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Drying of jujube (*Zizyphus jujube mill*) fruit: comparison of prediction from mathematical models and artificial neural networks

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Abstract

In this study, the application of artificial neural networks (ANNs) and mathematical models for hot-air drying of Jujube fruit is presented. Air velocity, temperature and drying time were used to predict moisture ratio (MR) and drying rate (DR) variations. Assessment of seven mathematical models revealed that the Midilli model exhibited the best performance in fitting the experimental data (R^2=0.9996, RMSE= 0.005112 and χ^2=2.61E-05). Using some of the experimental data, an ANN, trained by standard back-propagation algorithm, was developed. The ANN model was able to predict variations of MR and DR quite well with determination coefficients (R^2) of 0.9997, 0.9993 and 0.9996 for training, validation and testing, respectively. The prediction mean square error was obtained as 0.001, 0.0011 and 0.0013 for training, validation and testing, respectively. Results show good agreement between the experimental data on the one hand and mathematical models as well as the ANN model on the other. However, neural network modeling yielded a better prediction of moisture ratio and drying rate of jujube fruit compared to all of the mathematical models studied.

Keywords: Drying characteristics, Jujube fruit, artificial neural networks, mathematical models.

Abbreviations:

MR	Moisture ratio (dimensionless)
M_t	Moisture content at any time (kg water/kg dry solid)
M_e	Equilibrium moisture content (kg water/kg dry solid)
M_0	Initial moisture content (kg water/kg dry solid)
R^2	Correlation coefficient
RMSE	Root mean square error
χ^2	Chi square
$MR_{exp,i}$	i_{th} experimental moisture ratio
$MR_{pred,i}$	i_{th} predicted moisture ratio
N	Number of observations
n	Number of drying constants
DR	Drying Rate (g/min)
MSE	Mean square error

Introduction

Jujube (*Zizyphus jujube Mill*) is a fruit of *Rhamnaceae* family. It is both consumed fresh and dried for its high medicinal value. For two millennia Jujube fruit, seeds, leaf, skin and root have been used for remediation of fever (Omid Beigi, 1997). Drying is an old technique for the preservation of agricultural and medicinal plants (Koyuncuet et al., 2007). Solar energy has been a usual energy source for the traditional dryers. However, it is riddled with numerous problems including: undesirable variations in food quality, insufficient drying control, long drying times and weak hygienic aspects. Industrial dryers offer numerous advantages such as on time harvesting, loss reduction in the field, programmable harvesting in undesirable weather conditions, longer shelf time, decreased costs and better processing time management. However drying is an energy-intensive process which should be monitored and controlled closely (Sahin and Dincer, 2002). Mathematical modeling of hot air drying is commonly based on thin layer drying assumptions (Ozdemir and Devres, 1999). Drying of fruits depends on their mass and heat transfer specifications. Therefore, moisture and temperature diffusion parameters are essential for the design process, quality control, selection of storage facility and transportation of fruits. Diffusivity is a major parameter in agriculture products which is needed for modeling mass transfer processes such as surface absorption and moisture desorption during the storage period (Rafiee et al., 2008). Although a considerable amount of data has been reported in the literature regarding the thin-layer drying modeling of various agricultural products (fruits, crops and vegetables) such as millet (Ojediran and Raji, 2010) bananas (Prachayawarakorn et al., 2007), figs (Stamatios et al., 2006), pistachio nuts (Kashaninejad et al., 2007), pomegranate arils (Motevali et

Table 1. Thin-layer drying models tested for moisture ratio values of jujube.

Model	Equation	Reference
Midilli et al.	$MR = exp\ (-kt^n) + bt$	Menges and Ertekin, (2005)
Newton	$MR = exp\ (-kt)$	O'Callaghan et al. (1971)
Page	$MR = exp\ (-kt^{\,n})$	Page, (1949)
Henderson and Pabis	$MR = a\ exp\ (-kt)$	Henderson and Pabis, (1969)
Logarithmic	$MR = a\ exp\ (-kt)+c$	Motevali et al., (2010)
Tow term	$MR= a\ exp\ (-k_0t) + b\ exp\ (-k_1t)$	Henderson, (1974)
Approximation of diffusion	$MR= a\ exp\ (-kt) + (1-a)\ exp\ (-kbt)$	Yaldiz et al., (2001);

