Effect of Moisture Content on Thermodynamic Characteristics of Grape: Mathematical and Artificial Neural Network Modelling

Reza Amiri CHAYJAN[1] and Mahmood ESNA-ASHARI[2]

[1]Department of Agricultural Machinery Engineering and [2]Department of Horticultural Sciences, Faculty of Agriculture, Bu-Ali Sina University, Hamedan, Iran

Abstract

Chayjan R.A., Esna-Ashari M. (2011): **Effect of moisture content on thermodynamic characteristics of grape: mathematical and artificial neural network modelling**. Czech J. Food Sci., **29**: 250–259.

Artificial neural networks (ANNs) and four empirical mathematical models, namely Henderson, GAB, Halsey, and Oswin were used for the estimation of equilibrium moisture content (*EMC*) of the dried grape (black currant). The results showed that the *EMC* of the grape were more accurately predicted by ANN models than by the empirical models. The heat and entropy of sorption of the grape have separately been predicted by two mathematical models as a function of *EMC* with desirable coefficient of determination ($R^2 \approx 0.99$). At the *EMC* above 7% (d.b.), the heat and entropy of the grape sorption were smoothly decreased, while they were the highest at the moisture content of about 7% (d.b.). Better equations could be developed for the prediction of the heat of sorption and entropy based on the data from the ANN model.

Keywords: sorption; thermodynamic; drying, neural network; grape

Abbreviations

a_w – water activity (decimal); a, b, c, d, e, k, X_m – constants; b_j – bias of j^{th} neuron for networks; *EMC* – equilibrium moisture content (% d.b.); E_{mr} – mean relative error; ΔH – heat of sorption (kJ/mol); m – number of output layer neurons; M – number of training patterns; *MSE* – mean square error; N – number of training patterns or number of output neurons; R_o – universal gas constant (8.315 kJ/kmol/K); R^2 – determination coefficient; SD_{mr} – standard deviation of mean absolute error; S_{ip} – network output in i^{th} neuron and p^{th} pattern; S_k – network output for k^{th} pattern; ΔS – entropy (J/mol/K); T– environmental absolute temperature (K); T_{ip} – target output at i^{th} neuron and p^{th} pattern; T_k – target output for k^{th} pattern; W_{ij} – weight of between i^{th} and j^{th} layers; Y_i – i^{th} output neuron

Dried grape is one of the most important Iranian horticultural products with a high export value. The standard processes of post harvest, such as drying, packaging, and storage of the grapes, would guarantee the quality of the product, increasing its export value as well as producer's income. Post harvest quality of the grape, with a high moisture content of grains at the harvesting time, is very important.

Aeration, which relates the air relative humidity and moisture content, is essential for optimising, the dried grape quality. Energy consumption of the drying process with regard to the final moisture content is a criterion for the selection of the dryer or type of drying process. Equilibrium moisture content (*EMC*), defined as the moisture content of the respective agricultural material in equilibrium with the environmental conditions (air temperature and air relative humidity), is a vital parameter in studying the drying process. Studies have showed that, if the two above environmental factors are not controlled, the mold activities increase (Brooker & Bakker-Arkema 1992).

EMC is a durability index and any change in the quality of foods or agricultural products during storage and packaging is crucialy important (Veltchev & Menkov 2000). Fundamental relationship between *EMC* and relative humidity of foods and agricultural products is known as sorption isotherms (Palipane & Driscoll 1992). Sorption characteristics are used for designing, modelling, and optimising some post harvest processes such as drying, aeration, and storage (Labuza 1975; Bala 1997). Pahlevanzadeh *et al.* (2000) have investigated the moisture sorption isotherms of the grape (cultivar Thompson Seedless) at low temperatures. In their research, the sorption isotherms of the grape were determined at temperatures between 20°C to 40°C, Halsey model giving the best results for the *EMC* prediction.

Gabas *et al.* (1999) proposed a model for water absorption of Italian grape cultivars. They determined the moisture sorption isotherm for temperatures between 35°C to 75°C and found that GAB model was the best for *EMC* prediction. Post harvest quality of the grape, considering high moisture content of grains at the harvesting time, is very important.

