Int. Agrophysics, 2007, 21, 335-348

INTERNATIONAL
Agrophysics
www.international-agrophysics.org

Modeling of thin-layer drying kinetics of sesame seeds: mathematical and neural networks modeling**

J. Khazaei[1]* *and S. Daneshmandi*[2]

[1]Department of Agricultural Technical Engineering, University College of Aburaihan, University of Tehran, Tehran, Iran
[2]Islamic Azad University of Fasa, Fasa, Iran

Received June 13, 2006; accepted October 29, 2007

A b s t r a c t. Natural drying characteristics of sesame seeds (SS) were investigated under indoor conditions with both forced convection (FC) and natural convection (NC) of air. The drying kinetics of SS was characterized in terms of effective diffusion coefficient and resistance to diffusion. For the FC method, seeds were dried at a constant air velocity of 1.1 m s^{-1} and air temperature and relative humidity in the range of 25-29°C and 35-40%, respectively. For the NC method, air temperature and relative humidity were in the range of 32-36 and 30-35%, respectively. Six thin-layer drying models, namely, Khazaei, Peleg, Page, Handerson and Pabis, logarithmic, and Weibull, were fitted to drying data. Modelling the correlation between moisture ratio with drying time and drying method was also carried out using artificial neural networks (ANN).

SS of average initial moisture content of around 50.8% (d.b.) were dried to the final moisture content of about 3.0-3.7% (d.b.) until no further changes in their mass were observed. The drying of sesame seeds took place in the falling rate period. During the FC experiments, the time to reach the final moisture content of 3% was found to be 400 min. The same moisture content of sesame seeds was found to achieve its equilibrium moisture content (3.7%) after 900 min when seeds were dried using the NC method. Thus, the FC drying times were around 55% shorter than the NC drying times.

In the FC and NC drying methods, the drying rates of sesame seeds at the very beginning times of drying were equal to 22.47 and 6.9 (g H_2O kg^{-1} dry matter min^{-1}), respectively. The effective water diffusion coefficients of SS under FC and NC conditions were 3.1×10^{-11} and 1.1×10^{-11} m^2 s^{-1}, respectively. Corresponding values for overall resistance to diffusion were 70.8×10^5 and 19.6×10^6 m^2 s kg^{-1}, respectively.

The results showed that the Khazaei model gave better fit than the other five models. The Peleg and logarithmic models also had an acceptable accuracy in predicting the drying kinetics of SS. The ANN technology was shown to be a useful tool for predicting the moisture ratio of SS as a function of drying method and drying time. The optimal ANN model was found to be a 2-6-3-1 structure with hyperbolic tangent transfer function. This optimal model was capable of predicting the moisture ratio with R^2 higher than 0.998, RMSE of less than 0.0192 and MRE about 2.63%. It was concluded that ANN represented SS drying characteristics better than the mathematical models.

K e y w o r d s: sesame seed, natural drying, neural network, mathematical modelling

INTRODUCTION

Sesame (*Sesamum indicum* L.) is one of the oldest cultivated plants in the world. Sesame is harvested either for the whole seed used in baking, for confectionery purposes, cake, and flour, or for cooking-oil extraction. Sesame seed contains approximately 45% by weight of oil, compared to 20% of seed weight for soybeans, and 25% protein. It is a good source of essential amino acids and minerals. It is also consumed for its medicinal qualities.

Dehulling has always been a major problem for the sesame industry and a variety of solutions have been sought. The dehulling process, no matter what the method, always involves wetting the seed to loosen and remove hulls from the seed. Dehulled seed is then washed and dried to produce a premium bakery and confectionary product.

Since sesame seeds (SS) are more sensitive to high drying temperature, seeds are dried naturally indoor, with either natural or forced convection air. Natural drying is a well-known, popular, and inexpensive method to reduce the moisture contents of agricultural products, which prevents deterioration within a period of time regarded as the safe storage period.

*Corresponding author's e-mail: jkhazaei@ut.ac.ir
**This work was supported by the University of Tehran, Rresearch Project No. 7301021/1/04.

No paper was found in the literature on the drying characteristics of SS. The availability of such information is relevant for understanding the drying process of the SS. Also, effective design of drying and storage systems for SS needs knowledge of their drying kinetics. They determine the end point to which the seeds must be dried in order to achieve a stable product with optimal moisture content, and yield a figure for the theoretical minimum amount of energy required to remove a given amount of water from the seeds.

One of the most important aspects of drying technology, especially for industrial processes, is modelling of the drying processes. The purpose of modelling is to allow the engineers to choose the most appropriate method of drying for a given product as well as to choose suitable operating conditions. Full-scale experimentation for different products and system configurations is sometimes costly and not possible. And so, the prediction of drying kinetics of specific crops under various conditions is very useful in the design and optimisation of dryers. The use of a simulation model is also a valuable tool for prediction of performance of drying systems.

Nomenclature	
A	dimensionless drying constant
B	dimensionless drying constant
D_e	effective water diffusivity, (m^2s^{-1})
D_o	constant equivalent to diffusivity at infinitely high temperature, (m^2s^{-1})
E_a	activation energy, (kJ mol^{-1})
K	drying rate constant (1 min^{-1})
K_1	page rate constant (min/% d.b.)
K_2	page capacity constant (1/% d.b.)
M_t	moisture content at any time of drying (% d.b.)
Mr	moisture ratio
M_e	final moisture content, (% d.b.)
M_o	initial moisture content, (% d.b.)
$Mr_{M,i}$	ith measured moisture ratio
$Mr_{P,i}$	ith predicted moisture ratio
n	dimensionless drying constant
N	number of observations
R^2	coefficients of determination
R_e	equivalent radius of seeds being dried, (mm)
R_{ds}	resistance to diffusion, (m^2 s kg^{-1})
t	drying time (min)
T	drying temperature (°C)
W_o	initial weight of the product (g)
W_t	weight of the product to be dried at any time (g)
Abbreviations	
ANN	artificial neural networks
SS	sesame seeds

Thin-layer drying models can be categorized as theoretical, semi-theoretical, and empirical models. The most widely studied theoretical model in thin layer drying of various foods is given by solution of Fick second law. The Fick law in spherical coordinates can be expressed as (Crank, 1975):

$$\frac{\partial M}{\partial t} = \frac{\partial}{\partial r}\left(D_e \frac{\partial M}{\partial r}\right). \tag{1}$$

General series solution of the Fick second law in spherical coordinates with the assumptions of moisture migration being by diffusion, negligible shrinkage, and constant diffusion and temperature is given as follows (Crank, 1975; Kashaninejad *et al.,* 2007):

$$\frac{M_t - M_e}{M_o - M_e} = \frac{6}{\pi^2} \sum_{n=1}^{\infty} \frac{1}{n^2} \exp\left[-\frac{n^2 \pi^2 D_e t}{R_e^2}\right]. \tag{2}$$

Drying of many food products, such as amaranth grain (Resio *et al.,* 2004), wheat (Gaston *et al*., 2004), chestnuts (Guine and Fernandes, 2006), hull-less seed pumpkin (Sacilik, 2007), and pistachio nuts (Kashaninejad *et al.,* 2007) has been successfully predicted using Fick second law.

Some semi-theoretical drying models that have been widely used in the literature are presented in form of models, namely: the Page, the Henderson and Pabis, and the Logarithmic models (Table 1). These models have been widely used to model drying of different agricultural products (Akpinar *et al.,* 2006; Gunhan *et al.,* 2005; Midilli and Kucuk, 2003; Togrul and Pehlivan, 2004; Yaldiz and Ertekin, 2001). In these models the term of moisture ratio, *Mr*, is usually expressed as:

$$M_r = \frac{M_t - M_e}{M_o - M_e}. \tag{3}$$

The Weibull distribution function, which is an empirical model, describes the process as a sequence of probabilistic events. This model is able to describe the behaviour of

Table 1. Mathematical models applied to the drying curves of the sesame seeds

Model name	Model	Eq.
Page	$M_r = Exp(-Kt^n)$	(4)
Henderson and Pabis	$M_r = AExp(-Kt)$	(5)
Logarithmic	$M_r = AExp(-Kt) + C$	(6)
Weibull	$M_r = Exp(-(\frac{t}{\beta})^{\alpha})$	(7)

systems or events that have some degree of variability, such as drying, water absorption, and soluble solids losses during hydration of grains and dried fruits (Machado *et al.,* 1999; Marabi *et al.,* 2004). Typically, the Weibull distribution is described by two parameters: the scale parameter, β which is related to the reciprocal of the process rate constant, and the shape parameter, α. When $\alpha = 1$, the Weibull distribution reduces to 1st order kinetics (Machado *et al.,* 1999). As theoretical models are complex and cumbersome, sometimes researchers have been interested to use simple empirical and semi-empirical models to fit drying data of food materials.