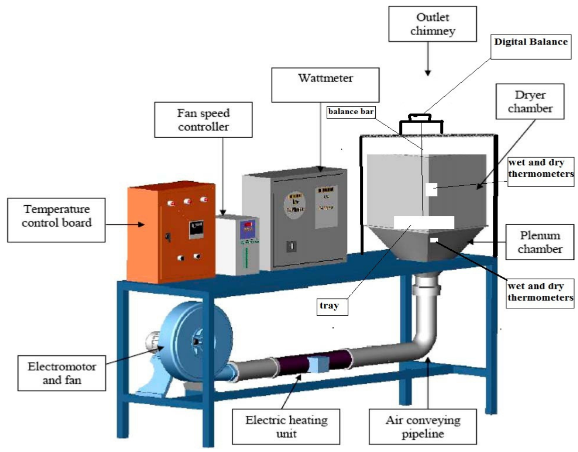

Fig 1. Schematic description of the laboratory equipment used for drying.

al., 2010; 2011a), mushroom slices (Motevali et al., 2011b) tropical fruits (Ceylan et al., 2007), apples (Sacilik and Konuralp Elicin, 2006), sesame hulls (Al-Mahasneh et al., 2007), sesame seeds, seedless grapes (Amiri Chayjan et al., 2011) and bell peppers, little information is available on medicinal fruits such as Jujube. Artificial neural networks (ANNs) have been successfully used to solve a wide variety of problems in science and engineering, particularly for some areas where the conventional modeling methods fail. A well-trained ANN can be used as a predictive model for a specific application, which is a data-processing system inspired by biological neural systems. The predictive ability of ANN models results from the training on experimental data and then validation using independent data. ANN has the ability to re-learn to improve its performance if new data are available (Hertz et al., 1991). ANN models can accommodate multiple input variables to predict multiple output variables. The prediction by a well-trained ANN is normally much faster and less complex compared to most of the conventional simulation methodologies or mathematical models. However, the selection of an appropriate neural network topology is important in terms of model accuracy and model simplicity. Prediction of heat and mass transfer in the drying process of mango and cassava has been achieved using neural networks (Hernandez-Perez et al., 2004). Erenturka et al. (2004) reported on the comparison of neural networks and regression analysis for the estimation of drying behavior of *Echinacea anguishfolia.* Neural networks as an approximation approach has also been used for the prediction of microwave-assisted drying process (Pedren et al., 2005), prediction of drying kinetics (Tomczak and Kaminski, 2001), solar drying performance (Tripathy and Kumar, 2009), Lasagnas angustifolia for commodities such as (Abbaszadeh et al., 2011), tomato drying (Movagharnejad and Nikzad, 2007) pomegranate arils (Motevali et al., 2010). The main objectives of this study were to investigate the drying behavior and to compare artificial neural network and mathematical models for the prediction of thin-layer drying of Jujube fruit in a hot air drier at various levels of air velocity and temperature.

Results and Discussion

Experimental results

Fig 3 shows how moisture ratio of jujube fruit decreased with increasing drying time under various drying conditions. It is clearly seen that jujube fruit most of its moisture within the first few minutes of drying while a long time is required to remove the remaining moisture. It is noteworthy that high air temperature and velocity led to higher moisture ratio at a reasonably shorter time. In drying of jujube by heated air, the time needed for conductive heating of the whole fruit to the evaporation temperature is long. This may be due to the low thermal conductivity of the fruit. In addition, the drying begins from the external fruit surface leading to hardening and lower permeability of the surface. The hardened layer then prevents moisture diffusion and prolongs moisture removal from the material. With increasing temperature, drying time decreases as a result of increase in thermal gradient inside the substance which consequently increases the drying rate. Also, by increasing the air velocity from 0.5 to 1.5 m/s, the drying time decreases significantly. This is because with increasing air velocity, the environment's vapor pressure decreases and therefore the product moisture would encounter less resistance on its way out and exits at a higher velocity (Fig-

Table 2. Statistical results obtained from various thin layer drying models correlation coefficients for v =0.5 m/s, at three temperatures

