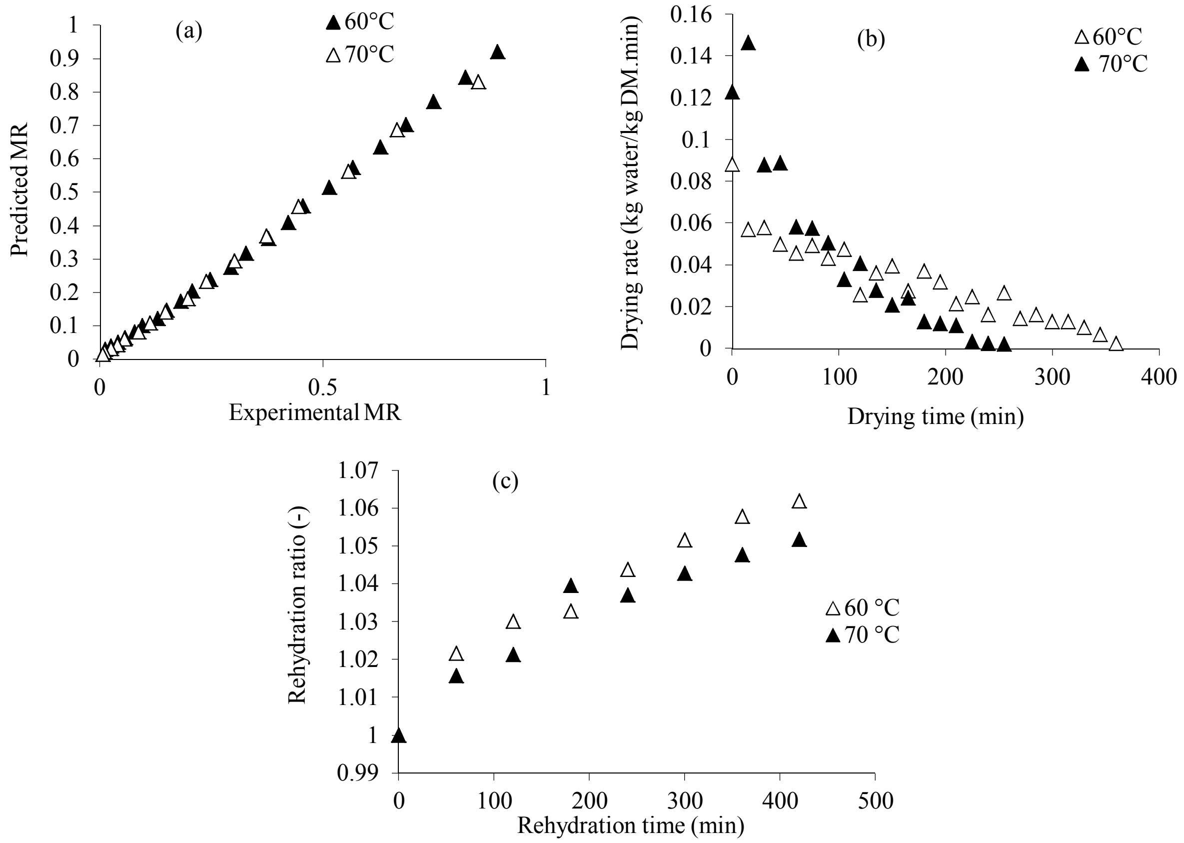

Fig. 2. **(a)** Correlation between experimental and predicted moisture ratio by Agh-m undergoing air drying, **(b)** the variation of drying rate vs. drying time at different temperature and **(c)** Rehydration ratio of dried tomato at different temperatures

Table 3. Effective diffusion coefficient of tomato fruit and other products and comparisons of quality properties of fresh and dried tomato slices

Products	Temp. (°C)	D_{eff} ** (m^2/s)	Reference
Apricot	55	$6.76\text{-}12.60\times10^{-10}$	(Doymaz, 2004b)
Sweet cherry	60-75	$1.54\text{-}5.68\times10^{-10}$	(Doymaz & İsmail, 2011)
Carrot	50-70	$0.77\text{-}9.33\times10^{-9}$	(Doymaz, 2004a)
Tomato	65-95	$0.158\text{-}1.283\times10^{-9}$	Present research
Quality properties	Fresh	Dried tomato	
		60 °C	70 °C
Color (A420 nm)	0.199±0.001[c]	0.381±0.001[b]	0.542±0.002[a]
Shrinkage (%)	-	87.354±1.15[a]	88.803±0.92[a]
pH	4.24±0.00[a]	4.20±0.005[b]	4.18±0.005[c]
Acidity (% citric acid)	0.486±0.00[c]	0.755±0.01[b]	0.789±0.009[a]

*The same letters in each column indicate not significant effect (P<0.01).
** This factor was analyzed as experimentally. To calculate this factor, MR data drawn Vs. drying time and D_{eff} was obtained from slope of regression line.

