International Food Research Journal 18(4): 1321-1328 (2011)

Evaluation of thin-layer drying models and neural network for describing drying kinetics of *Lasagnas angustifolia* L.

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Abstract: The thin-layer drying behavior of *Elaeagnus angustifolia* in a laboratory scale hot-air dryer was examined. Drying characteristics of *Elaeagnus angustifolias* were determined using heated ambient air at temperatures of 50, 60 and 70°C and air velocities of 0.5, 1 and 1.5 m/s. To select a suitable drying curve, 6 thin-layer drying models were fitted to the experimental data. All the models were compared according to three statistical parameter; R^2, standard error of estimate (SSE) and root mean square error (RMSE). Using some of the experimental data, an ANN, trained by standard Back-Propagation algorithm, was developed to predict MR and DR values based on the three input variables (time, velocity and temperature). Different activation functions and several rules were used to assess percentage error between the desired and the predicted values. According to the results, a two-term drying model has better agreement with experiment. The effect of the drying air temperature and air velocity on the drying model constants and coefficients were also determined. Consequently, the estimating power of the new model was evaluated. The ANN model was able to predict the moisture ratio and drying rate quite well with coefficient of determination (R^2) of 0.9993, 0.9992 and 0.9996 for training, validation and testing, respectively. The prediction Mean Square Error was obtained as 0.00355, 0.00930 and 0.0016 for training, validation and testing, respectively.

Keywords: *Elaeagnus angustifolia*, thin-layer drying model, drying kinetics, neural network

Introduction

Elaeagnus angustifolia fruit is one of the horticultural products produced in the north east and west of Iran in an area of more than 2708.6 ha with an annual fresh production of 5443.45 tons and it is mostly supplied to the market in the dried form. The leaves and flowers of this plant are well-known for their use as diuretic and antipyretic in folk medicine. The analysis showed the occurrence of fructose and glucose in concentrations (w/w) of 32.62-34% and 23.37-34.60% (min-max), respectively (Ayaz *et al*., 1999). Drying of agricultural products has always been of great importance for the preservation of food by human beings. Ancient methods used the rays of the sun for the drying of agricultural products. The main advantages of sun drying are low capital and operating costs. However, this process has several disadvantages, such as undesirable changes in the quality of food products, a lack of control during the drying process, long drying times and contamination of the product, all of which necessitate the introduction of new technologies to the drying process (Raouzeos and Saravacos, 1986; Ertekin and Yaldiz, 2004). The objective of drying fruits is to reduce the moisture content to a level that allows safe storage over an extended period of time (Doymaz, 2004). Thin layer equations describe the drying phenomena in a unified way, regardless of the controlling mechanism. They have been used to estimate drying times of several products and to generalise drying curves (Midilli *et al*., 2002). Thin-layer drying refers to the grain drying process in which all grains are fully exposed to the drying air under constant drying conditions, i.e., at constant air temperature and humidity. All commercial flow dryers are designed on thin-layer drying principles. Thus, thin-layer drying simulation is the best criterion to model the food drying process (Chakraverty and Singh, 1988). 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) like Cobia (Amiza and Aishah, 2011), *Centella asiatica* (Mohd Zainol *et al*., 2009), Gooseberry powder (Thankitsunthorn *et al*., 2009), kiwifruits (Diamante *et al*., 2009), chilli (Wiriya *et al*., 2009), millet (Ojediran and Raji, 2010), banana (Prachayawarakorn *et al*., 2007), figs (Stamatios *et al*., 2006), pistachio nuts (Kashaninejad *et al*., 2008), pomegranate arils (Kingsly and Singh, 2007), tropical fruits (Ceylan *et al*., 2007), apple (Sacilik and Konuralp, 2006), sesame hulls (Al-Mahasneh *et al*., 2007) but little information is available on medicinal fruits such as the *Elaeagnus angustifolia* fruit.