Temperature (°C)	50			60			70		
	R^2	RMSE	χ^2	R^2	RMSE	χ^2	R^2	RMSE	χ^2
Midilli et al.	0.9994	0.01317	0.000174	**0.9995**	**0.008187**	**6.7E-05**	0.9989	0.01025	0.000105
Newton	0.9991	0.01082	0.000117	0.9977	0.01525	0.000232	0.9952	0.02244	0.000503
Page	0.9986	0.01325	0.000176	0.9928	0.0284	0.000807	0.9952	0.02244	0.000503
Henderson and Pabis	0.9953	0.02302	0.000533	0.9951	0.02319	0.000538	0.9991	0.009493	9.01E-05
Logarithmic	0.9894	0.02747	0.000755	0.9944	0.02456	0.000604	0.9986	0.0114	0.00013
Tow term	0.9912	0.02548	0.000649	0.9942	0.0249	0.00062	0.9944	0.02421	0.000586
Approximation of diffusion	0.9958	0.01802	0.000325	0.9968	0.01816	0.00033	0.9961	0.01998	0.000399

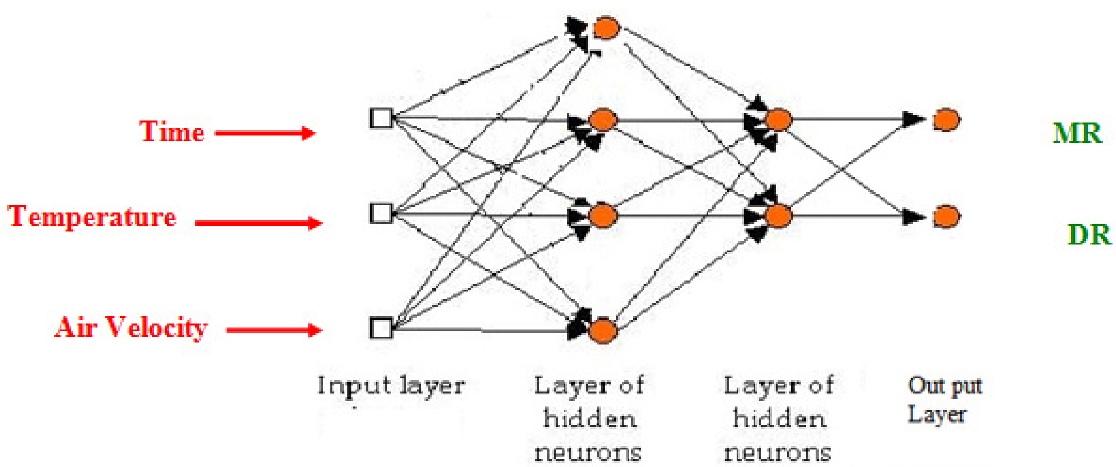

Fig 2. Configuration of multilayer neural network for predicting moisture ratio (MR) and drying rate (DR) of Jujube fruit.

3). These results resemble those reported by (Kostaropoulos and Saravacos, 2006; Tahmasebi et al., 2011; Zomorodian and Moradi, 2010; Motevali et al., 2010; Mousavi and Javan, 2009; Rafiee et al., 2009 a, b).

Model application

The results of fitting experimental data to the seven empirical models are given in Tables 2, 3 and 4. The best results R^2 of 0.9996, χ^2 of 2.61E-05 and RMSE of 0.005112 were obtained with the Midilli et al. model at 60 °C and 1 m/s. Validation of the selected model was established by comparing the experimental data, for the drying curve (at 60 °C and 1 m/s), with the values predicted by the Midilli et al. model and the results are plotted in Fig 4. The data points are banded around a 45° straight line, demonstrating the suitability of the model in describing the thin-layer drying behavior of the jujube fruit.

Artificial neural networks

Results of artificial neural network (ANN) modeling showed that the back propagation training algorithm was well suited for prediction of moisture ratio based on air velocities (0.5, 1 and 1.5 m/s) temperatures (50, 60 and 70 °C) and drying times. After evaluation of different trials, the optimal model was a four-layered back- propagation ANN, with 15 and 25 neurons in the first and the second hidden layers, respectively. Plot of values predicted by the ANN approach versus experimental data for the drying rate and moisture ratio are given in Fig 5 which indicates excellent agreement between the predicted and measured values. Accuracy of various proposed prediction models is tested through the comparison of predicted and experimental MR and DR values with the test pattern during the drying process. Fig 6 shows the results of analysis for moisture ratio and drying rate. It can be seen that the prediction model simulates the experiments satisfactorily for both moisture ratio and drying rate. Thus, neural network model can be used to determine moisture ratio and drying rate of Jujube fruit under dynamic drying conditions. Process control and its simulation in the field of drying technology has always been a challenging task for engineers due to the time-varying properties and non-linearity of the drying phenomena. The ANN approach is an attractive alternative to classical methods, providing a higher estimation power and making it possible to work in a wider range. The ANN model was able to predict moisture ratio quite well with R^2 values of 0.9997, 0.9993 and 0.9996 for training, validation and testing, respectively. Prediction mean square errors were obtained as 0.001, 0.0011 and 0.0013 for training, validation and testing, respectively. Summary of the evaluation of various ANN networks for yielding the best determination coefficient (R^2) and mean square error is given in Table 5. Also, the criteria for network performance evaluation are cited in Table 6. It can be seen that the determination coefficient is quite high for both drying rate and moisture ratio implying the desirability of ANN for prediction of drying kinetics of jujube fruit. The statistical results showed that R^2, MSE of