Sorption isotherms of agricultural products are usually sigmoid-shape curves difficult even to draw and manipulate with (Bala 1997). Numerous complex mathematical models for describing sorption isotherms have been developed by many researches (Kaymak-Ertekin & Gedik 2004; Reddy & Chakraverty 2004; Cervenka *et al.* 2008; Blahovec & Yanniotis 2009; Yanniotis & Blahovec 2009). Non-linear direct optimisation techniques are required for the estimation of these model parameters. Such estimations reduce the accuracy and the shape of the isotherms as well as the reliability of the predictions over the whole range of the relative humidity. Therefore, research is necessary to find alternative computational methods calculating the relationships of agricultural products isotherms for increasing the accuracy and reliability of predictions. Artificial neural network (ANN) can be a suitable alternative for this purpose.

ANN is one of the soft computing methods. It uses simple processing elements named neurons. ANNs tries to discover the inherent relationship between the parameters through the learning process. It creates a mapping between the input space (input layer) and target space (output layer). The processing of the input data is carried out in hidden layer/layers. Training is a process that finally results in learning. Each network is trained with the presented patterns. During this process, the connection weights between layers is changed until the differences between the predicted values and the target (experimental) are reduced to permissible limits. Under the aforementioned conditions, the learning process was performed. Trained ANN can be used for the rediction of the outputs of new unknown patterns. ANNs were used for the modelling of drying by some workers (Huang & Mujumdar 1993; Bala *et al.* 2005; Movagharnejad & Nikzad 2007; Poonnoy *et al.* 2007; Lertworasirikul & Tipsuwan 2008). Other researchers used the ANN model for modelling black tea and grape starch sorption isotherms (Panchariya *et al.* 2002; Peng *et al.* 2007). In all of these studies, the ANN models were found to be better than the mathematical models.

The heat of sorption is an important parameter for drying and for the measure of the water-solid binding strength. It can be used to determine the energy requirements and to show the state of water within the dried material. The moisture content of a material, at which the heat of sorption reaches the value of the latent heat of sorption, is often considered as the indication of the amount of bound water existing in the material (Wang & Brennan 1991).

Researchers have proposed an empirical exponential relationship between the heat of sorption and material moisture content for some fruits and also a mathematical model for pineapple (Tsami 1994; Hossain *et al.* 2001; Simal *et al.* 2007; Chayjan 2010; Chayjan & Esna-Ashari 2010). The differential entropy of a material is proportional to the number of sites at a specific energy level (Madamba *et al.* 1996). Madamba *et al.* (1996) adopted an exponential relation to describe the entropy of garlic sorption as a function of moisture content. McMinn *et al.* (2004) reported that the net isosteric heat of sorption and differential entropy of potato decreased with increasing moisture content, and these were adequately characterised by an empirical model.

Literature survey showed that no detailed study has so far been carried out on the prediction of the sorption isotherm of Black Currant grape cultivar using ANN method. Also, the heat of sorption and differential entropy models of the grape (Black Currant) are not available in the literature. The objectives of this study were: (1) to develop both ANN and empirical models on experimental data of sorption, (2) to find an improved empirical model for the heat of sorption, and (3) to find a new empirical model for the entropy of the grape.

MATERIAL AND METHODS

Experimental Setup and Mathematical Models. Fresh grape samples (Black Currant) were supplied by a farm in the Hamedan province, Iran. The samples were dried to the moisture content of 15% (d.b.) by open sun drying method. Salt saturated solutions including LiCl, $KC_2H_3O_2$, $MgCl_2$, K_2CO_3, NaBr, $NaNO_2$, NaCl, and K_2SO_4 (all from Merck, Darmstadt, Germany) were used to provide the needed relative humidity. Ensuring such relative humidities by the saturated solutions has been reported in the literature (Bala 1997). Besides, these values were also checked using a hygrometer.

One of the most common methods used for *EMC* determination is the gravimetric one, having high precision and not needing a complex implement (Spiess & Wolf 1983). Fifty grams of the sample were considered as an experimental specimen. Each sample was placed into a Petri dish (90 mm in diameter). All dishes were then transferred into a desiccator and kept for five weeks while they were weighed every single day. Equilibrium was considered when the difference between two successive weighings was lower than 0.001 g (Ayranchi *et al.* 1990; Gabas *et al.* 1999). Three to four weeks were needed for the samples to reach equilibrium.

The temperature needed for the experiment was ensured by using a sample box with a temperature controller to maintain the temperature. An electric fan was fitted to circulate the air inside the box to accelerate the moisture transfer between the samples and air inside the box. In order to determine the final moisture content, the equilibrated samples were placed in a vacuum oven (70°C and 150 mbar) for 6 hours. All the experiments were conducted in three replications.