Assessment of the Quality properties

Table (3) indicates some quality features of fresh and dried tomatoes. As observed, drying temperature significantly influenced (P<0.01) the quality features of final product, while, there was an exception in case of shrinkage. Dried sample showed higher shrinkage at 70 °C compared to those at 60 °C. This can be attributed to differences which had been taken between glass transition (GT) and temperature of samples at higher drying temperatures. Thus, structural mobility of matrix was not adequate for supporting the solid material and more collapse happened (Castro, Mayorga, & Moreno, 2018; Mayor & Sereno, 2004).

Also, Table (3) presents the evaluation of tomato color undergoing drying at different air temperatures. The fresh tomato slices had a glossy color compared to dried ones. It can be seen that the drying temperature had a considerable impact (P<0.01) on color of dried samples during process. Therefore, sample dried at 70 °C showed more color changing compared to the sample dried at 60 °C (Pu & Sun, 2017). The non-enzymatic browning reaction is probably the main factor for degradation of the tomato quality parameters during the process of drying (Cernîşev, 2010).

One of the most important features that is used for measurement of dried food quality is rehydration. Fig. (2c) indicates rehydration changes of dried samples versus time. According to the results, rehydration capacity of sample dried at 60 °C was higher than the ones dried at 70 °C. It was due to high shrinkage of sample dried at temperature of 70 °C. Maximum rehydration rate was obtained when structural and cellular disruptions like shrinkage were minimized. Hence, lower drying temperatures should be used for minimizing shrinkage in order to least moisture gradients throughout the product.

Performance of ANN and GA approaches

The genetic algorithm approach was used (i.e., Agh-m) to optimize the best empirical model for predicting MR in tomato slice. In this model, the following features like population size of 100, number of generations between 8 to 300, number of mutations as 2 and survivors per generation as 50 were utilized in order to estimate the optimal point. The best number of genetic generation (number of genetic generations included 0, 8, 29, 42, 87, 110, 154, 242, and 300 being randomly selected) was used in order to optimize the model constant coefficients and it was specified using trial and error method (Fig. 3a).

As observed, R^2 value was accompanied by increasing trend of genetic generations number from zero to 300 (in all temperatures) so thatany changes in R^2 values will follow a parabolic curve. As it can be seen in Fig. (2c), R^2 value significantly increased with the increase in the number of genetic generations from starting point of optimization process to 29 genetic generations in all drying temperatures; while, R^2 value increasing trend was not the same in the area of genetic generation numbers from 29 to 300. Actually, this part of curve showed almost a straight line behavior. In general, based on findings, 29 genetic generations were reported as the best genetic generation for an optimized model constant coefficient. Table (4) indicates the values of model constant coefficients following optimizing with 29 genetic generations (as optimized generation).

ANN was used in the current work for predicting the moisture ratio (MR) of dried tomato. To this end, a combination of neurons and layers with logarithmic sigmoid (logsig) was utilized for modeling a multi-layer perceptron neural network (MLP). The neural network contains 1 and 2 hidden layers (HL), 2 to 35 neurons were randomly chosen and it was estimated that the network power could predict MR of dried tomato slices. Fig. (3b) contains the MLP results with different arrangements and results obtained for MLP with 1 and 2 HL. As it can be observed, the topology of 2-27-1 (i.e., network with 27 neurons, 2 inputs in the 1st HL and 1 output) provided the best outcome for MR prediction. This network had the capacity for predicting MR with regression coefficient (R^2) as 0.993. In addition, P (%) and RMSE values for MR were calculated as 5.5604 and 0.18003, respectively. There was a high correlation between the findings by Tavakolipour & Mokhtarian (2012) and the results of the current research.