The Peleg model (Peleg, 1988) is also a simple empirical model that has been used successfully to describe the drying behaviour of agricultural products (Sopade and Kaimur, 1999). The linearized form of the Peleg equation to regress the moisture content versus drying time is as follows (Sopade and Kaimur, 1999; Turhan *et al.,* 2002):

$$M - M_o = -\frac{t}{K_1 + K_2 t} . \tag{8}$$

The drying rate (R) can be obtained from first derivative of the Peleg equation as follows (Turhan *et al.,* 2002):

$$R = \frac{dM}{dt} = -\frac{K_1}{\left(K_1 + K_2 t\right)^2} . \tag{9}$$

The Peleg rate constant K_1 relates to drying rate at the very beginning times of drying (R_o) *ie* $t \rightarrow 0$ min:

$$R_o = \left(\frac{dM}{dt}\right)_{t=0} = -\frac{1}{K_1} . \tag{10}$$

Although all the above models have been successful in explaining the drying kinetics of agricultural products, they are just related to drying time and do not include the interaction effect of other related parameters. Thus, it is important to researchers to find a model that incorporates a large number of variables. However, the relationships between drying kinetics and related variables are almost always very complicated and highly non-linear, which makes developing a single, general, and accurate mathematical model almost impossible. This problem can be overcome by using the soft computing methods same as artificial neural networks.

Khazaei model

Drying behaviour, like viscoelastic properties of food products, is a time-dependent behaviour (Mohsenin, 1986). Therefore, it is possible to model these two different properties of agricultural materials with the same model as follows:

$$M_t = M_o - M_{rel}(1 - e^{-t/T_{rel}}) - K_{rel} t . \tag{11}$$

In this model, time of retardation, T_{rel}, is the time required to reach the moisture content of seeds to about 63% of the total removed moisture, M_{ret} (Fig. 1). In other words, T_{ret} shows the rate of drying of seeds in the first phase of the process. The highest amount of this term shows the higher rate of drying in the first phase of the process. Also the K_{rel} shows the rate of drying in the relaxation phase and is calculated with determining the slope of the tangent line on the end part of graph (Fig. 1).

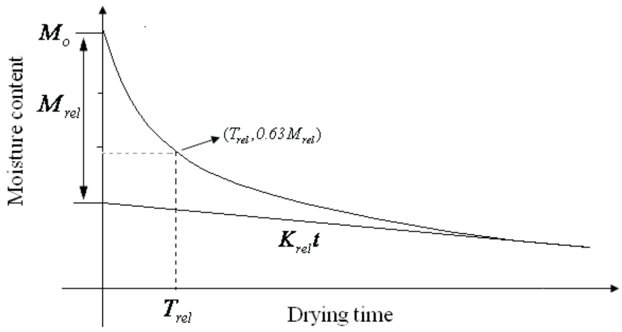


Fig 1. Graphical method to determine the constant parameters in Khazaei model (Eq. (11)).

The advantage of this model over the empirical and semi-empirical models is the ability to determine all of the parameters directly from drying curves (Fig. 1). The other benefit of this model in respect with other drying models is its ability to describe the second phase of drying (relaxation phase). The empirical and semi-empirical models are able just to describe the drying behaviour in the initial times of the process (first phase).

This model, in the form of moisture ratio, may presented as follows:

$$M_r = \frac{M_t - M_s}{M_o - M_s} = 1 - \frac{M_{ret}}{M_o - M_s}\left(1 - e^{-t/T_{ret}}\right) - \frac{K_{rel}}{M_o - M_s} t , \tag{12}$$

$$M_r = A + Be^{-t/T_{rel}} - Ct = A + Be^{-bt} - Ct . \tag{13}$$

METHODOLOGY OF ANN MODELLING

An artificial neural network (ANN) is a computer program capable of learning from examples through iteration, without requiring prior knowledge of the relationships between process and product parameters (Chegini *et al.,* 2007). This technique has been successfully applied to the prediction of drying kinetics of seeds, vegetables, and fruits (Erenturk and Erenturk, 2007; Farkas *et al.,* 2000; Kaminski *et al.,* 1998; Satish and Setty, 2005).

The best example of a neural network is probably the human brain. In fact, the human brain is the most complex and powerful structure known today. Artificial neural networks are composed of simple elements operating in parallel (Razmi-Rad *et al.,* 2007). These elements are inspired by biological nervous systems. The unit element of an ANN is the neuron (node). As in nature, the network function is determined largely by the connections between the neurons (Tsoukalas and Uhrig, 1997).

Figure 2 illustrates how information is processed through a single node. The node receives weighted signals from other nodes through its incoming connections. First, these are added (summation function). The result is then passed through an activation function, the outcome being the activation of the node. For each of the outgoing connections, this activation value is multiplied with the specific weight and transferred to the next neuron (Chegini *et al.,* 2007; Kalogirou, 2000).

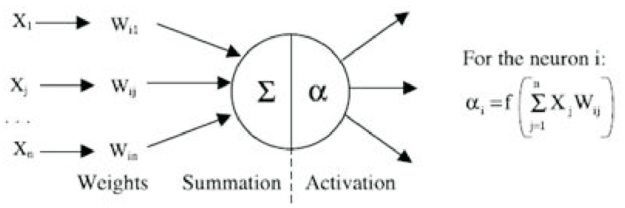


Fig. 2. Information processing in an artificial neural network unit.

The ANN modelling is carried out in two steps; the first step is to train the network whereas the second is to test the network with data which were not used for training. It is important that all the information the network needs to learn is supplied to the network as a data set. The training data set is used for the training of the network, usually by suitable adaptation of synaptic weights. Indeed, the knowledge obtained during training phase is not stored as equations or in a knowledge base, but is distributed throughout the network in the form of connection weights between neurons (Mittal and Zhang, 2000).

A training data set is a group of matched input and output patterns. Each pattern may be represented as (X_1, X_2 ...., X_m, Y_1, ..., Y_n) where X and Y represent independent and dependent variables, respectively, and n and m are the number of independent and dependent variables, respectively. The outputs are the dependent variables that the network produces for the corresponding input. When each pattern is read, the network uses the input data to produce an output which is then compared to the training pattern *ie* the correct or desired output. If there is a difference, the connection weights (usually, but not always) are altered in such a direction that the error is decreased. After the network has run through all the input patterns, if the error is still greater than the maximum desired tolerance, the ANN runs through all the input patterns repeatedly until all the errors are within the required tolerance. When the training reaches a satisfactory level, the network holds the weights constant and the trained network can be used to make decisions, identify patterns, or define associations in new input data sets not used to train it (Chegini *et al.,* 2007; Kalogirou, 2000). A learning rule defines how the network weights should be adjusted between each training cycle (epoch). One of the most frequently used training algorithms is the back-propagation paradigm (BP).

The specific objectives of this study were to:

- determine the natural drying kinetics of sesame seeds under both natural convection and forced convection air,
- mathematical modelling of thin layer drying of sesame seeds,
- develop an ANN model for the prediction of moisture ratio of sesame seeds as a function of drying time and drying method,
- compare the performance of the ANN model with that for the mathematical models.