Four common mathematical models were used for the prediction of the sorption isotherms in this study as follows:

$$EMC = \left[\frac{-1}{aT}\ln(1-a_w)\right]^{\left(\frac{1}{b}\right)} \quad \text{(Henderson)} \quad (1)$$

$$EMC = a\left[\frac{a_w}{1-a_w}\right]^{b} \quad \text{(Oswin)} \quad (2)$$

$$EMC = \frac{X_m k c a_w}{(1-ka_w)(1-ka_w+kca_w)} \quad \text{(GAB)} \quad (3)$$

$$EMC = \left[\frac{-a}{T\ln(a_w)}\right]^{\left(\frac{1}{b}\right)} \quad \text{(Halsey)} \quad (4)$$

where:

EMC – equilibrium moisture content in % d.b.
a_w – water activity in decimal
T – environmental absolute temperature in K
R – universal gas constant (8.314 J/mol/K)
X_m, *k*, *a*, *b*, *c*, *d*, *e* – constants for different materials calculated by the experimental method

The supremacy of each model for the prediction of *EMC* is expressed by three indices of coefficient of determination (R^2), mean relative error (E_{mr}), and standard error (*SE*). The fit was performed by non-linear regression based on the minimisation of the least square technique by Statistica 8 software.

Artificial neural networks modelling. In this research, two types of Multi layer perceptron (MLP) neural network, namely the feed and cascade forward networks, were utilised. Also, several learning algorithms were used. Feed Forward neural network (FFNN) consists of one input layer, one or several hidden layers, and one output layer (Jam

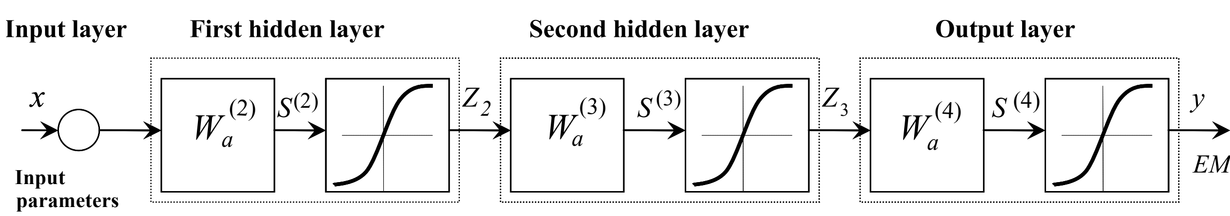

Figure 1. Neural network topology of equilibrium moisture content of grape

Table 1. Input parameters for ANNs and their limits for the prediction of equilibrium moisture content of grape

No. of levels	High limit	Low limit	Input variables
4	60	30	environmental air temperature (°C)
8	83.62	10.51	air relative humidity (%)

& Fanelli 2000). For learning this network, back propagation (BP) learning algorithm was used. In the case of BP algorithm, the first output layer weights were updated. The weight coefficient was updated by the weight values and learning rules. During training this network, calculations were carried out from the network input toward output and the values of error were then propagated to the preceding layers. Cascade forward neural network (CFNN) is similar to FFNN in using the BP algorithm for weights updating, but the main symptom of this network is that each layer neuron relates to all previous layer neurons. The Levenberg-Marquardt and Bayesian algorithms were used for updating the network weights.

Networks with two neurons in the input layer (air relative humidity and air temperature) and one neuron in the output layer (*EMC*) were designed. Figure 1 shows the considered neural network topology and interconnections between the input and output parameters. Boundaries and levels of the input variables are shown in Table 1. Neural network toolbox (ver. 4.1) of Matlab software was used in this study. Various transfer functions were used to reach the optimised status (Demuth & Beale 2003):

$$Y_j = \frac{1}{1+\exp(-X_j)} \quad \text{(Logarithmic sigmoid-LOGSIG)} \quad (5)$$

$$Y_j = \frac{2}{(1+\exp(-2X_j))-1} \quad \text{(Hyperbolic tangent sigmoid-TANSIG)} \quad (6)$$

$$Y_j = X_j \quad \text{(Linear-PURELIN)} \quad (7)$$

where: X_j – computed as follows:

$$X_j = \sum_{i=1}^{m} W_{ij} \times Y_i + b_j \quad (8)$$

where:
m – number of output layer neurons
W_j – weight between ith and j^{th} layers
Y_j – i^{th} neuron output
b_j – bias of j^{th} neuron for FFNN and CFNN networks

The experimental data obtained at 30°C, 40°C, and 60°C were selected for the training network to find suitable topology and training algorithm. Also, the data obtained from the experiment at 50°C were used for testing the trained network.