The present research findings figured out that, genetic algorithm as a non-destructive approach is a useful method for optimizing the best empirical model in order to do MR prediction. Based on findings, this approach showed the capability of MR prediction in dried tomato slices with high accuracy by slight modification of Aghbashlo et al (Agh-m) constant coefficient (Table 4). The accuracy order of models from high to low was as follow: GA>Agh-m>ANN (Table 4). Erenturk & Erenturk (2007) reported similar results concerning mono-layer drying of apricot. They used GA and NNA approaches for prediction of moisture content and compared results obtained from these methods (ANN and GA) with the best predictive model (i.e., Modified Page) (Erenturk & Erenturk, 2007). According to their results, ANN showed the best accordance to predicting the moisture content of dried apricot (Aktaş, Şevik, Özdemir, & Gönen, 2015).

Fig. (3c) indicates the diagram of experimental values versus the predicted values for the GA approach. As data were located randomly around the regression line; therefore, the genetic algorithm chould be evaluated accurately for prediction of MR of dried tomato slice.

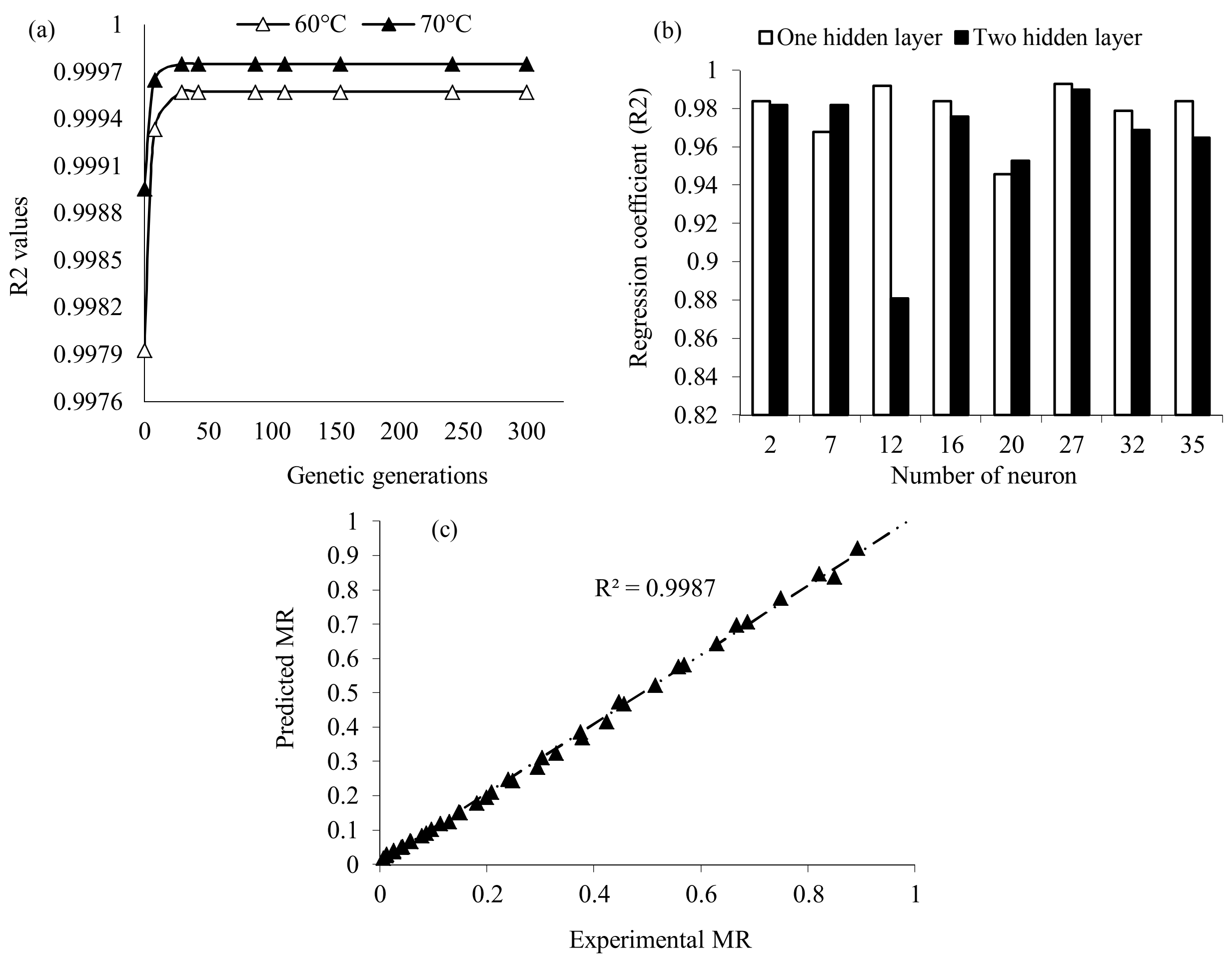

Fig. 3. (a) Evaluation of the effect of increasing the genetic generation number on the variation of R^2 value to optimize the empirical model, (b) ANN results of dried tomato slices to predict MR accompanied by logsig activation function and (c) predicted and experimental values of the GA approach for predicting MR

