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Prediction of Papaya fruit moisture content using hybrid GMDH - neural network modeling during thin layer drying process

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Abstract

In this work, a hybrid GMDH–neural network model was developed in order to predict the moisture content of papaya slices during hot air drying in a cabinet dryer. For this purpose, parameters including drying time, slices thickness and drying temperature were considered as the inputs and the amount of moisture ratio (MR) was estimated as the output. Exactly 50% of the data points were used for training and 50% for testing. In addition, four different mathematical models were fitted to the experimental data and compared with the GMDH model. The determination coefficient (R^2) and root mean square error (RMSE) computed for the GMDH model were 0.9960 and 0.0220,and for the best mathematical model (Newton model) were 0.9954 and 0.0230, respectively. Thus, it was deduced that the estimation of moisture content of thin layer papaya fruit slices could be better modeled by a GMDH model than by the mathematical models.

Keywords: Drying process; GMDH; Mathematical Modeling; Papaya fruit; Neural Network

Introduction

Papaya (*Carica papaya* L.) also called papaw is a tropical fruit that is widely cultivated and consumed, both for its agreeable flavor as well as its many pharmacological properties (De Oliveira and Vitória, 2011). Papaya is rich in vitamin C, K+, carotenoid and fiber content and has been considered as a top-ranking fruit (Liebman, 1992). FAO reported that papaya has been ranked third with 11.2 million tons or 15.36 percent of the total tropical fruit production in 2010.

Water is one of the major food components which affects on many physico-chemical and biological attributes. The amount of moisture content has a decisive effect on the quality of foodstuffs. Drying due to reducing the moisture content or making water hard to access, is of the most effective operations to reduce the spoilage of agricultural products (Izadifar and Mowla, 2003).

In characterizing the drying parameters, the thin-layer drying procedure was found to be the most feasible tool (Aghdam *et al.*, 2015). Different types of models have been used by several researchers to predict the moisture content/drying rate of food materials which finally led to different expression for the prediction (Dinani *et al.*, 2014; Kingsly and Singh, 2007; Koukouch *et al.*, 2015; Wang *et al.*, 2007; Yousefi *et al.*, 2013a; Yousefi *et al.*, 2013b). Most of these models are mathematical ones which classified to theoretical, semi-theoretical and empirical models (Demirtas *et al.*, 1998; Midilli *et al.*, 2002). Lately, a new predictive method based on artificial neural networks systems (ANNs) has been used to model the drying process of different food and agricultural products like potato and green pea (Kamiński *et al.*, 1998), Echinacea angustifolia (Erenturk *et al.*, 2004), grain (Liu *et al.*, 2007), tomato (Movagharnejad and Nikzad, 2007), shelled corn (Momenzadeh *et al.*, 2011) and pomegranate arils (Nikbakht *et al.*, 2014). The ANNs are mostly considered as nonlinear and highly flexible universal approximators (Park and Sandberg, 1991; Powell, 1987). Nonetheless, its main drawback is that the detected dependencies are concealed behind neural network structure (Nariman-Zadeh and Jamali, 2007). Contrarily, the group method of

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data handling (GMDH) is applied to develop a model which is hidden in the empirical data (Ivakhnenko, 1971). The GMDH method was originated by Ivakhneko in 1966 and it has been improved and evolved over the past 40 years. The GMDH algorithm connects the inputs to outputs with high order polynomial networks which are mainly feed-forward and multi-layered neural networks (Onwubolu, 2009). In this approach, the nodes are hidden units and the activation polynomial coefficients are weights which are estimated by ordinary least square regression (Ghanadzadeh *et al.*, 2012; Onwubolu, 2009). In recent years, however, the use of such self-organized networks has led to successful application of the GMDH-type algorithm in a wide range of areas in engineering and science (Abdolrahimi *et al.*, 2014; Ahmadi *et al.*, 2007; Atashrouz *et al.*, 2015; Najafzadeh, 2015; Pazuki and Kakhki, 2013).

Based on the literature review, no specific study was found to be associated with the estimation of moisture content of papaya fruit using GMDH. Therefore, the purpose of this work was to undertake a study to investigate the thin-layer drying process of papaya slices in a cabinet drier and modeling of the experimental data using group method of data handling (GMDH) to estimate the moisture content of papaya fruit. In addition to GMDH, four well-known thin-layer empirical models were employed for the estimation, and finally the estimation quality of both types of models was evaluated and compared.