The following index of the mean square error has been defined to minimise the learning error (Demuth & Beale 2003):

$$MSE = \frac{1}{nN}\sum_{p=1}^{n}\sum_{i=1}^{N}(S_{ip} - T_{ip})^2 \quad (9)$$

where:
MSE – mean square error
S_{ip} – network output in i^{th} neuron and p^{th} pattern
T_{ip} – target output at i^{th} neuron and p^{th} pattern
N – number of output neurons
n – number of the training patterns

To optimise the selected network from the prior stage, the secondary indices were used as follows:

$$R^2 = 1 - \frac{\sum_{k=1}^{n}[S_k - T_k]}{\sum_{k=1}^{n}[S_k - \frac{\sum_{k=1}^{n} S_k}{n}]} \quad (10)$$

$$E_{mr} = \frac{100}{n}\sum_{k=1}^{n}\left|\frac{S_k - T_k}{T_k}\right| \quad (11)$$

$$SD_{mr} = \sum_{k=1}^{n}\sqrt{\frac{(S_k - T_k)^2}{d.f.}} \quad (12)$$

where:
R^2 – determination coefficient
E_{mr} – mean relative error
SD_{mr} – standard deviation of mean absolute error
S_k – network output for k^{th} pattern
T_k – target output for k^{th} pattern
n – number of the training patterns. To increase the accuracy and processing velocity of the network, the input data were normalised at the boundary of [0, 1]

Heat and entropy computation. The heat of sorption can be determined by the Clausius-Clayperon's equation (Rao & Rizvi 1995; Hossain *et al.* 2001; Phomkong *et al.* 2006):

$$\frac{d\ln(a_w)}{dT}=\frac{\Delta H}{R_oT^2} \tag{13}$$

The following relationship is used for the heat and entropy of sorption in thermodynamics:

$$-\ln(a_w)=(\frac{\Delta H}{R_o})\frac{1}{T}-\frac{\Delta S}{R_o} \tag{14}$$

When $\ln(a_w)$ are plotted against $1/T$, a straight line graph is obtained with the y-intercept of $\Delta S/R_o$. From the values of this y-intercept and R_o, ΔH and ΔS can be computed.

RESULTS AND DISCUSSION

Equilibrium curves (moisture content and water activity)

The average of *EMC* versus water activities of salt solutions is shown in Figure 2. These curves are the moisture sorption isotherm of the grape at four temperature levels of 30°C, 40°C, 50°C, and 60°C in the range of relative humidity 10.95–83.62%. These curves are the moisture sorption isotherm of dried grape. As depicted from this figure, over the whole range of water activity *EMC*decreased with increasing temperature. The increase of water activity caused an increase in the grape *EMC* at all temperatures. The changes in water activity of more than 0.5 are quite obvious.

The dried grape, like other high glucose dried fruits, absorbs less moisture at low water activity and absorbs more moisture at high water activity. Because of the moisture absorbing properties of biopolymers in all food materials, the curve slope increases and this phenomenon is also seen in the dried grape because of its high absorbing moisture rate which is in turn related to glucose. At low water activity, physical properties of glucose have no significant effect on the moisture absorption. Amorphous glucose absorbs more moisture as compared with crystal glucose.

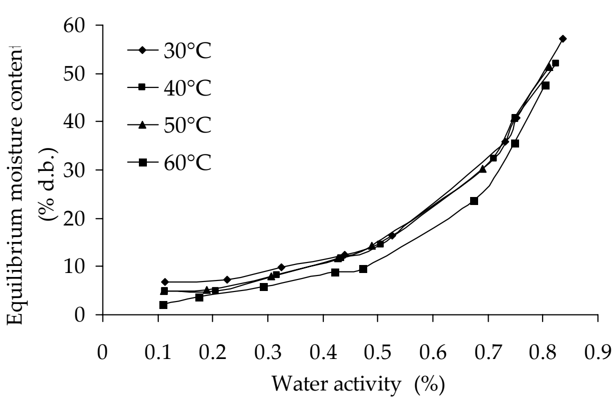

Figure 2. Sorption isotherm of grape from the experiments at temperature levels

Mathematical models

The results of empirical models fitting at the temperatures of 30°C, 40°C, 50°C, and 60°C are shown in Table 2. For these temperatures, Halsey model produced the best results, including the highest R^2, the lowest E_{mr} and SD_{mr}. Therefore, this model is capable of producing the best results for the four temperature levels that could be used for the *EMC* estimation of the grape, and heat and entropy of sorption at various temperatures and water activities. Any empirical model has an equation with the constants which are presented in Table 2.