Table 3. Statistical results obtained from various thin layer drying models correlation coefficients for v =1 m/s, at three temperatures.

Temperature (°C)	50			60			70		
	R^2	RMSE	χ^2	R^2	RMSE	χ^2	R^2	RMSE	χ^2
Midilli et al.	0.9988	0.01138	0.000129	**0.9996**	**0.00605**	**3.66E-05**	0.9993	0.01039	0.000108
Newton	0.9976	0.0159	0.000254	0.9911	0.00573	3.29E-05	0.9967	0.01457	0.000212
Page	0.9971	0.0176	0.000311	0.9993	0.00867	7.52E-05	0.9962	0.01664	0.000277
Henderson and Pabis	0.9995	0.0068	5.03E-05	0.9932	0.00719	5.18E-05	0.9935	0.02089	0.000436
Logarithmic	0.9981	0.0056	3.2E-05	0.9941	0.00834	6.97E-05	0.9989	0.00950	9.03E-05
Tow term	0.9988	0.0113	0.000129	0.9912	0.00862	7.44E-05	0.9892	0.00670	4.49E-05
Approximation of diffusion	0.9988	0.0113	0.000129	0.9984	0.01333	0.000178	0.9903	0.00731	5.36E-05

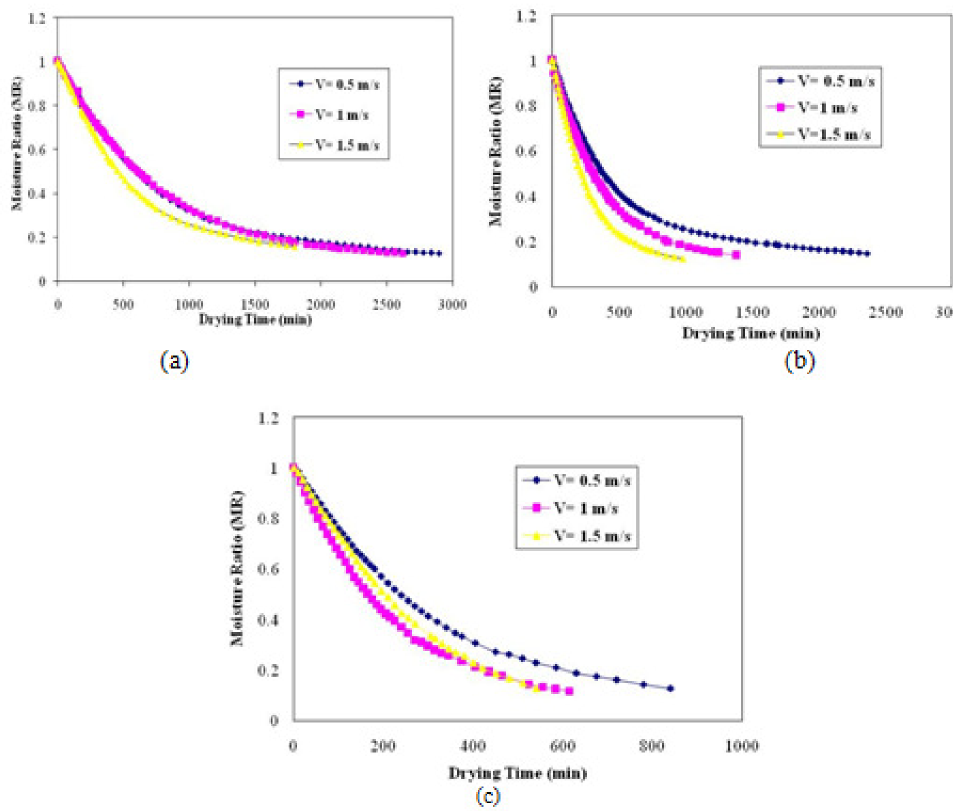

Fig 3. Dimensionless moisture ratio as a function of drying time for hot-air drying of Jujube fruit, (a) T=50 ºC, (b) T=60 ºC and (c) T=70 ºC.