MATERIALS AND METHODS

Sample preparation

The sesame seeds (SS) used in this study were obtained from a local market in Pakdast, Iran. The seeds contained 56.87% crude fat, 23.04% crude protein, 13.25% carbohydrate, 3.52% ash and 3.4% moisture. The seeds were cleaned by manually removing all foreign matter such as stones, dirt and broken seeds. The initial moisture content of the seeds was determined using the ASAE standard oven method (ASAE, 1997) and was found to be 3.5% (d.b.).

Physical properties of sesame seeds

The size of randomly selected 100 seeds was determined from the principal dimensions. For each seed, the length, width and thickness were measured using a micrometer gauge reading to 0.001 mm. The geometric mean diameter (G_{md}) and sphericity (Φ) of sesame seeds were calculated by using the following relationships (Altuntas *et al.*, 2005):

$$G_{md} = (LWT)^{1/3}, \tag{14}$$

$$\Phi = \frac{G_{md}}{L}. \tag{15}$$

The surface area of the seeds was found by analogy with a sphere of the same geometric mean diameter, using the expression cited by Altuntas *et al.* (2005) and Tunde-Akintunde and Akintunde (2004):

$$S = \pi G_{md}{}^2 \tag{16}$$

To evaluate 100 seed mass, seven samples, each of 100 seeds, were picked at random and weighed using a balance with a precision of 0.001 g and the average reading was taken (Mwithiga and Sifuna, 2006). The volume to surface area ratio (V/S) of the sesame seeds was calculated using the expression cited by Verma and Prasad (1999):

$$\frac{V}{S} = \frac{\pi G_{md}^3}{6S} = \frac{G_{md}}{6}\phi. \tag{17}$$

The true density (ρ_k) of SS was determined by the toluene displacement method (Demir *et al*., 2002). Bulk density (ρ_b) of SS was determined by filling the grains in a cylinder of known volume (200 cm^3) and weighing in an electronic balance. The bulk density was then calculated from the mass and volume. The porosity was calculated using the following equation (Mwithiga and Sifuna, 2006):

$$\varepsilon = \frac{\rho_k - \rho_b}{\rho_k} 100 . \tag{18}$$

All the physical properties of the sesame seeds were investigated at moisture content of 3.5% (d.b.).

Experimental set-up

The tests were conducted to study the thin-layer drying characteristics of sesame seeds (SS) under indoor drying conditions with both natural and forced convection air. The drying experiments were performed during July and August, 2005, in Pakdasht, Iran, with minimum and maximum air temperatures of around 32 and 36°C over a one day drying cycle with relatively low air humidity which never exceed 40%.

Wet samples of SS used in the drying tests were prepared by soaking the seeds in distilled water (T = 25°C) for about 6 h to reach 50.8% (d.b.) moisture content. The wet samples of the seeds were then dried under indoor drying with both natural convection (NC) and forced convection (FC) air. A schematic diagram of the experimental set-up is shown in Fig. 3. Wire mesh trays of 150 mm in diameter and 70 mm in depth were used to place the seed samples on. The trays were placed at a reasonable height above a high steel frame to ensure a reasonable level of air circulation under and around the SS.

During the FC drying experiments, the mean values of temperature and the relative humidity of air ranged from 25 to 29°C and from 35 to 40%, respectively. Corresponding values for the NC drying experiments were in the range of 32 to 36°C and 30 to 35%, respectively.

The air temperatures, relative humidity, and air velocity just above the sample bed surface were measured during the experiments. The air velocity was measured using a digital anemometer (TESTO, 405-VI, Taipei, Taiwan) with a measurement range of 0-15 m s^{-1}. In all FC drying tests, the air velocity just above the samples bed was constant and was equal to 1.1 m s^{-1}. A thermo-hygrometer (Extech 444731, Shenzhen, China) was used to measure air temperature and relative humidity.

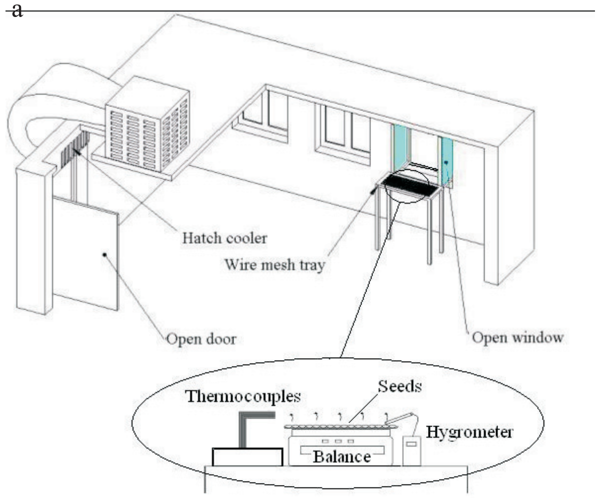
Experimental procedure

For each drying test, a sample of 30 g of moist seeds was evenly spread on the wire mesh baskets as thin-layer with a thickness of approximately 0.4 cm. The moisture content loss of the samples was accomplished by periodical weighing of the mass, using a digital balance, having an accuracy of 0.01 g. Seed samples were weighed at various time intervals, ranging from 5 min at the beginning of the drying to 80 min during the last stage of the process. The instantaneous moisture content on dry basis (M_t) was calculated from the following equation (El-Sebaii *et al*., 2002):

$$M_t = \left[\frac{(M_o + 1)W_t}{W_o} - 1\right] 100 \,(\%\mathrm{d.b.}) . \tag{19}$$

The drying process was continued until no further change in their mass was observed. Each experiment was replicated three times and the average values were used for analysis.

a



b

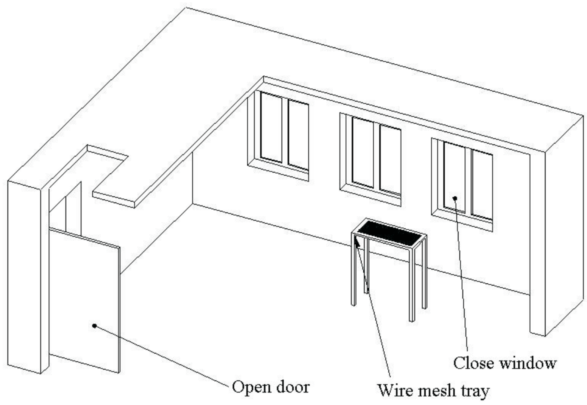


Fig. 3. Flow diagram of indoor natural drying of sesame seeds: a) forced convection air and, b) natural convection air.

Mathematical modelling

For both the FC and NC drying methods, the moisture content data were converted to the most useful moisture ratio expression and then curve fitting computations with the drying time were done by using the drying models in Table 1. In this study, the moisture ratio *Mr* was simplified to M_t / M_o instead of Eq. (3). Previous studies have shown that if the values of the equilibrium moisture content (M_e) be relatively small compared to M_o, *Mr* may be reduced to M_t / M_o (Akpinar *et al.,* 2006; Doymaz, 2006; Gunhan *et al.,* 2005; Midilli and Kucuk, 2003; Togrul and Pehlivan, 2003).

The parameters of the mathematical models were estimated using a non-linear regression procedure performed using the SigmaPlot software (SigmaPlot 6.0 scientific graphing software from SPSS Inc., Chicago). The suitability of the models was evaluated and compared using the coefficient of determination, R^2, and root mean square error, RMSE (Sacilik *et al.,* 2006):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (M_{r\,M,i} - M_{r\,p,i})^2}{N}} \,. \tag{20}$$

The higher values for R^2 and the lower value for RMSE the better the goodness of fit (Akpinar, *et al.,* 2006; Togrul and Pehlivan, 2003; Yaldiz and Ertekin, 2001).

In this study, the Khazaei and Peleg models (Eqs (7) and (11)) were also used to regress the moisture content versus drying time. For this matter, the moisture content data were converted to the $M\text{-}M_o$ expression and then curve fitting computations with the drying time were done by using the SigmaPlot software to find the constants of the models.

Neural networks model development

Using the drying tests, a total of 32 patterns was obtained, each with 3 components (X_1, X_2, Y_1), which were used for training and testing the neural networks. Two of the components were the input variables, drying method and drying time, whereas the last component was the output variable representing the moisture ratio (Fig. 4). The 32 patterns were randomly divided into 22 and 10 data sets for the training and testing of the neural networks, respectively.