ANN models. FFNN and CFNN networks with a BP algorithm, various transfer functions, and training rules were evaluated for mapping between the inputs and outputs patterns. The best values obtained from the training of the networks with different topologies are given in Table 3.

As found, the best results were obtained with FFNN network, TANSIG-TANSIG-TANSIG threshold function, and 2-3-3-1 topology. This composition produced MSE = 0.00059, R^2 = 0.9991, E_{mr}= 4.993 and SD_{mr} = 0.5997 converged in 69 epochs. The R^2 of optimised ANN and real errors are presented in Figure 3.

The comparison of the ANN method and the mathematical model results showed that the artificial neural network had the supremacy in the equilibrium moisture content prediction for the grape. The optimised artificial neural network topology was therefore used for the prediction of the grape heat and entropy of sorption.

Grape heat and entropy of sorption

Equilibrium moisture content values of the grape at the four temperature levels (30°C, 40°C, 50°C, and 60°C) and eight moisture levels (7%, 10%, 13%, 16%, 19%, 22%, 25%, and 28%) were computed using the optimised neural network model. The values of $\ln(a_w)$ versus $1/T$ were plotted for the grape at constant moisture contents (Table 4). These values

Table 2. Coefficients and outputs of mathematical models for all temperatures of desorption isotherm of the grape

Model	Temperature (°C)	a	b	c	d or k	e or X_m	MSE	R^2	E_{mr}
Oswin	30	21.445	0.645	–	–	–	3.46	0.9882	14.86
	40	19.894	0.681	–	–	–	2.28	0.9914	11.11
	50	19.489	0.715	–	–	–	1.61	0.9912	11.68
	60	12.075	0.985	–	–	–	0.55	0.9973	11.32
GAB	30	–	–	3.211	0.970	0.540	2.66	0.9910	10.53
	40	–	–	1.155	0.895	17.78	2.04	0.9922	12.10
	50	–	–	1.162	0.950	13.73	1.46	0.9923	10.21
	60	–	–	1.358	0.024	10.02	1.46	0.9974	29.06
Halsey	30	13.790	0.941	–	–	–	2.25	0.9923	8.28
	40	10.924	0.990	–	–	–	3.53	0.9879	9.93
	50	9.816	1.027	–	–	–	1.31	0.9941	7.78
	60	5.073	1.230	–	–	–	0.53	0.9985	7.22
Henderson	30	–0.075	0.809	–	–	–	5.34	0.9822	18.88
	40	–0.084	0.780	–	–	–	2.79	0.9908	16.17
	50	–0.085	0.774	–	–	–	2.62	0.9901	16.99
	60	–0.151	0.630	–	–	–	2.02	0.9912	23.05

were estimated by the optimised ANN. The slopes of the lines at constant moisture contents were the net isosteric heat of sorption for the grape. The slopes were determined by linear regression analysis. The heat of sorption for the grape at different moisture contents is presented in Figure 4.

The heat of sorption was found to decrease with increasing moisture content. Water was absorbed in the most accessible locations on the exterior surface of the solid. As the moisture content increases, the material swells and due to it new high-energy sites are opened up for water to bind. This causes the heat of sorption to increase as with moisture content decrease. This trend is similar to those reported for agricultural, food, medicinal, and aromatic plants (Hossain *et al.* 2001; Lahsasni *et al.* 2004; Phomkong *et al.* 2006; Chayjan *et al.* 2010). The net isosteric heat of sorption was found to fit a power relation. The following equation was developed for the grape:

$$\Delta H = 9.2513(EMC)^{-0.7489} \quad R^2 = 0.9898 \tag{15}$$

This relation showed that the heat of sorption for grape increases following a power relationship. This relation has also a better fit than the exponential relation previously developed for some agricultural products (Janjai *et al.* 2006; Chayjan *et al.* 2010). The relationship between the heat of