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Prediction of heat and mass transfer in the drying process of mango and cassava was achieved using neural networks (Hernandez-Perez *et al*., 2004). Erenturka *et al*. (2004) reported on the comparison of neural networks and the regression analysis for the estimation of drying behavior of *Echinacea anguishfolia*. Neural networks as an approximation approach has been also used for the prediction of microwave-assisted drying process (Pedren *et al*., 2005), prediction of drying kinetics with neural networks (Tomczak and Kaminski, 2001), solar drying performance (Tripathy and Kumar, 2009) and tomato drying (Movagharnejad and Nikzad, 2007) pomegranate arils (Motevali *et al*., 2010). The objective of this study was to investigate the adaptability of a thin-layer drying model to *Elaeagnus angustifolia*, by choosing the best among six thin-layer drying equations and compare neural networks with the mathematical models for the prediction of thin-layer drying of *Elaeagnus angustifolia*.

Material and Methods

The experimental facility

A laboratory scale hot-air dryer developed at the Biophysical Properties Laboratory of Agriculture faculty, Tarbiat modares University (Iran), was used for this study. The essential parts of dryer system consists of an adjustable centrifugal blower, air heating chamber (1.5 kW), drying chamber, system controller, an inverter (Parto Sanat, Igbt and Co, Iran) and a tray sample. The dryer had an automatic temperature controller with an accuracy of ±0.1°C deviation. Air velocity was kept at previously mentioned values (0.5, 1 and 1.5 m/s) with an accuracy of ±0.1m/s using an Ljt lutrun AM-4204 (Taiwan) Vane probe anemometer. Air velocity was fixed by using an inverter that directly acted on the blower motor (1.5 kW). The hot air orientation on samples was vertical. The dried samples were manually weighted using an electronic balance having accuracy ±0.01 g, resolution 0.01 g and maximum capacity, 0.61 kg (AND GF-600, Japan). Samples used in the experiment were about 100 g in weight. During the drying process, experiments continued until the moisture content of the sample reached about 0.3 (kg water/kg dry matter). A temperature controller fixed the temperature of the air chamber at ±0.1°C model Poyesh digital instument, type TMC 101, (Iran). Before the start of any experiments, the dryer system was started in order to achieve desirable steady-state condition. Experiments were replicated three times.

Material preparation and drying conditions

Freshly harvested *Elaeagnus angustifolia* fruits were purchased from the local farms at Mayvan regin of North Khorasan municipality (Iran) and stored in the refrigerator at about +5°C for experiments. Generally, samples of uniform size were selected. Immature and spoiled *Elaeagnus angustifolias* were separated manually. The initial moisture content of the *Elaeagnus angustifolia* was determined by the oven drying method. About 50 g sample was placed in a pre-weighed box and was weighed again accurately to give the exact weight of sample. It was kept in hot air oven maintained at 105±1°C until the variations between two weighing intervals mass were within 0.04 g. At least five replicates of experiment were measured. The fresh *Elaeagnus angustifolias* used in this investigation had 24% (w.b) initial moisture content. The temperature level in the dryer was set constant at mean free-stream temperatures of 50, 60 and 70°C and regulated to ±1°C by means of the temperature controller. For each temperature, a drying test was performed with the air velocity at the measurement point set constant at 0.5, 1 and 1.5 m/s.

Mathematical modeling of the drying curves

Drying curves were fitted with six different moisture ratio models: the Newton, the Page, Henderson and Pabis, Logarithmic, Tow term and Approximation of diffusion model (Table 1). 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). The moisture ratio of the *Elaeagnus angustifolias* fruits during the drying experiments was found using Eq. (1):

$$\mathrm{MR}= \frac{M_t - M_e}{M_0 - M_e} \tag{1}$$

where MR is the moisture ratio (dimensionless), M_t is the moisture content at any time (kg water/kg dry solid), M_e is the equilibrium moisture content (kg water/kg dry solid) and M_0 is the initial moisture content (kg water/kg dry solid). Three criteria were used to determine best fit are correlation coefficient (R^2), root mean square error (RMSE) and standard error of estimate (SSE). R^2, RMSE and SSE were calculated using the following equations:

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

Table 1. Thin-layer drying models tested for moisture ratio values of *Elaeagnus angustifolia*