Materials and methods

Experimental Study

Papaya fruits used in this research were purchased from a local market in the Bahookalat region (Sistan & Baluchestan province, Iran) and stored in a refrigerator at 4 ± 1 °C before they were subjected to the drying process. The fruits were washed, peeled and cut into three thicknesses of 3, 5 and 7 mm. A cabinet dryer (Model JE10 TECH, F-02G, South Korea) with controllable airflow, temperature and air humidity monitoring systems was applied for the hot air drying process. The absolute humidity and the hot-air velocity for all drying temperatures were 0.6±0.02 g/kg dry air and 1±0.1 m/s, respectively. The schematic figure of the drying system used is shown in Fig. 1. The initial moisture content of papaya slices was measured using a laboratory oven dryer (Galenkamp, UK) operated at 105 °C. The initial moisture content obtained for the slices was 84.48%±0.05% (w. b.). During the drying period, the weight of the samples was recorded by programmable balance software at intervals of 5 min. The moisture content in the final product was 15±0.02% (w. b.). Drying was performed at three temperature levels of 40, 50 and 60 °C. Moisture ratio (MR) variations with time were plotted for various conditions. MR is defined by the equation:

$$MR = \frac{M - M_e}{M_0 - M_e} \quad (1)$$

Where M is the moisture content of the samples at any drying time and M0 is the initial moisture content. The moisture ratio equation was simplified to M/M0 as value of Me (equilibrium moisture content) is relatively small compared with that of M or M0 (Akgun and Doymaz, 2005).

Group Method of Data handling (GMDH):The Group method of data handling (GMDH) is a polynomial based model. According to the GMDH approach, each layer can be obtained from a quadratic polynomial function. Thus the input variables are projected to the output variable. The main goal in this method is finding of function, f, that project the input variables to the output variable.

Therefore, the output variable (Y_i) can be written from the input variables as the following form:

$$Y_i = f(X_{i1}, X_{i2}, X_{i3}, ..., X_{in})\, i = (1,2,3,..., M) \quad (2)$$

Where, X s are input variables. The structure of the GMDH can be obtained using the minimization of an objective function. The objective function can be written as:

$$\omega = \sum_{i=1}^{M} [Y(X_{i1}, X_{i2}, ..., X_i) - y_i]^2 \quad (3)$$

Where, in the above equation y_i is actual data.

The general function between the inputs and the output variables was proposed by Ivakhnekoin the following form (Ivakhnenko, 1968):

$$Y = a_0 + \sum_{i=1}^{n} a_i X_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} X_i X_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} X_i X_j X_k + \ldots \quad (4)$$

In this work, a quadratic polynomials function with only two variables (neurons) is considered

$$Y = G(X_i, X_j) = a_0 + a_1 X_i + a_2 X_j + a_3 X_{ij} + a_4 X_i^2 + a_5 X_j^2 \quad (5)$$

Where, parameters ą can be calculated from the minimization of Eq. (3). The least squares technique from multiple regression analysis is applied to calculate these parameters which obtained from solution of the following matrix:

$$Aa = Y \quad (6)$$

Where, a is the vector of unknown parameters of the quadratic polynomial (Eq. (6)):

$$A = \{a_0, a_1, a_2, a_3, a_4, a_5\} \quad (7)$$

and

$$y = \{ y_1, y_2, y_3, \ldots, y_M \}^T \quad (8)$$

Where, y is the vector of the actual data.

$$A = \begin{bmatrix} 1 & X_{1p} & X_{1q} & X_{1p} X_{1q} & X_{1p}^2 & X_{1q}^2 \\ 1 & X_{2p} & X_{2q} & X_{2p} X_{2q} & X_{2p}^2 & X_{2q}^2 \\ \vdots & \vdots & \vdots & \vdots\ \vdots & \vdots & \vdots \\ 1 & X_{Mp} & X_{Mq} & X_{Mp} X_{Mq} & X_{Mp}^2 & X_{Mq}^2 \end{bmatrix} \quad (9)$$

Therefore, the vector of unknown parameter is given as below:

$$a = (A^T A)^{-1} A^T Y \quad (10)$$

Results and discussions

The influence of drying factors (Time, Thickness and Temperature) and their interactions on MR is shown in Table 1. It can be observed that the influence of all factors and their interactions was statistically significant ($p<0.05$). In this work, hybrid GMDH-type neural network was developed for estimation of papaya fruit MR during drying in a cabinet dryer. The experimental data contained 390 points while 50% of these data points were randomly used for training and 50% for testing. To further check for any possibility of over-fitting, different ratios in a range from 1 to 9 with increment of 0.5 are consecutively tested to find the optimum value. No over-fitting and considerably lesser error were observed that can be justified by rough linearity of data set.