A supervised artificial neural network (ANN) trained by back-propagation algorithms was developed to predict moisture ratio based on the two input variables. The back-propagation algorithm was implemented using the ANN Toolbox of the MATLAB computer-aided design software (The MathWorks Inc., Natick, MA).

Three steps were used to select an optimal ANN model. The first step was to determine the best number of hidden layers, number of neurons in each hidden layer, and activation function. The best four models were selected based on training and prediction accuracy. The second step was to work with these four selected models to find optimum epoch size. The third step was to find optimum learning rate and momentum of the ANN. Once a given neural network was trained using the appropriate training dataset, its performance was then evaluated using the appropriate testing dataset. This is very important to avoid over-training the system.

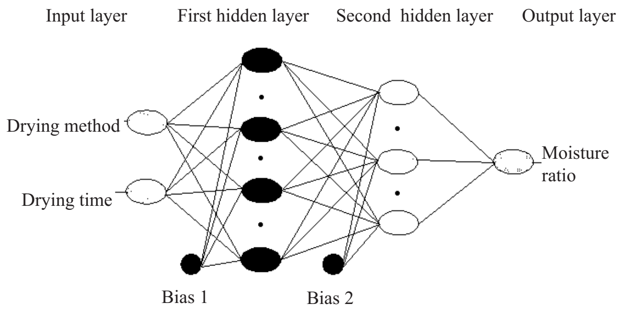


Fig. 4. ANN model used for sesame moisture ratio prediction.

The performance of the various ANN configurations was compared using the coefficient of determination (R^2) and RMSE (Eq. (20)). The final network was selected on the basis of the lowest error on train and test sets of data.

In one- and two-layer networks, the number of hidden neurons varied from 0 to 20 with a step of 3. Three forms of activation function were also tried for each structure: sigmoid, linear, and hyperbolic tangent.

RESULTS AND DISCUSSION

Physical properties

The dimensional properties of sesame seeds are given in Table 2. The length of the seeds ranged from 2.61 to 3.77 mm, width ranged from 1.4 to 2.05 mm, and thickness ranged from 0.66 to 1.01 mm. The geometric mean diameter ranged from 1.42 to 1.91 mm, while the sphericity of the seeds ranged from 0.45 to 0.59. The relationships between length, width, thickness and geometric mean diameter are given by the following equation:

$$L = 1.788W = 3.76T = 1.886G_{md} \,. \tag{21}$$

The sesame seeds used in this study had a true density of 1230-1234 kg m^{-3}. The mean value of volume to surface area ratio (V/S) of single seed was found to be 2.8x10^{-4} m from Eq. (17). Based on the equivalent dimensions given in Table 2, the mean value of surface area per unit mass (specific surface area) of the seeds was equal to 2.74 mm^2 mg^{-1}. The physical properties of the sesame seeds used in this study are in general agreement with those reported by Tunde-Akintunde and Akintunde (2004).

Drying characteristics

The drying curves for thin layer drying of sesame seeds under indoor drying with both natural convection (NC) and forced convection (FC) conditions are shown in Fig. 5. The SS of average initial moisture content of around 50.8%(d.b.) were dried to the final moisture content of about 3-3.7% (d.b.) until no further changes in their mass were observed. It is evident from these curves that the moisture content decreased continuously with the drying time. It can be seen that the drying curve consists of an initial fast reduction in moisture (first phase) followed by a constant drying rate period (relaxation phase). As expected, the drying method had a significant effect on the moisture content of the samples. During the FC experiments, the time to reach the final moisture content of 3% was found to be 400 min. The same moisture content of sesame seeds was found to achieve its equilibrium moisture content (3.7%) after 900 min when seeds were dried using the NC method. Thus, the FC drying times were around 55% shorter than the NC air drying times.

Moisture content data versus drying time were fitted into Khazaei and Peleg model (Eqs (7) and (11)) for both NC and FC drying methods. Table 3 presents the results of non-linear regression analysis of fitting the two models to the experimental data and comparison criteria used to evaluate goodness of fit namely, R^2 and RMSE. Both Khazaei and Peleg models provided an excellent fit to the experimental data with a value for R^2 of greater than 0.996, indicating a good fit. The values of RMSE obtained from the two models were less than 1.08, which is in the acceptable range. However, the values for RMSE obtained from the Khazaei model were significantly lower than those attained from the Peleg model. Hence, the Khazaei model was considered the best model in the present study to represent the natural drying behaviour of sesame seeds. Figure 5 suggests the experimental moisture contents fitted with the Khazaei and Peleg model for both NC and FC drying conditions. It can be seen from these curves there was a good conformity between experimental and predicted moisture content data.

Moisture content evolution in time is the first indication of how and to what extent the drying process is going on. It is used as an element of comparison. The drying rate, dM/dt, as a function of time or moisture content, is also an important parameter. The changes in the drying rates of sesame seeds versus moisture content are shown in Fig. 6. It is apparent that drying rate decreased continuously with improving drying time. The results indicated that diffusion was the most likely physical mechanism governing moisture movement in the SS samples. The results were generally in agreement with some literature studies on drying of various food products (Doymaz, 2006; Lahsasni *et al.,* 2004; Togrul and Pehlivan, 2004).

In Fig. 6, the drying rate data at the very beginning times of drying *ie* at t = 0 min were determined from the Peleg model (Eq. (9)). Peleg drying rate constant K_1 is a constant

T a b l e 2. Some physical characteristics of sesame seeds

Parameter	Mean	Min	Max	SD*
Length (mm)	3.14	2.61	3.77	0.20
Width (mm)	1.76	1.4	2.05	0.11
Thickness (mm)	0.84	0.66	1.01	0.07
Geometric mean dia (mm)	1.67	1.42	1.91	0.09
Sphericity (%)	0.53	0.45	0.59	0.02
Mass of 100 seeds (g)	0.275	0.143	0.296	0.02
Surface area (mm^2)	8.77	6.41	11.50	0.95
Volume of a single seed (mm^3)	2.47	1.54	3.69	0.39
Volume per unit surface area (mm^3 mm^{-2})	0.28	0.24	0.32	0.01
Bulk density (kg m^{-3})	577	575	579	1.30
True density (kg m^{-3})	1231	1230	1234	2.40
Porosity (%)	53.1	53.0	53.2	0.01

*Standard deviation

T a b l e 3. Parameter estimation and curve fitting criteria for the Khazaei and Peleg models for the thin layer natural drying of sesame seeds

Model	Drying method	Parameters				R^2	RMSE
		M_o (% d.b.)	M_{rel} (% d.b.)	T_{rel} (min)	K_{rel} (% d.b. min^{-1})		
Khazaei	FC	50.8	43.861	26.18	0.0113	0.9993	0.011
	NC	50.8	43.799	84.746	0.0041	0.9996	0.008
Peleg		K_1 (% d.b. min^{-1})		K_2 (% d.b. min^{-1})			
	FC	0.445		0.0193		0.996	1.02
	NC	1.444		0.0188		0.996	1.08

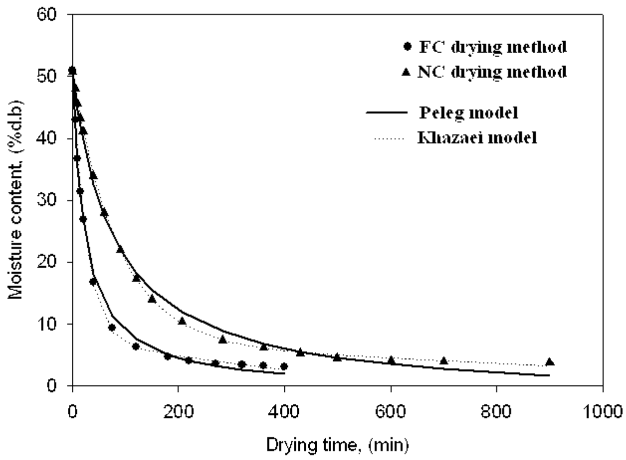


Fig. 5. Comparison of the thin layer drying characteristics of sesame seeds in drying by FC and NC methods.