Model	Equation	Reference
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	$MR = a\exp(-kt) + c$	Yagcıoglu *et al.* (1999)
Tow term	$MR = a\exp(-k_o t) + b\exp(-k_1 t)$	Henderson (1974)
Approximation of diffusion	$MR = a\exp(-kt) + (1-a)\exp(-kbt)$	Yaldiz *et al.* (2001); Bakri and Hobani (2000)

$$RMSE = \left(\frac{1}{N}\cdot\sum_{i=1}^{N}(MR_{pred,i} - MR_{\exp,i})^2\right)^{1/2} \quad (3)$$

$$SSE = \left(\frac{\sum_{i=1}^{N}(MR_{pred,i} - MR_{\exp,i})^2}{N-n}\right)^{1/2} \quad (4)$$

where $MR_{\exp,i}$ is the ith experimental moisture ratio, $MR_{pred,i}$ is the ith predicted moisture ratio, N is the number observations and n the number of drying constants. The best fit that could describe the thin-layer drying characteristics of *Elaeagnus angustifolias* fruit was selected as the highest value of correlation coefficient (R^2), and the lowest value of RMSE and SSE. To account for the effect of the drying variables on the Tow 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 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 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 the experimental tests. The three input variables are time (in minute) temperature (°C) and velocity (m/s). The two outputs for evaluating dryer performance are MR and DR. Therefore the input layer consisted of 3 neurons and the output layer had 2 neurons (Figure 1).

Figure 5 shows the configuration of multilayer neural network for predicting MR (Moisture Ratio) and DR (Drying Rate). Tangent (Tan) function suited best for the output layer. This arrangement of functions in function approximation problems or modeling is common and yields better results. 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 (MSE) was chosen to be .00001 for all 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 (trainlm) was selected. The computer program MATLAB R2008a, neural network toolbox was used for ANN design.

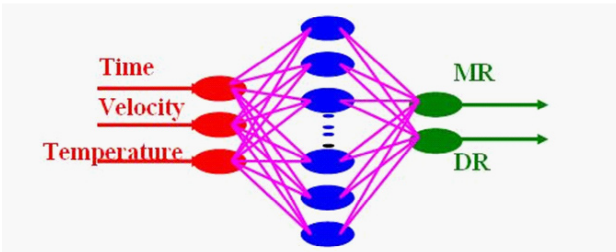

Figure 1. Configuration of multilayer neural network for predicting MR (Moisture Ratio) and DR (Drying Rate)

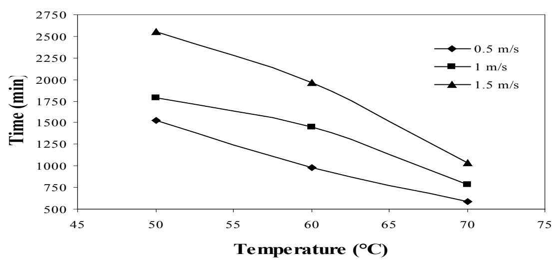

Figure 2. Drying air temperature vs. final drying time at different air velocities for thin-layer drying of *Elaeagnus angustifolia*

Results and Discussion

Drying curves

Figure 2 shows final drying time versus temperature at constant air velocity. It is evident that at high temperature levels, the difference between total drying times is lowest compared to low temperatures. Total drying time at 1.5 m/s is about 1.6 to 2 times longer compared with experiments performed at 0.5 m/s at constant air temperature, whereas increasing air velocity to 70°C resulted in 2.3–2.6 times larger drying time. In the other words, the effect of air temperature compared with air velocity is significant in total thin-layer drying time of *Elaeagnus angustifolia*. Figures 3 to 5 present the experimental data (moisture ratio vs. time) obtained for air at temperatures ranging from 50, 60 and 70°C, and flowing at a constant velocity of 0.5, 1 and 1.5 m/s. In all three figures, the best fitting curve is also included (as will be discussed later). The effect of increasing air temperature on the drying rate, while air velocity was kept constant, is evident. Moreover, it is proven that drying of *Elaeagnus angustifolia* fruit occurred in the falling rate phase.