Fig 2 shows the optimal structure of GMDH–Neural Network model developed with one hidden layer. As it can be seen from Fig 2, the proposed model has one input layer, one middle layer and one output layer.

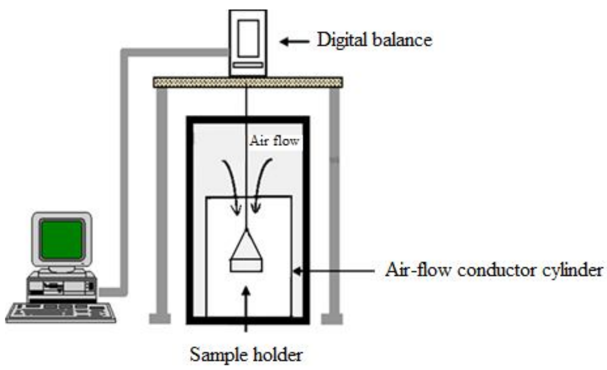

Fig. 1. Schematic figure of the drying system used.

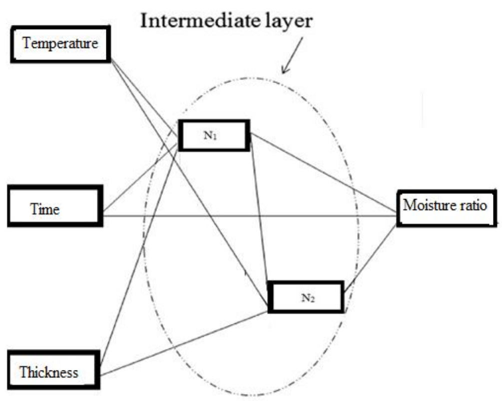

Fig.2. A schematic diagram of the GMDH model

Table 1. Effect of drying factors (Time, Thickness and Temperature) and their interactions on MR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Temperature	.043	2	.021	350.386	.000
Thickness	.113	2	.056	922.568	.000
Time	4.937	3	1.646	26931.061	.000
Temperature* Thickness	.002	4	.000	7.023	.000
Temperature * Time	.005	6	.001	13.174	.000
Thickness * Time	.005	6	.001	13.447	.000
Temperature * Thickness * Time	.002	12	.000	2.629	.012
Error	.002	36	6.111E-005		
Total	18.785	72			
Corrected Total	5.109	71			

Generated functions corresponding to each node with total correlation function are reported in Table 2. It is worth meaning that all input variables were accepted by the model. In other words, the GMDH model provided an automated selection of essential input variables and built polynomial equations to model. These polynomial equations showed the quantitative relationship between input and output variables (Table 2). It should be noted that, the GMDH was modeled with three inputs (temperature (°C), thickness (mm) and time (min)) and three neurons in the hidden layer and one in the output layer (moisture ratio). The performance of the training and testing by the network were estimated by *AAD %* (Average Absolute Deviations) as bellow:

$$\% AAD = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{Y_i^{model} - Y_i^{actual}}{Y_i^{actual}}\right| \quad (11)$$

Where, the superscripts of “model” and “actual” refer to the model and actual results, respectively. The actual and predicted results together with related Average Absolute Deviations Percent (AAD %) are reported in Table 3. This table demonstrated the differences between experimental data and GMDH model that clearly shows the reliability and accuracy of the proposed GMDH model in estimation of moisture ratio.

Moreover, the experimental and predicted values were compared in Fig. 3 and 4. As it can be observed, the results of the GMDH model were in very good agreement with the experimental data (R^2= 0.9960).