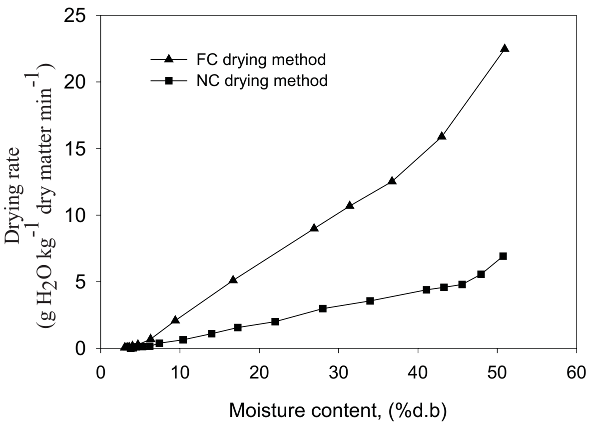


Fig. 6. Variation of the drying rate of the sesame seeds versus moisture content.

related to mass transfer rate eg the lower the K_1, the higher the initial drying rate. The SS dried using FC and NC methods exhibited a statistically significant difference in K_1 (Table 3). The drying rate of SS dried by FC and NC methods at the very beginning times of drying were equal to 22.47 and 6.9 (g H_2O kg^{-1} dry matter min^{-1}), respectively. According to Eq. (22), the mean drying rates of SS dried by the FC and NC methods were equal to 1.2 and 0.5 (g H_2O kg^{-1} dry matter min^{-1}), respectively.

$$\text{Mean drying rate} = \frac{M_e - M_o}{\text{Total drying time}}. \qquad (22)$$

As indicated in Fig. 6, there is no constant drying rate period in the drying of SS and the two drying operations are seen to occur in the falling rate period. During the falling rate period, the drying rate decreases continuously with decreasing moisture content and increasing drying time. In the falling rate period the material surface is no longer saturated with water and drying rate is controlled by diffusion of moisture from the interior of the seeds to the surface (Diamante and Munro, 1993). These results are in agreement with the observations of earlier researchers of other seeds and grains (Doymaz, 2006; Ece and Cihan, 1993; Sacilik, 2007).

According to Fig. 5, free water dries during a first short period and subsequently intermolecular water dries during longer periods. At the beginning of the drying, free water was available and the rate of drying was controlled by free water on the surface or outer layers of seeds. The drying rate then decreased lower than the first stage of the drying period. At this stage, water was no longer free; water in the seeds was held by molecular adsorption and capillary condensation. It can, therefore, be considered a diffusion-controlled process in which the rate of moisture removal is limited by diffusion of moisture from inside to the surface of the product. Previous studies have also shown that the drying of biological material is a diffusion-controlled process and may be represented well by Fick law.

As expected, the rate of drying of sesame seeds under the FC drying method was much higher than that at the NC method (Fig. 6). It can be seen from Fig. 6 that the influence of drying conditions on drying rate is markedly higher when the moisture is higher. At moisture content of less than 7% (d.b.) there is no difference in the drying rates between the two drying methods, indicating the significance of internal resistance to mass transfer at low water content in the material.

Calculation of effective diffusivity of sesame seeds

Fick second law of diffusion was used to calculate the effective water diffusivity of sesame seeds under FC and NC drying conditions. There are three different forms of Fick equation that depend on the shape of the product being dried. Crank (1975) gave analytical solutions of Eq. (1) for various regularly shaped bodies such as rectangular, cylindrical, and spherical. Therefore, Fick second law is expressed in three basic coordinate systems: Cartesian, cylindrical, and spherical, which corresponds to the following cases: an infinite plate exposed to drying, an infinite cylinder, and a sphere. In this study, although sesame seed appears to be flat material, but since the seed thickness/width ratio (0.48) is not small enough to neglect diffusion through the edge surfaces, so the seeds used in the drying tests cannot be supposed to be flat material. Hence, an analytical solution for a sphere was chosen as the starting point to be used in determining the diffusion coefficients of sesame seeds (Eq. (2)). Other researchers have also reported similar assumptions for white rice and wheat kernels (Kang and Delwiche, 2000; Steffe and Singh, 1980).

For long drying periods, the Fick second law equation (Eq. (2)) can be further simplified to only the first term of the series and the moisture ratio Mr was reduced to M_t/M_o

because M_e was relatively small compared to M_t and M_o (Doymaz, 2006). Then, Eq. (2) can be written in logarithmic form of:

$$\ln\frac{M_t}{M_o}=\ln\frac{6}{\pi^2}-\left(\frac{\pi^2 D_e t}{R_e^2}\right). \quad (23)$$

The diffusion coefficient can be calculated from the slope of the left-hand side of Eq. (23) versus time (Fig. 7). It is expected that a plot of $\ln(M_r)$ versus drying time gives a straight line with a slope of (Kashaninejad *et al.,* 2007):

$$\text{Slope}=-\frac{\pi^2 D_e}{R_e^2}. \quad (24)$$

It is evident from Fig. 7 that Eq. (23) is valid for $\ln(M_r)<-1.3$ ($M_r<0.3$) and not in the practical range of drying of high moisture seeds. Then, the complete series of the Fick second law equation (Eq. (2)) would be required for this work, but this includes numerous shortcomings previously listed by Giner and Mascheroni (2001). Marquez *et al*. (2006) have also reported similar limitations of Eq. (23) for drying of rose hip fruits.

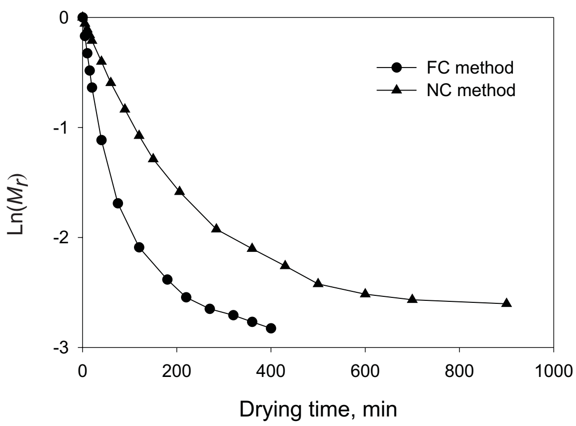


Fig. 7. Comparison of $\ln(M_r)$ versus drying time for sesame seeds.

In spite of this limitation, the diffusion coefficient of many grains and fruits such as amaranth, wheat, chestnuts, hull-less seed pumpkin, pistachio nuts, and black grapes have been successfully predicted using this simplified form of Fick second law, Eq. (23), (Doymaz, 2006 ; Gaston *et al.*, 2004; Guine and Fernandes, 2006; Kashaninejad *et al.,* 2007; Resio *et al.,* 2004 ; Sacilik, 2007).

The mean equivalent radius of sesame seeds was determined as equal to 0.84 mm (Table 2). The calculated values of effective diffusion coefficient, D_e, of sesame seeds for the FC and NC drying conditions were 3.1×10^{-11} and 1.1×10^{-11} m^2 s^{-1}, respectively. The value of D_e for the FC drying method was 2.8-fold higher than that for the NC method. The values of D_e lay in general within the range of 10^{-11} to 10^{-9} m^2 s^{-1} for food materials dried using the conventional and solar drying methods (Doymaz, 2006).

During the falling rate period and with continuous decrease of the drying rate, there also appears resistance to water vapour diffusion. The overall resistance to diffusion, R_{ds}, is characterized by the following equation (Toure and Nkembo, 2004):

$$\ln(M_r)=-\frac{S}{mR_{ds}}t, \quad (25)$$

where: R_{ds} is the overall resistance to diffusion (m^2 s kg^{-1}). From Eq. (25), the resistance to diffusion can be determined by the slope of the straight line obtained by plotting the experimental data from ln (M_r) as a function of drying time (Fig. 7). The overall resistance to diffusion of sesame seeds dried by the FC and NC drying methods was calculated as equal to 70.8×10^5 and 19.6×10^6 m^2 s kg^{-1}, respectively. As expected, the drying method had a significant effect on resistance to diffusion.