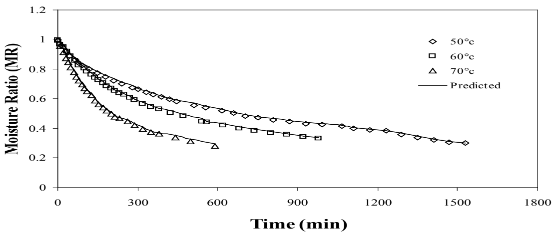

Figure 3. Drying curves (symbols) and approximation (lines) using the two-term model for different air temperature values when air velocity 0.5 m/s

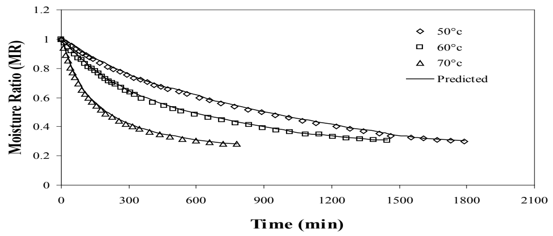

Figure 4. Drying curves (symbols) and approximation (lines) using the two-term model for different air temperature values when air velocity 1 m/s

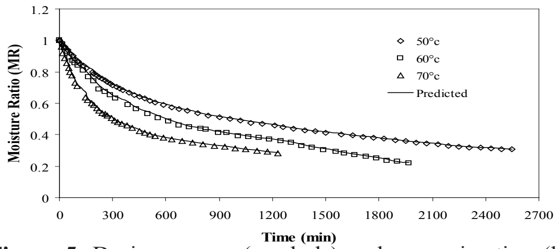

Figure 5. Drying curves (symbols) and approximation (lines) using the two-term model for different air temperature values when air velocity1.5 m/s

Analysis of data

The moisture ratio, *MR* of each experimental series was calculated. Non-linear regression analysis using MATLAB computer program was made for fitting the measured data (Moisture ratio and time) into six thin-layer drying models, displayed in Table 1. Tables 2–4 show the fitting results (R^2, RMSE and SSE) for the models listed in Table 1, using the experimental data, with the best-fitting model in bold type. The best model describing the thin-layer drying kinetics was selected with the highest R^2 average values, and the lowest RMSE and SSE average values. By comparing R^2, RMSE and SSE average values, it is clear that the Tow term model satisfactorily fits experimental data on drying kinetics observed in the falling rate period and has better agreement with the experiments. The Tow term model constants are reported in Table 5. In all of the experiments, R^2, RMSE and SSE values for the Tow term model were 0.9981–0.9999, 0.0021–0.0089 and 0.0003–0.0026, respectively.

The fitting procedure indicated that the results of the Tow term model could be used to model the drying behaviour of *Elaeagnus angustifolia* in single-layer, but it did not indicate the effects of temperature and velocity of drying air. To account for the effect of the drying variables on the Tow term model constant, k_0 and k_1 (h^{-1}) and the coefficients a and b (dimensionless), the values of k_0, k_1, a and b were regressed against those of the drying air, temperature T (°C) and velocity V (m/s) using multiply regression analysis, and the equation and related R^2 values are reported. Regression analyses for these parameters yielded the following relationships at the statistically significant level of 1%:

$$a = -0.062V + 0.007T \qquad R^2 = 0.96 \tag{5}$$

$$b = 0.0107V + 0.007T \qquad R^2 = 0.87 \tag{6}$$

$$k_0 = 0.001V + 6.5\times10^{-5}T \qquad R^2 = 0.83 \tag{7}$$

$$k_1 = -0.004V + 0.0001T \qquad R^2 = 0.73 \tag{8}$$

Consequently, the following equation was obtained for thin-layer drying of *Elaeagnus angustifolia* fruit:

$$MR(V,T,t) = \left(-0.062V + 0.007T\right)\times\exp\left(-\left(0.001V + 6.5\times10^{-5}T\right)t\right) + \left(0.0107V + 0.007T\right)\times\exp\left(-\left(-0.004V + 0.0001T\right)t\right) \tag{9}$$

Validation of the determined model was established by comparing the experimental data, for each drying curve, with the values predicted by the Two-term model and the results are plotted in Figure 6. 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 *Elaeagnus angustifolia* fruit.