Some statistical tests can be used for determining the models accuracy and reliability of the GMDH model. These statistical values can be defined as shown in Table 4 and their values were calculated based on the output of the network. The high value of R^2 (0.9960) in addition with the low values of RMSE (0.022), MSE (0.00048) and MAD (0.0099) for GMDH model indicated the high performance of that for estimation of MR.

Fig 5 shows the sensitivity of moisture ratio to input variables. It is found that the sensitivity to the temperature was more than other inputs so that sensitivity of this parameter was near 40%. It can be concluded that the temperature has the most important role in this system.

In agreement with this result, the high sensitivity of many agricultural crops to drying temperature is reported using activation energy parameter (Kaleemullah and Kailappan, 2005; Park *et al*., 2002). Variation of MR with respect to drying time for the three temperatures and three thicknesses (experimental data) are shown in Fig 6 (a) and (b), respectively.

In addition with the GMDH modelling, the moisture ratio values obtained under various experimental conditions were subjected to four empirical mathematical models. Calculated R^2 and RMSE indicated that the Newton model was the best among the mathematical models considered for fitting the experimental data (Table 5).

The comparison between R^2 (0.9954) and RMSE (0.0230) of Newton and GMDH network models (R^2 = 0.9960, RMSE = 0.022) demonstrated that GMDH predicted the closest data to the experimental ones.

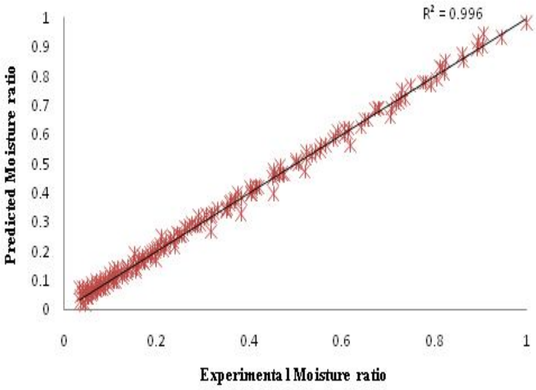

Fig. 3. Comparison of actual and predicted data by group method of data handling (GMDH).

Table 2. Polynomial equations for prediction of moisture ratio (MR) with GMDH model*

Nod 1	$N_1 = 0.923027 - Time\times0.0071617 - Time\times Thickness\times1.76534e\text{-}05 + Time^2\times1.43249e05 + Tem.\times0.00609525 + Tem.\times Thickness\times0.00043174 - Tem.^2\times0.000178618$
Node 2	$N_2 = 0.059891 + Tem.\times8.72889e\text{-}05 + Tem.\times Thickness\times4.42286e\text{-}05 + Tem.\times N_1\times0.0058998 - Tem.^2\times2.32451e\text{-}05 - Thickness\times N_1 * 0.00692694 + N_1\times0.549558 + N_1^2\times0.260731$
Output	Moisture ratio= $-0.869111 + Time\times0.00743856 + Time\times N_1\times0.0290015 - Time\times N_2\times0.0415924 - Time^2\times1.2391e\text{-}05 + N_2\times3.34531 - N_2^2\times1.46832$

*Variables' units (Tim (min), Thickness (mm), Temperature (°C)).