Mathematical models for fitting drying curves

The results of statistical analyses undertaken for the Page, Handerson and Pabis, logarithmic, and Weibull models are given in Table 4. The best model describing the thin layer drying characteristics of sesame seeds was chosen as the one with the highest R^2 value and the lowest RMSE value. The proposed models gave R^2 values greater than 0.958. Comparison of R^2 and RMSE values of the four models showed that the logarithmic model gave better fit than the other models. Figures 8 and 9 show the experimental and predicted moisture ratios with the four models versus drying time for the two drying methods.

The shape parameter (α) of the Weibull model is a behaviour index that depends on the process mechanism and the higher its value the slower is the process in the initial phase (Cunha *et al.,* 1998; Machado *et al.,* 1999). Like the effective diffusion coefficient, the shape parameter (α) of the Weibull model showed a great difference for the two drying methods. Indeed, the reciprocals of K_1 in the Peleg model and α in Weibull model could be compared to the effective diffusion coefficient of the diffusion models since those three parameters are the kinetic constants for each model.

The scale parameter β of the Weibull model is also an important parameter. As discussed by Hahn and Shapiro (1967), Nelson (1969), and Gacula and Kubala (1975), β defines the time needed to accomplish approximately 63% of the process, like the T_{rel} parameter in the Khazaei model. The mean values of T_{rel} parameter of the Khazaei model determined for the FC and NC drying methods were 26.18 and 84.746 min, respectively. Corresponding values for the scale parameter β of the Weibull model were 56.43 and 148.68 min, respectively. In general, T_{rel} and β parameters are indicators of the drying rate in the first phase of drying. According to the T_{rel} and β values in Tables 3 and 4, it can be found that the time needed to dry sesame seeds using the NC method was about 2.6 times higher than that for the FC method.

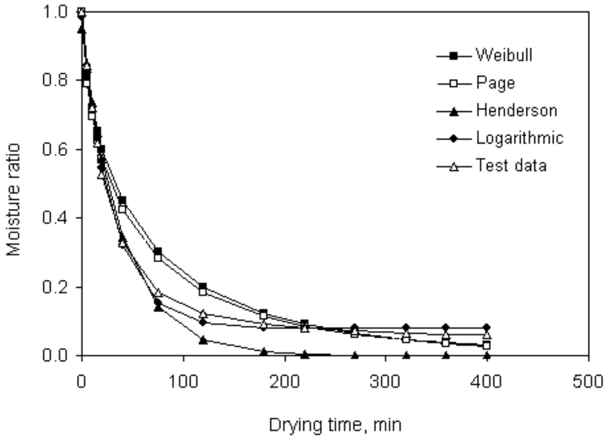


Fig. 8. Variation of moisture ratios versus drying time for sesame seeds being dried using FC method.

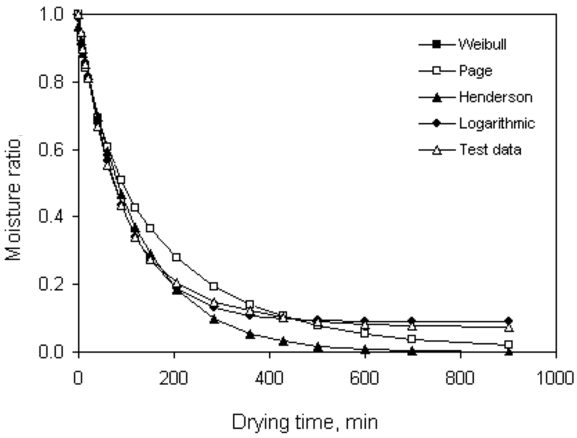


Fig. 9. Variation of moisture ratios versus drying time for sesame seeds being dried using NC method.

Of all the models tested, namely: Khazaei, Peleg, Page, Handerson and Pabis, logarithmic, and Weibull, the Khazaei model gave better predictions than the others, and satisfactorily described the thin-layer drying characteristics of sesame seeds. The Khazaei model offered the lowest value for RMSE, followed by the logarithmic and the Peleg model.

Neural networks modelling

In this study, an ANN model was developed to predict the moisture ratio of sesame seeds based on the drying time and drying method. The training error associated with different one- and two-hidden layer ANN configurations is presented in Fig. 10. It is evident that the learning ability of the two-hidden layer networks was significantly higher than that for one-hidden layer. This indicates that increasing the number of hidden layers increased the learning capability of the networks. Also, the number of neurons in each hidden layer had a significant effect on learning performance of the ANN models. The number of neurons within each hidden layer can be varied based on the complexity of the problem and data set. However, a well trained ANN model is the key to build an ANN model to be able to predict outputs precisely.

Among the various structures, models of good training performance were produced by the 2-13-9-1 (RMSE of 0.0120), 2-15-5-1 (RMSE of 0.0132), 2-6-3-1 (RMSE of 0.0165), and 2-12-3-1 (RMSE of 0.0179) structures with hyperbolic tangent transfer function in the hidden and output layers. Indeed, a well-trained ANN model is the key to design and analysis of the input and output relations.

In order to avoid possible over-training, the primary aim is to obtain an ANN model with a minimal dimension and minimum errors in training and testing. In this study, the most suitable ANN to correlate the moisture ratio with

T a b l e 4. Parameter estimation (R^2) and RMSE of the four drying models for natural drying of sesame seeds

Model	R^2	RMSE $x10^{-2}$
	FC method	
Page (K=0.0877, n=0.6183)	0.958	4.7
Henderson and Pabis (A=0.9514, K=0.0255)	0.968	5.5
Logarithmic (A=0.9042, K=0.0331, C=0.0788)	0.997	1.6
Weibull (α = 0.6444, β = 56.43)	0.963	5.6
	NC method	
Page (K=0.0217, n=0.7661)	0.974	4.6
Henderson and Pabis (A=0.9611, K=0.0080)	0.979	4.8
Logarithmic (A=0.8996, K=0.0106, C=0.0881)	0.999	0.9
Weibull (α = 0.7661, β = 148.68)	0.974	4.6

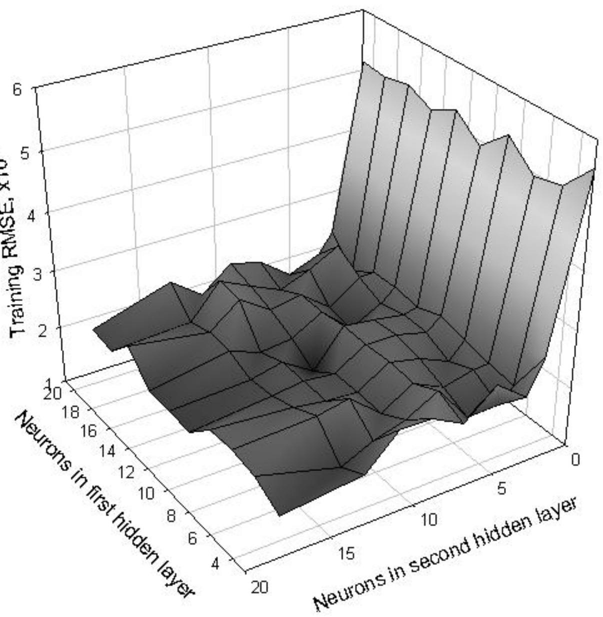


Fig. 10. Learning ability of ANN as a function of number of hidden layers and number of neurons within each hidden layer (with hyperbolic tangent transfer function).