the selected ANNs are highly applicable to predict for prediction of the drying kinetics. These values show a good trend during drying of Jujube because convection drying was able to maintain stable temperature and humidity at a constant rate over a period of time. This could be related to the increase in the resistance for heat and mass transfer in samples during drying. Similar results have been reported for other agricultural products (Motevali et al., 2010; Erenturka et al., 2004; Movagharnejad and Nikzad, 2007; Liu et al., 2007; Tripathy and Kumar, 2009). These results have shown that the indicators for goodness of fit of the proposed neural network model are better than the values obtained by the mathematical model (Compassion of Figs 4 and 5; Tables 3 and 5). Therefore, the proposed neural network model was selected to predict the thin-layer drying behavior of Jujube fruit.

Materials and methods

Drying conditions and experimental set up

A laboratory scale hot-air dryer developed at Agriculture Faculty, Tarbiat Modares University (Iran), was used for this study (Fig 1). The dryer consists of an adjustable centrifugal blower, electrical heating elements (1.5 kW), drying chamber, system controller, an inverter (Parto Sanat, Igbt and Co, Iran) and a sample tray. The dryer has an automatic temperature controller with an accuracy of ±0.1 °C (Pooyesh digital instruments, TMC 101, Iran). Using a vane probe anemometer, (Lutron AM-4204, Taiwan) air velocity was adjusted to the desired level with an accuracy of ±0.1m/s. Utilizing an inverter that directly acted on the blower motor (1.5 kW).

Table 4. Statistical results obtained from various thin layer drying models correlation coefficients for v =1.5 m/s, at three temperatures.

Temperature (°C)	50			60			70		
	R^2	RMSE	χ^2	R^2	RMSE	χ^2	R^2	RMSE	χ^2
Midilli et al.	**0.9995**	**0.005112**	**2.61E-05**	0.9953	0.004821	2.32E-05	0.9991	0.008776	0.000077
Newton	0.9901	0.004012	1.61E-05	0.9990	0.008384	7.03E-05	0.9962	0.005096	2.6E-05
Page	0.9922	0.02232	0.000498	0.9991	0.008058	6.49E-05	0.9991	0.009576	9.17E-05
Henderson and Pabis	0.9967	0.01394	0.000194	0.9917	0.004423	1.95E-05	0.9986	0.011591	0.000134
Logarithmic	0.9988	0.009041	8.17E-05	0.9988	0.009777	9.56E-05	0.9964	0.004664	2.18E-05
Tow term	0.9994	0.006298	0.000397	0.9971	0.014594	0.000213	0.9992	0.008975	8.05E-05
Approximation of diffusion	0.9991	0.007553	5.7E-05	0.9983	0.011613	0.000135	0.9985	0.01281	0.000164

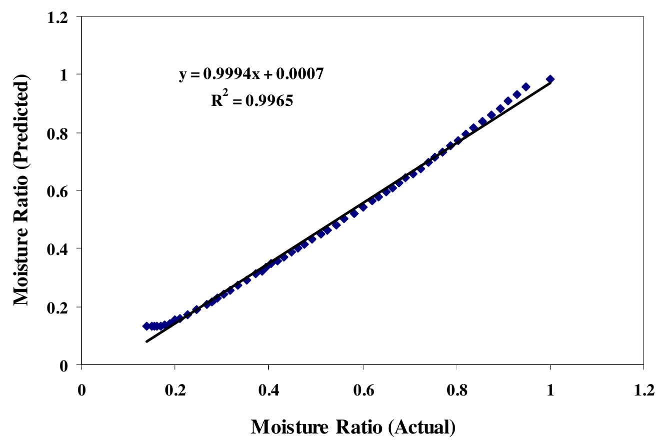

Fig 4. Comparison of experimental moisture ratio with predicted moisture ratio from the Midilli model.