$$MR_{pre} = 0.997MR_{\exp} + 0.0019 \qquad R^2 = 0.9982 \tag{10}$$

Table 2. Coefficient of determination for v =0.5 m/s, Varying T

Model	Temperature								
	50°C			60°C			70°C		
	R^2	RMSE	SSE	R^2	RMSE	SSE	R^2	RMSE	SSE
Newton	0.8893	0.0657	0.1553	0.9192	0.0564	0.1048	0.9315	0.0544	0.0798
Page	0.9982	0.0085	0.0025	0.9949	0.0144	0.0066	0.9904	0.0208	0.0112
Henderson and Pabis	0.9631	0.0385	0.0517	0.9607	0.0399	0.0509	0.9590	0.0429	0.0478
Logarithmic	0.9916	0.0186	0.0128	0.9987	0.0074	0.0017	0.9990	0.0067	0.0011
Tow term	**0.9981**	**0.0089**	**0.0026**	**0.9999**	**0.0025**	**0.0002**	**0.9997**	**0.0036**	**0.0003**
Approximation of diffusion	0.9979	0.0095	0.0032	0.9998	0.0029	0.0003	0.9997	0.0036	0.0003

Table 3. Coefficient of determination for v = 1 m/s, Varying T

Model	Temperature								
	50°C			60°C			70°C		
	R^2	RMSE	SSE	R^2	RMSE	SSE	R^2	RMSE	SSE
Newton	0.9827	0.0290	0.0345	0.9282	0.0548	0.1110	0.8134	0.0945	0.2411
Page	0.9994	0.0055	0.0012	0.9952	0.0143	0.0074	0.9846	0.0277	0.0199
Henderson and Pabis	0.9928	0.0189	0.0143	0.9671	0.0376	0.0509	0.9064	0.0682	0.1209
Logarithmic	0.9986	0.0084	0.0028	0.9987	0.0076	0.0020	0.9960	0.0144	0.0052
Tow term	**0.9996**	**0.0048**	**0.0009**	**0.9998**	**0.0027**	**0.0003**	**0.9995**	**0.0053**	**0.0007**
Approximation of diffusion	0.9996	0.0047	0.0009	0.9998	0.0033	0.0004	0.9986	0.0091	0.0033

Table 4. Coefficient of determination for v = 1.5 m/s, Varying T

Model	Temperature								
	50°C			60°C			70°C		
	R^2	RMSE	SSE	R^2	RMSE	SSE	R^2	RMSE	SSE
Newton	0.8618	0.0784	0.3874	0.9185	0.0595	0.1488	0.8587	0.1009	0.4075
Page	0.9951	0.0149	0.1380	0.9967	0.0121	0.0060	0.9829	0.0272	0.0289
Henderson and Pabis	0.9459	0.0494	0.1516	0.9667	0.0385	0.0608	0.9540	0.0709	0.1958
Logarithmic	0.9927	0.0183	0.0205	0.9921	0.0189	0.0143	0.9935	0.0170	0.0109
Tow term	**0.9999**	**0.0021**	**0.0003**	**0.9988**	**0.0075**	**0.0022**	**0.9994**	**0.0051**	**0.0009**
Approximation of diffusion	0.9999	0.0021	0.0004	0.9986	0.0091	0.0033	0.9992	0.0058	0.0013

Table 5. Regression analysis coefficients related to the Tow-term model for each experiment

Temperature	50°C	60°C	70°C
v = 0.5 m/s			
a	0.2422	0.4181	0.4477
K_0	0.006663	0.004877	0.007653
b	0.7415	0.5768	0.5543
K_1	0.000576	0.000582	0.000795
v = 1 m/s			
a	0.1512	0.4129	0.5177
K_0	0.004212	0.003788	0.009777
b	0.8494	0.5843	0.4743
K_1	0.000611	0.000483	0.000733
v = 1.5 m/s			
a	0.3421	0.2618	0.4782
K_0	0.003543	0.004512	0.007239
b	0.6556	0.7343	0.5110
K_1	0.000308	0.000409	0.000497

The residuals plot, seen in Fig.7, was also used to evaluate the selected model. Chen and Morey (1989) and Xanthopoulos *et al*. (2007) stated that data points in a plot of the residuals versus predicted values should tend to fall in a horizontal band centered on zero line, displaying no systematic tendencies toward a clear pattern. Therefore, plotting the residuals against the predicted values of dimensionless moisture ratio, Fig. 6, there were no systematic patterns. The proximity of residuals around zero line shows the sufficiency of the derived model.