Table 4. The constant coefficient of Agh-m with slight amendment

Temperature (°C)	Constants		
	k (min^{-1})	k_1	R^2
Dried at 60 °C	0.0052515	-0.00138	0.99957
Dried at 70 °C	0.0114790	-0.00125	0.99975
Method	RMSE	P (%)	R^2
Agh-m	0.05278	0.9911	0.9983
Agh-m optimized by means GA	0.10243	1.2227	0.9987
MLP model (logsig activation function)	0.18003	5.5604	0.9930

Conclusions

The two models derived from biological systems (neural networks and genetic algorithms) were used to predict the MR of tomato slices during drying process. The comparison was made between obtained results and the empirical model results. Among four considered mathematical drying kinetic models, the model proposed by Agh-m was found to be the most appropriate for predicting drying curve of tomato slices. According to the research findings, all models were reported suitable for prediction of MR and minimum correlation coefficients (R^2=0.993) in dried tomato. Typically, the results suggest that the GA approach had higher ability for predicting the MR of dried tomatoes compared to other ones. As a result, the GA as the best model was able to estimate moisture ratio of dried tomato using genetic generation 29 (R^2=0.9987). Additionally, considering the results, it can be found that neural network with 27 neurons in the HL was able to predict MR of dried tomato (R^2=0.993). Thus, seemingly the presentation and application of the advanced approaches as well as novel algorithms can decrease trial and error steps through introducing new methods for predicting the industrial parameters.

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پیش‌بینی نسبت رطوبت ورقه‌های خشک‌شدهٔ گوجه‌فرنگی با استفاده از مدل‌سازی شبکهٔ عصبی مصنوعی و الگوریتم ژنتیک

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چکیده

امروزه، استفاده از شبیه‌ساز ریاضی و مدل‌سازی منحنی‌های خشک‌کردن، ابزار مفیدی برای بهبود سیستم‌های کنترل کیفیت محصول نهایی در شرایط مختلف است. این روش‌ها معمولاً برای مطالعهٔ عوامل موجود در فراآیند، بهینه‌سازی شرایط و فاکتورهای کاری و پیش‌بینی سینتیک خشک‌شدن محصول اعمال می‌شود. در مقالهٔ حاضر به‌منظور پیش‌بینی نسبت رطوبت ورقه‌های گوجه‌فرنگی خشک‌شده از دو ابزار هوشمند ازجمله شبکهٔ عصبی مصنوعی (ANN) و الگوریتم ژنتیک (GA) استفاده شده است. برای‌این‌منظور، ابتدا ۴ مدل ریاضی از سایر مطالعه‌ها گرفته شد و سپس با داده‌های تجربی مطابقت داده شدند. سپس بهترین مدل برازش برای منحنی خشک‌کردن گوجه‌فرنگی انتخاب شد. طبق نتایج، مدلی که توسط آغباشلو و همکاران پیشنهاد شده است، عملکرد بسیار خوبی به‌منظور پیش‌بینی نسبت رطوبت ورقه‌های گوجه‌فرنگی خشک‌شده نشان داد. علاوه‌بر این، از الگوریتم ژنتیک برای بهینه‌سازی بهترین مدل تجربی استفاده شد. درنهایت، نتایج این تحقیق با نتایج مشاهده‌شده در مدل‌های شبکهٔ عصبی مصنوعی و الگوریتم ژنتیک مقایسه شد. نتایج نشان داد که مدل الگوریتم ژنتیک دقت بالاتری را به‌منظور پیش‌بینی نسبت رطوبت گوجه‌فرنگی خشک با ضریب همبستگی (R^2) ۰/۹۹۸۷ ارائه می‌دهد.

واژه‌های کلیدی: الگوریتم ژنتیک، خشک‌شدن لایهٔ نازک، شبکهٔ عصبی مصنوعی، ورقهٔ گوجه‌فرنگی