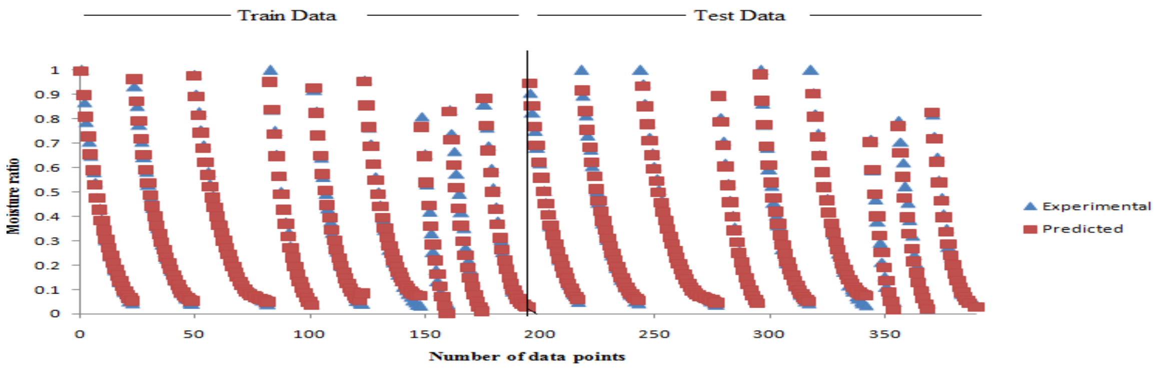

Fig. 4. Predicted moisture ratio plotted against data number

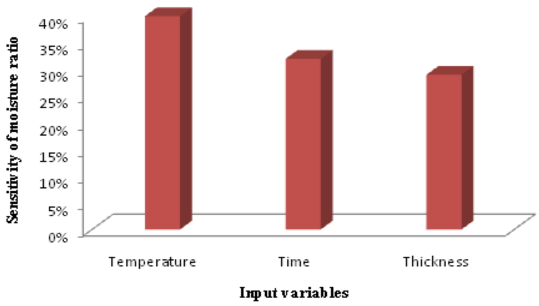

Fig. 5. Comparison of moisture ratio sensitivity with input variables.

Table 3. Comparison between GMDH model and experimental data based on computed average absolute deviation (AAD %) for summary of results

No.	Actual	Predicted(GMDH)	AAD%(GMDH)
1	1	0.995202	0.479838
2	0.868176	0.896439	3.255500
3	0.785821	0.807018	2.697410
4	0.704622	0.726257	3.070438
5	0.646416	0.653413	1.082482
6	0.579872	0.587718	1.353096
7	0.539785	0.528405	2.108246
8	0.477067	0.474735	0.488791
9	0.429248	0.426016	0.752928
10	0.388898	0.381618	1.871908
11	0.338726	0.340986	0.667144
12	0.301440	0.303642	0.730385
13	0.270976	0.269198	0.656167
14	0.235537	0.237348	0.769148
15	0.206465	0.207872	0.681891
16	0.176211	0.180628	2.506822
17	0.155078	0.155544	0.300634
18	0.12841	0.132612	3.272015
19	0.103101	0.111870	8.505066
20	0.088343	0.093395	5.719329
21	0.070668	0.077284	9.361598
22	0.050300	0.063633	26.50629
23	0.041000	0.052526	28.11122
24	0.932317	0.961745	3.156424
25	0.850333	0.871819	2.526847
26	0.774874	0.790389	2.002309
27	0.705421	0.716780	1.610281
28	0.641496	0.650269	1.367593
29	0.582659	0.590116	1.279865
30	0.528505	0.535594	1.34126
31	0.478662	0.486007	1.53462
32	0.432785	0.440714	1.832069
33	0.390561	0.399138	2.196197
34	0.351697	0.360777	2.581923
35	0.315926	0.325212	2.939219
36	0.283002	0.292106	3.216859
37	0.252699	0.261209	3.367482
38	0.224808	0.232349	3.354326
39	0.199137	0.20543	3.160208
40	0.175509	0.180423	2.799591
Total			03.63211

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Table 4. Model statistics GMDH model for predicting moisture ratio

Statistics		Training	Testing
Absolute Fraction of variance (R^2)	$R^2 = 1 - \left[\sum_{i=1}^{N} (Y_i^{model} - Y_i^{actual})^2 / \sum_{i=1}^{N} (Y_i^{actual})^2 \right]$	0.9989	0.9960
Root Mean Square Error (RMSE)	$RMSE = \left[\sum_{i=1}^{N} (Y_i^{model} - Y_i^{actual})^2 / N \right]^{1/2}$	0. 017	0.022
Mean Square Error (MSE)	$MSE = \sum_{i=1}^{N} (Y_i^{model} - Y_i^{actual})^2 / N$	0.00029	0.00048
Mean Absolute Deviation (MAD)	$MAD = \sum_{i=1}^{N} \lvert Y_i^{model} - Y_i^{actual} \rvert / N$	0. 0081	0.0099