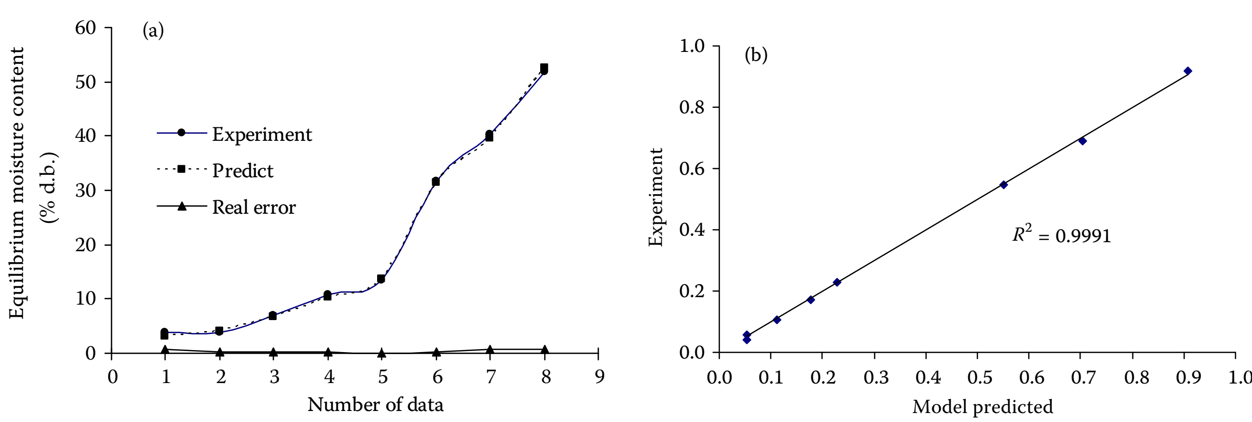

Figure 3. Predicted values of EMC using ANNs versus experimental values for testing data set (50°C): (a) real values of experimental, predicted and error data (b) coefficient of determination

Table 3. Training algorithms for different neurons and hidden layers for networks

Epoch	SE	E_{mr}	R^2	MSE	No. of layers and neurons	Threshold function	Training algorithm	Network
69	0.5997	4.993	0.9991	0.00059	2-3-3-1	TANSIG-TANSIG- TANSIG	Levenberg	FFNN
23	0.845	5.521	0.9951	0.00088	2-3-2-1	TANSIG- LOGSIG-PURELIN	Baisian	
38	0.989	7.108	0.9918	0.00095	2-4-2-1	TANSIG –TANSIG – TANSIG	Levenberg	CFNN
46	0.895	6.33	0.9935	0.00092	2-3-3-1	LOGSIG - LOGSIG – PURELIN	Baisian	

Table 4. Calculation of $\ln(a_w)$ as a function of $1/T$ at different moisture content in grape using artificial neural network

Equilibrium moisture content (% d.b.)	28	25	22	19	16	13	10	7
$1/T$	0.003300	0.003300	0.003300	0.003300	0.003300	0.003300	0.003300	0.003300
	0.003195	0.003195	0.003195	0.003195	0.003195	0.003195	0.003195	0.003195
	0.003096	0.003096	0.003096	0.003096	0.003096	0.003096	0.003096	0.003096
	0.003003	0.003003	0.003003	0.003003	0.003003	0.003003	0.003003	0.003003
$\ln(a_w)$	4.2138	4.1768	4.1283	4.0604	3.9650	3.8354	3.6564	3.3485
	4.2241	4.1875	4.1382	4.0726	3.9784	3.8506	3.6720	3.3834
	4.2343	4.1981	4.1506	4.0845	3.9958	3.8653	3.6929	3.4078
	4.2443	4.2075	4.1615	4.0920	4.0042	3.8801	3.7101	3.4308

sorption and *EMC* for some agricultural materials is given in Table 5. It is obvius that this relation for longan, corn, and sesame seed is a power equation model while litchi and mango correspond to the exponentioal equation model. This is because of the difference between the desorption properties of agricultural material tissues.