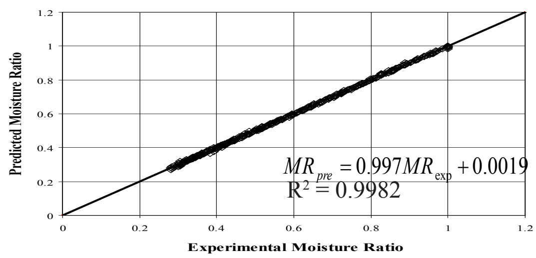

Figure 6. Comparison of experimental moisture ratio with predicted moisture ratio from the Two-term exponential mode for *Elaeagnus angustifolia* fruit

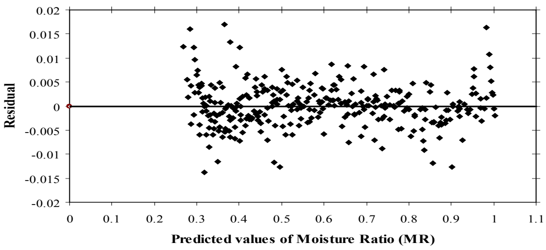

Figure 7. Residuals versus predicted values of moisture ratio derived by multiple

Results of artificial neural network modelling

An artificial neural network (ANN) was developed based on the experimental work. Results showed that Back Propagation training algorithm was well suited for prediction of Moisture Ratio and Drying Rate based on different time, velocity and temperature levels. Performance diagram of the ANN model is shown in Figure 8. Predicted versus experimental values for the studied parameters are indicated in Figure 9. This figs show the results of analysis for drying rate and moisture ratio respectively. As can be seen, all the investigated prediction models simulate the experiments satisfactorily for both moisture ratio and drying rate. The developed network had a good generalization in predicting the quality of the mushroom slice from the drying process. Thus, this network model could be used to determine the moisture ratio and drying rate of the agriculture product under the dynamic drying system. ANN predictions for the (B) *MR* and, (A) DR yield coefficient of determination (R^2) of 0.9993, 0.9992 and 0.9996 for training, validation and testing, respectively (Table 6). Prediction Mean Square Error (MSE) values of 0.00355, 0.00930 and 0.0016 were obtained for training, validation and testing, respectively (Table 7).

Conclusions

The conducted regression analysis based on non-linear regression methods, tested six thin-layer drying models' capability to efficiently simulate convective drying of *Elaeagnus angustifolia* for the experimental data obtained when *Elaeagnus angustifolias* were dried in the range of mean air temperatures of 50-70°C and air velocity values from 0.5 m/s to 1.5 m/s in a laboratory scale hot-air dryer. It is found that the drying curves of fresh *Elaeagnus angustifolia* fruit demonstrated the falling rate period. Compared with the effect of air velocity, the effect of temperature was significant on the drying time for fresh *Elaeagnus angustifolia* fruits; on the other hand, by increasing air velocity at constant air temperature, the drying time increased. Regression coefficients for all models were calculated and assessed in terms of fitting performance. The final selected model, 3-30-20-2 (3 neurons in input layer, 30 neuron in hidden layer 1, 20 neuron in hidden layer 2 and 2 neurons in output layer), successfully learned the relationship between input and output parameters. The ANN results are

Table 6. Summary of the various ANN networks evaluated to yield the best coefficient of determination (R^2)