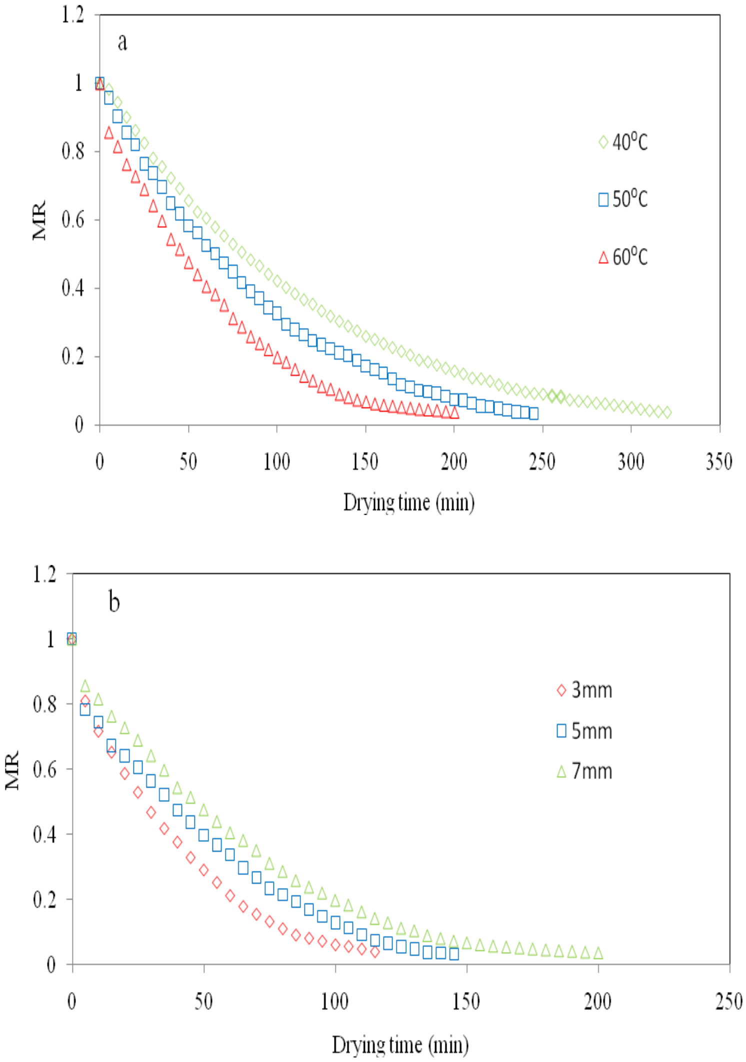


Fig. 6. (a) Effect of drying temperature on moisture ratio (MR) (for thickness of 7 mm), (b) effect of thickness on moisture ratio (MR) (for drying temperature of 60 °C).

Table 5. Statistical analyses for the mathematical models

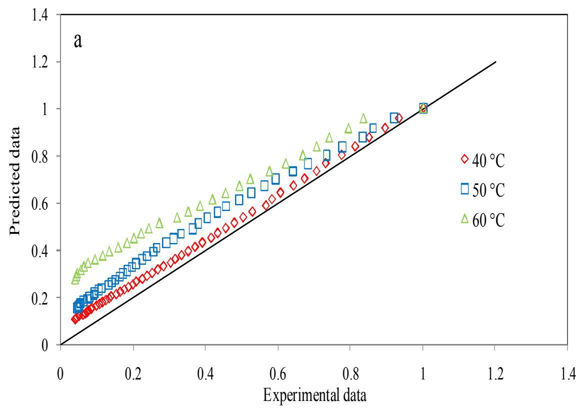
Model name	Model equation	Model constants	R^2	RMSE
Newton	$MR = \exp(-kt)$	k = 0.0089	0.9954	0.0230
Modified Page	$MR = \exp(-kt)^n$	k = 0.0126, n = 0.7074	0.9873	0.0487
Henderson and Pabis	$MR = a\exp(-kt)$	k = 0.0092, a = 1.0407	0.9880	0.0500
Wang and Singh	$MR = 1 + at + bt^2$	a = -0.0067, b = 0.00001	0.9918	0.0213