Hot air moves vertically over and through the horizontal sample tray. Dried samples were manually weighed using an electronic balance with an accuracy of ±0.01 g, (AND GF-600, Japan). Weighing of the samples was continued until no change was observed between two consecutive measurements. Before starting each experiment, the dryer was turned on for 30 minutes in order to achieve the desirable steady-state conditions. Fresh samples were gathered from Farouj city, north Khorasan (north east of Iran) and were kept at +5 ºC in a refrigerator. The initial moisture content of Jujube was determined by oven drying method. Thirty-gram samples were dried in an oven at 105 $\pm$ 1 ºC (Doymaz, 2005). Moisture content of fresh Jujube was determined to be 62.5 % d.b based on mean of 5 repetitions. Experiments were conducted at three levels of temperature (50, 60 and 70 ºC) and three levels of hot air velocity (0.5, 1 and 1.5 m/s). Relative humidities and temperatures of the environment during the experiments were 30–37 % and 23 - 28 ºC, respectively.

Mathematical modeling of the drying curves

Experimental drying data were fitted to seven moisture ratio models including: Midilli et al., Newton, Page, Henderson and Pabis, logarithmic, tow-term and approximation of diffusion model (Table1). These models are generally derived by simplifying the general series solutions of Fick's second law and considering a direct relationship between the average water content and drying time (Doymaz, 2004). Moisture ratio of the jujube fruits during the drying experiments was calculated using Eq. (1):

$$MR = \frac{M_t - M_e}{M_o - M_e} \tag{1}$$

Values of moisture content measured during the experiments were fitted to the given models using *MATLAB* R2008a. Three criteria used to determine the best fit included the correlation coefficient (R^2), root mean square error (RMSE) and chi square (χ^2). Values of R^2, *RMSE* and χ^2 were calculated using the following equations:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(MR_{pred,i} - MR_{\exp,i})^2}{\sum_{i=1}^{N}(\overline{MR}_{pred} - MR_{\exp,i})^2} \tag{2}$$

$$RMSE = \left(\frac{1}{N}\sum_{i=1}^{N}(MR_{pre,i} - MR_{\exp,i})^2\right)^{\frac{1}{2}} \tag{3}$$

$$\chi^2 = \frac{\sum_{i=1}^{N}(MR_{\exp,i} - MR_{pre,i})^2}{N - m} \tag{4}$$

The best fit that could describe the thin-layer drying characteristics of jujube fruit was selected based on the

Table 5. Summary of the various networks evaluated to yield the best determination coefficient (R^2) and mean square error.

Activation function	Neurons in hidden layer1	Neurons in hidden layer2	Training error	R^2 (training)	R^2 (validation)	R^2 (test)	MSE (training)	MSE (validation)	MSE (test)	Epoch
Log/Tan	5	0	0.00157	0.9308	0.9001	0.9238	0.0016	0.0024	0.0006	28
Log/Tan	10	0	0.00746	0.8738	0.9541	0.9532	0.0011	0.0007	0.0008	37
Log/Tan	20	0	0.00484	0.9436	0.9950	0.9981	0.0005	0.0002	0.0003	63
Log/Tan	30	0	0.00553	0.8951	0.9924	0.9696	0.0057	0.0045	0.0082	29
Log/Tan	50	0	0.00209	0.8994	0.9947	0.2154	0.0021	0.0002	0.0173	13
Log/Tan/ Tan	5	5	0.00600	0.8927	0.9934	0.9900	0.0006	0.0002	0.0002	38
Log/Tan/ Tan	5	10	0.00145	0.9986	0.9982	0.9984	0.0018	0.0004	0.0006	33
Log/Tan/ Tan	10	20	0.00434	0.9965	0.9974	0.9931	0.0008	0.0018	0.0006	45
Log/Tan/ Tan	10	30	0.00085	0.9981	0.9974	0.9934	0.0013	0.0004	0.0012	36
Log/Tan/ Tan	20	20	0.00087	0.9989	0.9985	0.9986	0.0005	0.0003	0.0013	48
Log/Tan/ Tan	**15**	**25**	**0.00037**	**0.9997**	**0.9993**	**0.9996**	**0.0010**	**0.0011**	**0.0013**	**28**
Log/Tan/ Tan	25	30	0.00223	0.9986	0.9987	0.9987	0.0017	0.0012	0.0004	28
Log/Tan/ Tan	30	30	0.00171	0.9987	0.9997	0.9995	0.0010	0.0026	0.0029	43
Log/Tan/ Tan	40	25	0.00182	0.9994	0.9988	0.9967	0.0027	0.0054	0.0030	38
Log/Tan/ Tan	20	10	0.00082	0.999	0.9996	0.9991	0.0041	0.0010	0.0022	51
Log/Tan/ Tan	35	25	0.00223	0.9996	0.9997	0.9991	0.0070	0.0056	0.0072	62

Table 6. Summary of ANN networks evaluated to yield the criteria of network performance.