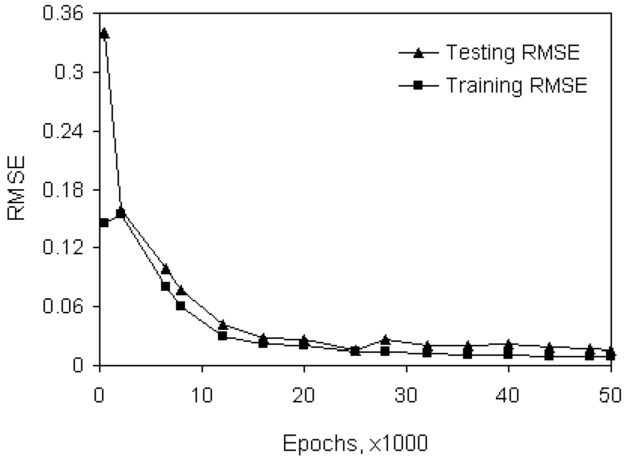


Fig. 11. Convergence of the RMSE during training of the final selected ANN.

drying time and drying method was selected as 2-6-3-1. For this structure, the best combinations of the ANN parameters that were used for predicting the moisture ratio are shown in Table 5. These results confirm that given sufficient hidden units, multi-layer feed-forward network architectures can approximate virtually any function of interest to any desired degree of accuracy.

Figure 11 shows the RMS error is represented as a function of the number of epochs for the final structure, 2-6-3-1. As can be seen, the training of the model was successfully accomplished. The error on training data generally decreases with increasing number of epochs, with an initial large drop in error which slows down as the network begins to learn the patterns representing the data set (Fig. 11). However, if training is allowed to continue beyond the point at which the error reaches the global minima, over-fitting (or over-training) may arise, where memorization of the training data occurs. Because of this over-fitting, if a network performance is monitored by training data alone, the network will perform with little error on the training data but will not be able to generalize well for testing data. In several neural network applications, this has been handled by monitoring test set performance during training and picking the network where performance on the test set was optimal (Uno *et al.,* 2005). In this study, the optimal network prediction was found at epochs near to $24x10^3$. This result implies that the designed ANN was able to properly learn the relationship between the input and output parameters.

To reveal the credibility of prediction from the optimal ANN model presented in Table 5, predicted versus actual values of moisture ratio were plotted in Fig. 12. The results demonstrate very good agreement between the predicted and the desired values of moisture ratio, R^2=0.998. For the final network, the RMSE and MRE between predicted and measured data were lower than 0.0192 and 2.63%, respectively. Ideally, the RMSE and MRE values should be close to zero, indicating that, on average, there is no difference between predicted and measured values. These results demonstrate that the ANN model used in this study can potentially be used to estimate drying kinetics of sesame seeds.

The results obtained from this study also showed that the learning rate and momentum values affected the ANN performance significantly. As clear from Table 5, a small learning rate and large momentum were desirable so that the achieved result was as precise as possible. A problem during the training of an ANN is the choice of a suitable learning rate and momentum (Chegini *et al.,* 2007). In the learning of

T a b l e 5. The optimum values of the ANN parameters used to predict moisture ratio of sesame seeds

Optimum			Transfer function	Mean value				Number of Epochs
MLP structure	learning rate	momentum		training RMSE	testing RMSE	testing mean relative error	R^2	
2-6-3-1	0.5	0.7	Tanh	0.0165	0.0192	2.63%	0.998	24000

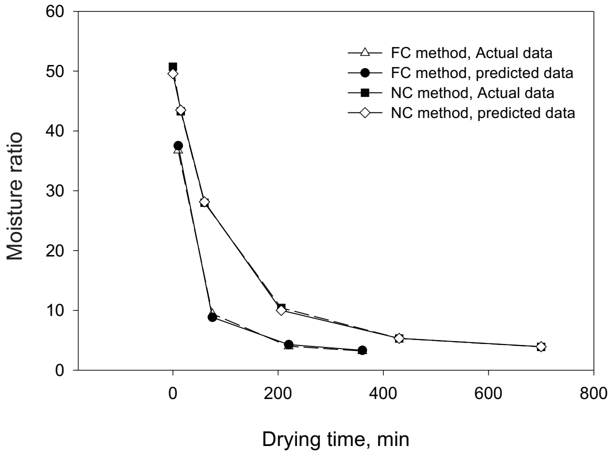


Fig. 12. Ten samples of moisture ratio data predicted using ANN model versus actual data.

an ANN, proper selection of learning rate and momentum are very important to obtain satisfactory ANN training (Anderson, 1995). An improper selection will result in more time for the training process, poor ANN performance, and sometimes unsatisfactory performance. Figure 13 shows the effects of the learning rate and momentum values on the learning capacity of the final selected ANN structure. It is evident that the values of 0.5 for learning rate and 0.7 for momentum were desirable so that the achieved training result was as precise as possible.

Here it is possible to compare the prediction ability of ANN models developed in this study, with that for mathematical drying models reported in Table 1. The results indicate that the use of ANN model resulted in higher R^2 and

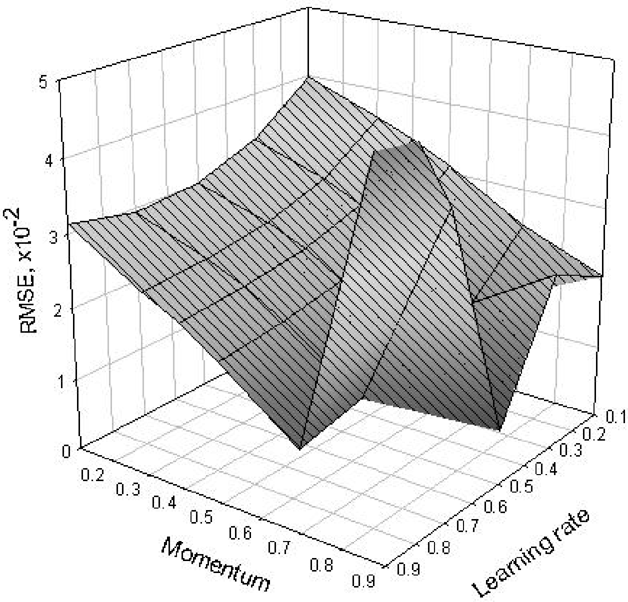


Fig. 13. Training RMSE as a function of learning rate and momentum values.

lower RMSE and MRE values in predicting the moisture ratio of SS. A simple ANN model instead of 2 logarithmic models (two models for FC and NC drying methods) is more powerful for accurate prediction of drying kinetics of agricultural products. This provides the gradual possibility of establishment of a unique powerful model which can be of paramount importance in automatic control system. Further, prediction by a well-trained ANN is normally faster than by mathematical models.

CONCLUSIONS

1. The time needed to dry sesame seeds with initial moisture content of 50.8% d.b, in drying by NC and FC methods, was 400 and 900 min, respectively. The drying rates of sesame seeds at the very beginning times of drying were equal to 22.47 and 6.9 (g H_2O kg^{-1} dry matter min^{-1}) for FC and NC drying methods, respectively. The calculated values of effective diffusion coefficient, D_e, of sesame seeds for FC and NC drying methods were 3.1×10^{-11} and 1.1×10^{-11} m^2 s^{-1}, respectively.

2. Among the considered semi-theoretical drying models, the Khazaei model was found to be more suitable for predicting moisture content of sesame seeds. The logarithmic and Peleg models also had acceptable accuracy in predicting the moisture ratio and moisture content of SS, respectively.

3. The mean values of T_{rel} parameter of the Khazaei model determined for FC and NC drying methods were 26.18 and 84.746 min, respectively. Corresponding values for the scale parameter β of the Weibull model were 56.43 and 148.68 min, respectively.

4. A feed-forward ANN trained by back-propagation algorithm was able to learn the correlation between moisture ratio of sesame seeds with drying method and drying time. The optimal ANN model was found to be a network with 6 neurons in the first hidden layer and 3 neurons in the second one with hyperbolic tangent transfer function. This optimal model was capable of predicting the moisture ratio with R^2 higher than 0.998, RMSE of less than 0.02 and MRE about 2.63%. It was concluded that the neural network represented drying characteristics of sesame seeds better than the mathematical models.

REFERENCES

Akpinar E.K., Bicer Y., and Cetinkaya F., 2006. Modeling of thin layer drying of parsley leaves in a convective dryer and under open sun. J. Food Eng., 75(3), 308-315.