Activation function	Neurons in hidden layer1	Neurons in hidden layer2	Training error	R^2 (training)	R^2 (validation)	R^2 (test)	Epoch
Log/Tan	10	0	0.007801	0.9961	0.9967	0.9979	84
Log/Tan	20	0	0.004541	0.9960	0.9918	0.9941	42
Log/Tan	30	0	0.004537	0.9939	0.9901	0.9941	24
Log/Tan	50	0	0.006545	0.9966	0.9968	0.9975	41
Log/Tan	10	10	0.005351	0.9948	0.9944	0.9875	21
Log/Tan	10	15	0.006801	0.9993	0.9984	0.9993	41
Log/Tan	15	25	0.001721	0.9871	0.9968	0.9958	35
Log/Tan	**30**	**20**	**0.000928**	**0.9993**	**0.9992**	**0.9996**	**24**
Log/Tan	50	40	0.004042	0.9991	0.9994	0.999	29
Log/Tan	10	20	0.002954	0.9994	0.999	0.9981	32
Log/Tan	15	25	0.003263	0.991	0.9988	0.9998	41
Log/Tan	25	40	0.001259	0.9988	0.9983	0.9993	27
Log/Tan	10	30	0.002371	0.9995	0.9986	0.9996	38
Log/Tan	35	20	0.009208	0.9998	0.999	0.9943	31

Table 7. Summary of ANN networks evaluated to yield the best Mean Square Error

Activation function	Neurons in hidden layer1	Neurons in hidden layer2	Training error	MSE (training)	MSE (validation)	MSE (test)	Epoch
Log/Tan	10	0	0.007801	0.0076	0.0034	0.0016	84
Log/Tan	20	0	0.004541	0.0045	0.0099	0.0112	42
Log/Tan	30	0	0.004537	0.0045	0.0144	0.0040	24
Log/Tan	50	0	0.006545	0.0053	0.0074	0.0010	41
Log/Tan	10	10	0.005351	0.0054	0.0121	0.0055	21
Log/Tan	10	15	0.006801	0.00353	0.00258	0.0008	41
Log/Tan	15	25	0.001721	0.00732	0.00149	0.0038	35
Log/Tan	**30**	**20**	**0.000928**	**0.00355**	**0.00930**	**0.0016**	**24**
Log/Tan	50	40	0.004042	0.00056	0.00758	0.0035	29
Log/Tan	10	20	0.002954	0.00125	0.00326	0.0009	32
Log/Tan	15	25	0.003263	0.00549	0.00567	0.0023	41
Log/Tan	25	40	0.001259	0.0012	0.00817	0.0029	27
Log/Tan	10	30	0.002371	0.00237	0.00122	0.0023	38
Log/Tan	35	20	0.009208	0.0077	0.00713	0.0027	31

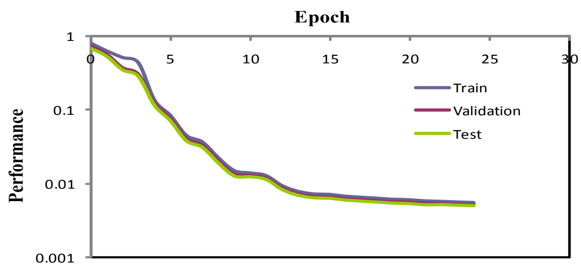

Figure 8. Training error curve

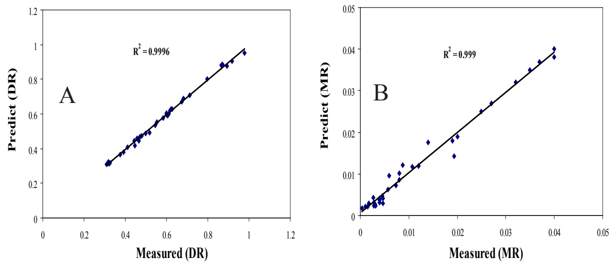

Figure 9. Correlation between the experimental data and the predicted values of the ANN model for prediction of: (A) Drying Rate (g/min) and (B) Moisture Ratio (%)

quite satisfactory in a way that R^2 values are close to one, while mean square errors (MSE) were found to be very low. Analysis of the experimental data by the ANN revealed that there is a good correlation between the ANN-predicted results and the experimental data. Generally speaking, ANN proved to be a reliable alternative for *Elaeagnus angustifolias* thin-layer drying prediction due to generality and simplicity.

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