Activation function	Training rules	Neurons in hidden layer1	Neurons in hidden layer2	Training error	R^2 (training)	R^2 (validation)	R^2 (test)	Epoch
Log/Tan	Trainlm	20	0	0.00094	0.9436	0.9950	0.9981	63
Log/Tan	Traingdx	20	0	0.00234	0.8186	0.9382	0.8984	44
Log/Tan	Trainscg	20	0	0.00252	0.8065	0.9074	0.9331	30
Log/Tan	Trainrp	20	0	0.00967	0.7581	0.8374	0.8234	26
Log/Tan/ Tan	**Trainlm**	**15**	**25**	**0.00037**	**0.9997**	**0.9993**	**0.9996**	**28**
Log/Tan/ Tan	Traingdx	15	25	0.00341	0.8389	0.8185	0.8586	41
Log/Tan/ Tan	Trainscg	15	25	0.00261	0.8687	0.9099	0.9376	51
Log/Tan/ Tan	Trainrp	15	25	0.00284	0.7086	0.7587	0.8187	33

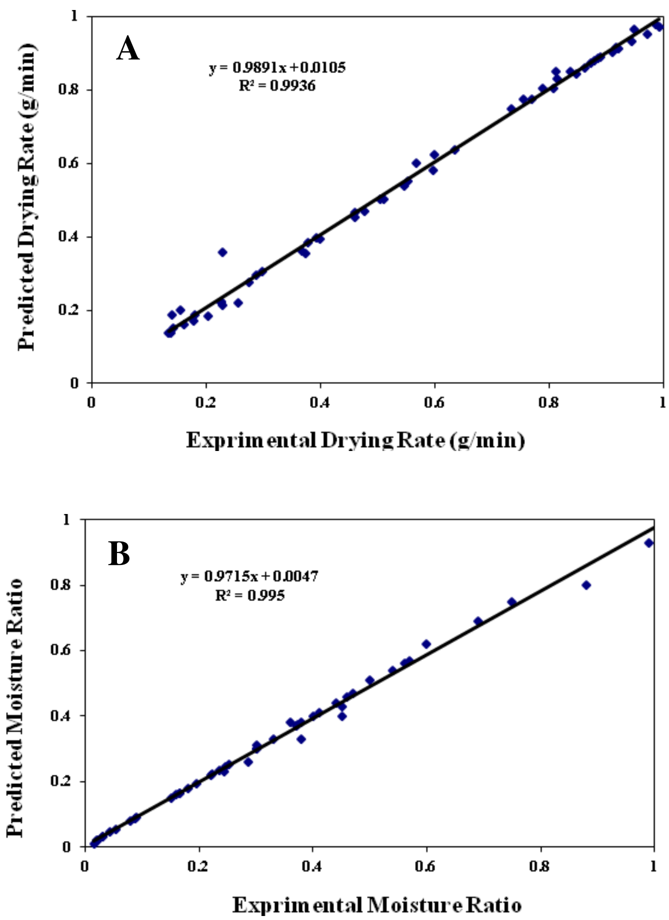

Fig 5. Correlation between the experimental data and the predicted values of the ANN model for prediction of A) drying rate (g/min) B) moisture ratio (%) .

highest value of the correlation coefficient (R^2), and the lowest values of *RMSE* and χ^2.

To account for the effect of the drying variables on the two-term model constants, the constants were regressed against drying air temperature and velocity, using multiple regression analysis. All possible combinations of the different drying variables were tested and was included in the regression analysis.

Neural network design

To obtain the best prediction by the network, several architectures were evaluated and trained using the experimental data. The back-propagation algorithm was utilized in training of all the ANN models. This algorithm uses the supervised training technique where the network weights and biases are initialized randomly at the beginning of the training phase. The error minimization process is achieved using a gradient descent rule. There were three inputs and two output parameters in this study. The three input variables included time (min), velocity (m/s), and temperature (°C). The two outputs for evaluating dryer performance were moisture ratio (MR) and drying rate (DR). Thus, the input layer consisted of 3 neurons and the output layer had 2 neurons. Schematic structure of the static ANNs utilized for predicting MR and DR values is shown in Fig 2. Several transfer functions including sigmoid, logarithmic and linear functions together with supervised training algorithms, and feed-forward back-propagation approach were evaluated. To ensure that each input variable provided an equal contribution to the ANN, the inputs of the model were preprocessed and scaled into a common numeric range [-1, 1]. The inputs of the model were preprocessed and normalized, after which, 60 and 25 % of input patterns were devoted to training and validation data sets, respectively. The remaining (15 %) of the data were utilized for verification. The learning rate of 0.2 and momentum of 0.1 were adjusted to all the tested networks. Optimum topologies were defined based on the highest R^2 and the lowest MSE values (Motevali et al., 2010).