Altuntas E., Ozgoz E., and Taser O.F., 2005. Some physical properties of fenugreek (*Trigonella foenum-graceum* L.) seeds. J. Food Eng., 71, 37-43.

Anderson J.A., 1995. An Introduction to Neural Networks. The MIT Press, Cambridge, MA.

ASAE, **1997.** ASAE standards 1997. St. Joseph, MI, USA.

Chegini G.R., Khazaei J., Ghobadian B., and Goudarzi A.M., 2007. Prediction of process and product parameters in an orange juice spray dryer using artificial neural networks. J. Food Eng., 84(4), 534-543.

Crank J., 1975. The mathematics of diffusion. London, Oxford University Press, UK.

Cunha L.M., Oliveira F.A.R., and Oliveira J.C., 1998. Optimal experimental design for estimating the kinetic parameters of processes described by the Weibull probability distribution function. J. Food Eng., 37, 175-191.

Demir F., Dogan H., Ozcan M., and Haciseferogullari H., 2002. Nutritional and physical properties of hackberry (*Celtis australis* L.). J. Food Eng., 54, 241-247.

Diamante L.M. and Munro P.A., 1993. Mathematical modelling of thin layer solar drying of sweet potato slices. Solar Energy, 51, 271-276.

Doymaz I., 2006. Drying kinetics of black grapes treated with different solutions. J. Food Eng., 76(2), 212-217.

Ece M.C. and Cihan A., 1993. A liquid diffusion model for drying rough rice. Transaction of the ASAE, 36, 837-840.

El-Sebaii A.A., Aboul-Enein S., Ramadan M.R.I., and El-Gohary H.G., 2002. Empirical correlations for drying kinetics of some fruits and vegetables. Energy, 27, 845-859.

Erenturk S. and Erenturk K., 2007. Comparison of genetic algorithm and neural network approaches for the drying process of carrot. J. Food Eng., 78(3), 905-912.

Farkas I., Remenyi P., and Biro A., 2000. Modelling aspects of grain drying with a neural network. Computer and Electronics in Agriculture, 29, 99-113.

Gacula M.C. and Kubala J.J., 1975. Statistical models for shelf life failures. J. Food Sci., 40, 404-409.

Gaston A.L., Abalone R.M., Giner S.A., and Bruce D.M., 2004. Effect of modelling assumptions on the effective water diffusivity in wheat. Biosystems Eng., 88(2), 175-185.

Giner S.A. and Mascheroni R.H., 2001. Diffusive drying kinetics in wheat. Part. 1. Potential for a simplified analytical solution. J. Agric. Eng. Res., 80, 351-362.

Guine R.P.F. and Fernandes R.M.C., 2006. Analysis of the drying kinetics of chestnuts. J. Food Eng., 76, 460-467.

Gunhan T., Demir V., Hancioglu E., and Hepbasli A., 2005. Mathematical modelling of drying of bay leaves. Energy Conversion and Manag., 46, 1667-1679.

Hahn G.J. and Shapiro S.S., 1967. Statistical Models in Engineering. Wiley Press, New York.

Kalogirou S.A., 2000. Applications of artificial neural networks for energy systems. Appl. Energy, 67, 17-35.

Kaminski W., Strumillo P., and Tomczak E., 1998. Neurocomputing approaches to modelling of drying process dynamics. Drying Technol., 16, 967-992.

Kang S. and Delwiche S.R., 2000. Moisture diffusion coefficients of single wheat kernels with assumed simplified geometries: analytical approach. Transactions of the ASAE, 43(6), 1653-1659.

Kashaninejad M., Mortazavi A., Safekordi A., and Tabil L.G., 2007. Thin-layer drying characteristics and modeling of pistachio nuts. J. Food Eng., 78(1), 98-108.

Lahsasni S., Kouhila M., Mahrouz M., and Jaouhari J.J., 2004. Thin layer convective solar drying and mathematical modeling of prickly pear peel (*Opuntia ficus indica*). Energy, 29, 211-224.

Machado M.D., Oliveira F.A.R., and Cunha L.M., 1999. Effect of milk fat and solid concentration on the kinetics of moisture uptake by ready-to-eat breakfast cereal. Int. J. Food Sci. Technol., 34, 47-57.

Marabi A., Dilak C., Shah J., and Saguy I.S., 2004. Kinetics of solids leaching during rehydration of particulate dry vegetables. J. Food Sci., 69(3), 91–96.

Marquez C.A., Michelis A.D., and Giner S.A., 2006. Drying kinetics of rose hip fruits (*Rosa eglanteria* L.). J. Food Eng., 77, 566-574.

Midilli A. and Kucuk H., 2003. Mathematical modeling of thin layer drying of pistachio by using solar energy. Energy Conversion and Management, 44, 1111-1122.

Mittal G.S. and Zhang J., 2000. Prediction of temperature and moisture content of frankfurters during thermal processing using neural network. Meat Sci., 55, 13-24.

Mohsenin N.N., 1986. Physical Properties of Plant and Animal Materials: Structure, Physical Characteristics and Mechanical Properties. Gordon Breach Sci. Publ., New York.

Mwithiga G. and Sifuna M.M., 2006. Effect of moisture content on the physical properties of three varieties of sorghum seeds. J. Food Eng., 75(4), 480-486.

Nelson W., 1969. Hazard plotting for incomplete failure data. J. Quality Technol., 1, 27-52.

Peleg M., 1988. An empirical model for the description of moisture sorption curves. J. Food Sci., 53, 1216-1217.

Razmi-Rad E., Ghanbarzadeh B., Mousavi S.M., Emam-Djomeh Z., and Khazaei J., 2007. Prediction of rheological properties of Iranian bread dough from chemical composition of wheat flour by using artificial neural networks. J. Food Eng., 81, 728-734.

Resio A.N.C., Aguerre R.J., and Suarez C., 2004. Drying characteristics of amaranth grain. J. Food Eng., 65, 197-203.

Sacilik K., 2007. Effect of drying methods on thin-layer drying characteristics of hull-less seed pumpkin (*Cucurbita pepo* L.). J. Food Eng., 79(1), 23-30.

Sacilik K., Keskin R., and Elicin A.K., 2006. Mathematical modelling of solar tunnel drying of thin layer organic tomato. J. Food Eng., 73(3), 231-238.

Satish S. and Setty Y.P., 2005. Modeling of a continuous fluidized bed dryer using artificial neural networks. Int. Communications in Heat and Mass Transfer, 32, 539-547.

Sopade P.A. and Kaimur K., 1999. Application of Peleg's equation in desorption studies of food systems: a case study with sago (*Metroxylon Sagu rottb.*) starch. Drying Technol., 17, 975-989.

Steffe J.F., and Singh R.P., 1980. Liquid diffusivity of rough rice components, Transactions of the ASAE, 23, 767-774.

Togrul I.T. and Pehlivan D., 2004. Modelling of thin layer drying kinetics of some fruits under open-air sun drying process. J. Food Eng., 65, 413-425.

Toure S. and Nkembo S.K., 2004. Comparative study of natural solar drying of cassava, banana and mango. Renewable Energy, 29, 975-990.

Tsoukalas L.H., and Uhrig R.E., 1997. Fuzzy and Neural Approaches in Engineering. Wiley Press, New York.

Tunde-Akintunde T.Y. and Akintunde B.O., 2004. Some physical properties of sesame seed. Biosystems Eng., 88(1), 127-129.

Turhan M., Sayar S., and Gunasekaran S., 2002. Application of Peleg model to study water absorption in chickpea during soaking. J. Food Eng., 53, 153-159.

Uno Y., Prasher S.O., Lacroix R., Goel P.K., Karimi Y., Viau A., and Patel R.M., 2005. Artificial neural networks to predict corn yield from Compact Airborne Spectrographic Imager data. Computers and Electronics in Agric., 47, 149-161.

Verma R.C. and Prasad S., 1999. Kinetics of absorption of water by maize grains. J. Food Eng., 39, 395-400.

Yaldiz O. and Ertekin C., 2001. Thin layer solar drying of some vegetables. Drying Technol., 19, 583-596.