R^2: Coefficient of determination; RMSE: Root-mean-square error

This matter is also proven by comparison of Fig 7 with Fig 3. As it can be seen from the Fig. 7, an overestimation obtained by fitting the best model (Newton mode) to the experimental data, so that this overestimation increased with increase in temperature and decrease in thickness. Erenturk *et al.* (2004) reported the same results for thin-layer drying of Echinacea Angustifolia root. They reported that the feed-forward neural network based estimation was more concise (R^2 = 0.999) even than the best mathematical model used (modified page) (R^2 = 0.993). For two varieties of green malt, Aghajani *et al.* (2012) found that the estimated moisture ratio by feed-forward back propagation neural network was more accurate than Page's model. Also, similar results which imply the high precision of neural network based modes for prediction of moisture content been reported (Huang and Chen, 2015; Khazaei *et al.*, 2013; Momenzadeh *et al.*, 2011; Nadian *et al.*, 2015; Yousefi *et al.*, 2013a). No specific work was found in the case of estimation of moisture content using GMDH-type neural network, but many researchers have reported the remarkable accuracy of this method in other fields (Abdolrahimi *et al.*, 2014; Ahmadi *et al.*, 2007; Atashrouz *et al.*, 2015; Najafzadeh, 2015).

Conclusions

In this study, drying kinetics of thin-layer papaya fruit was investigated experimentally. Besides, a comparative study between a regression analysis and GMDH for estimation of moisture ratio (MR) during drying process was performed. Newton model indicated the closest results to the experimental data among the four thin-layer mathematical models considered. Higher R2 and lower RMSE values calculated for GMDH proved the higher performance of GMDH for prediction of moisture content. It should be noted that the results obtained are only valid in the experimented range and are not necessarily correct outside of that. In brief, in a wider range of operating conditions the validity of the mathematical methods could be higher than that of the GMDH adjusted to a restricted range of conditions. Altogether, it can be concluded that due to the high precision, GMDH- type neural networks can be applied for on-line state estimation and control of drying processes in industrial operations successfully



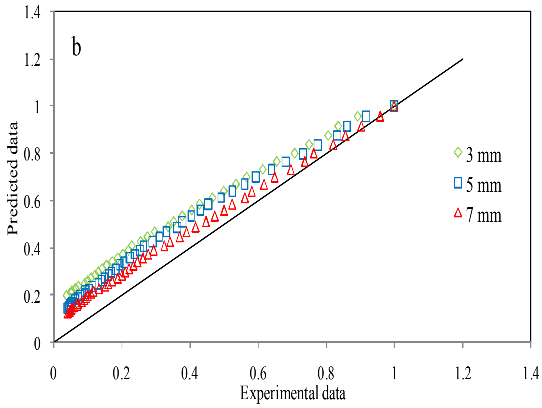


Fig. 7. (a) Comparison of actual and predicted data by Newton model for papaya fruit slices with 3 mm thickness, (b) comparison of actual and predicted data by Newton model for papaya fruit slices at 50 °C

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تخمین محتوای رطوبتی خربزه درختی با استفاده از مدلسازی GMDH حین خشک شدن لایه نازک

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چکیده

در این تحقیق یک مدل هیبریدی شبکه عصبی-GMDH جهت تخمین محتوای رطوبتی قطعات خربزه درختی در حین خشک شدن با هـوای داغ در یک خشک کن کابینتی تعیین شد. برای این منظور پارامترهای زمان خشک کردن، ضخامت قطعـات و دمـای خشـک‌کـردن بعنـوان ورودی تعریـف گردید و مقدار نسبت رطوبتی (MR) به عنوان خروجی تخمین زده شد. دقیقاً ۵۰ درصد داده‌ها جهت آموزش و ۵۰ درصد دیگر برای تسـت کـردن مـدل استفاده شد. بعلاوه، چهار مدل ریاضی مختلف بر داده‌های آزمایشگاهی برازش داده شدند و نتایج این مدلسازی با GMDH مقایسه گردید. مقدار ضریب تبیین (R^2) و جذر میانگین مربعات خطا (RMSE) بدست آمده برای مدل GMDH به ترتیب ۰/۹۹۶۰ و ۰/۰۲۲۰ بدست آمد، در حالی که برای بهترین مدل ریاضی (مدل نیوتن) این مقادیر به ترتیب برابر ۰/۹۹۵۴ و ۰/۰۲۳۰ تعیین شد. پس می توان نتیجه گرفت که مدلسازی با GMDH کارایی بالاتری نسبت به مدل ریاضی در تخمین محتوای رطوبتی قطعات لایه نازک خربزه درختی دارد.

واژه‌های کلیدی: خشک کردن، GMDH، خربزه درختی، شبکه عصبی

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