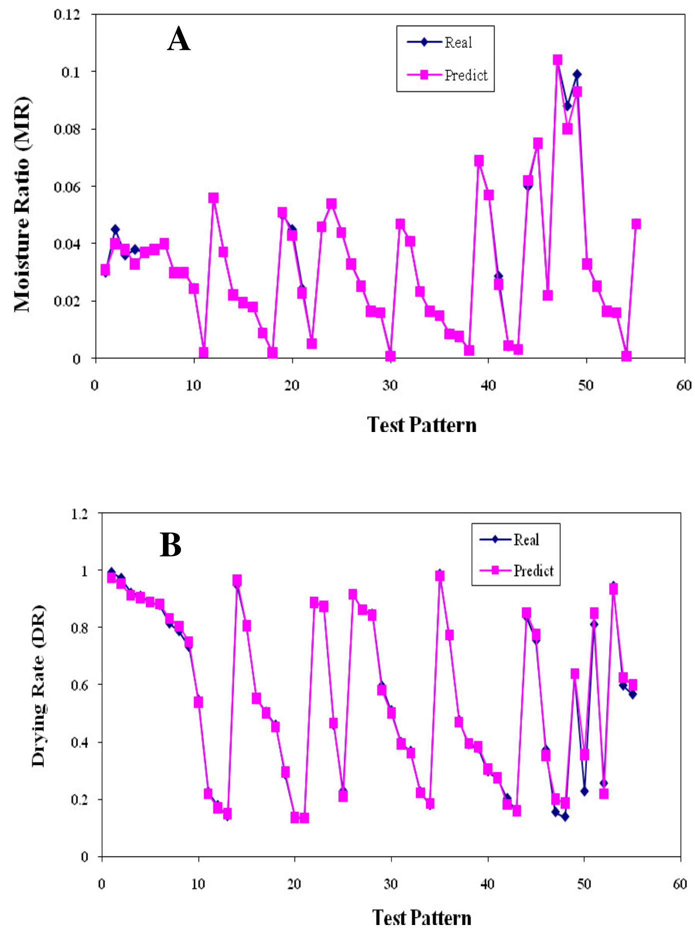

Fig 6. Comparison of experimental data and the ANN predictions for A) moisture ratio and B) drying rate.

The number of hidden layers and neurons within each layer can be designed based on the complexity of the problem and data set. In this study, the number of hidden layers varied from one to two. The activation function for the hidden layers was selected to be logarithmic (Log) while tangent (Tan) functions suited best for the output layer. This arrangement of functions in function approximation problems or modeling is common and yields better results (Motevali et al., 2010). However, many other networks with several functions and topologies were examined. Three criteria were employed to evaluate the networks and select the optimum one. The training and testing performance value (MSE) was chosen to be 0.00001 for all the ANNs. The complexity and size of the network was also important, so the smaller ANNs had the priority to be selected.

Finally, a regression analysis between the network response and the corresponding targets was performed to investigate the network response in more detail. Different training algorithms were also tested and finally Levenberg-Marquardt (LM) was selected. The neural network toolbox of MATLAB R2008a software was used for ANN design.

Conclusions

The following conclusions are drawn based on modeling of data obtained in convective drying of Jujube fruit:

1- Among the 7 mathematical models investigated, Midilli et al. model provided the best fit for the data, given the best goodness of fit indices (R^2, X^2, *RMSE*).

2- The ANN results were quite satisfactory, yielding R^2 values close to one, while mean square errors (MSE) were found to be very low.

3- The final selected model, 3-15-25-2 (3 neurons in input layer, 15 neurons in the hidden layer 1, 25 neurons in the hidden layer 2 and 2 neurons in the output layer), demonstrated learned the relationship between the input and output parameters.

4- Generally speaking, ANN proved to be a reliable alternative for jujube fruit thin-layer drying prediction owing to its generality and simplicity.

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