The maximum values of sorption heat for some agricultural products reported by researchers were compared with the grape (this study) and are given in Table 6. The lower values of the grape heat of sorption compared to the other agricultural products was due to the differences in the chemical composition and tissues of the grape. The heat of sorption of the grape is significantly high, while its equilibrium moisture content is lower than 10% (d.b.). This can be explained by the fact that, at the moisture content above 10% (d.b.), water is loosely bound in the grape. This implies that the grape needs less energy at a higher moisture content (above 10% d.b.) for drying but needs more energy at lower moisture contents, especially for storage. After processing, the dried grape with 16% (d.b.) moisture content is stored (Pahlevan-

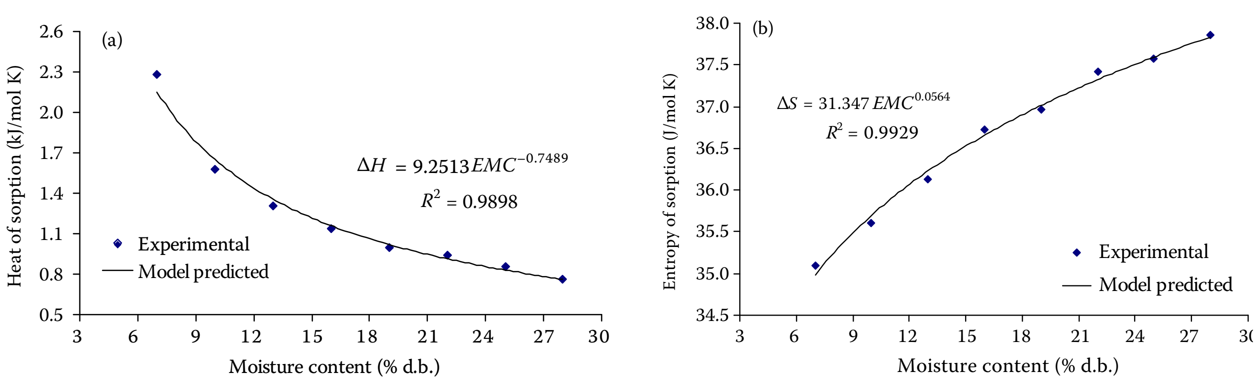

Figure 4. Heat and entropy of the grape sorption at different equilibrium moisture contents: (a) heat (b) entropy

Table 5. Heat and entropy of different agricultural materials obtained by researchers

Products	Heat		Entropy		Source
	model	R^2	model	R^2	
Longan	$2182.6\ EMC^{-1.2802}$	0.9900	$704.5\ EMC^{-0.5576}$	0.9700	Janjai *et al.* (2006)
Corn	$429.74\ EMC^{-1.523}$	0.9906	$300.4\ EMC^{-0.6077}$	0.9873	Chayjan *et al.* (2010)
Litchi	$50.89\ e^{-0.0232EMC}$	0.9500	–	–	Janjai *et al.* (2009)
Mango	$22.60\ e^{-0.0087EMC}$	0. 9700	–	–	Janjai *et al.* (2007)
Sesame seed	$16.333\ EMC^{-0.7789}$	0.9924	$55.87\ EMC^{-0.092}$	0.9811	Chayjan (2010)

Table 6. Values of isosteric heat for minimum *EMC* in some agricultural products compared with grape

Products	Minimum *EMC* (%, d.b.)	Heat of sorption (kJ/mol)	Source
Longan	40	19.5	Janjai *et al.* (2006)
Corn	8	18.68	Chayjan *et al.* (2010)
Litchi	20	32	Janjai *et al.* (2009)
Mango	30	18	Janjai *et al.* (2007)
Grape (black currant)	7	2.28	this study

zadeh *et al.* 2000), so the results showed that its isosteric heat at 16% (d.b.) falls into the normal range (1.1359 kJ/mol/K).

The entropy of sorption of the grape is presented in Figure 4. It is a function of the moisture content and the following power type equation model was fitted to the data:

$$\Delta S = 31.347(EMC)^{0.564} \qquad R^2 = 0.9929 \qquad (16)$$

The fitted curves for the entropy prediction provided good values compared to the experimental ones. These results proved that entropy increased smootly with the increase in the moisture content. Because of the high glucose content of the dried grape, its change pattern is different compared with the entropy of potato tuber and melon seed as well as cassava (Aviara & Ajibola 2002; McMinn & Magee 2003; Amiri Chayjan *et al.* 2010). The entropy models for some agricultural materials are given in Table 5. All reported models were power equations. This is because of the similarity of the desorption properties of agricultural material tissues.

The derived sorption equations of heat and entropy are necessary for the calculation of humidity during storage of the dried grape. These results showed that the ANN method has supremacy over mathematical models because it provides more accurate data to develop better equations for isosteric heat and entropy of sorption.

CONCLUSION

Generally, the following conclusions can be drawn from the experiments:

– The Halsey model produced the best prediction for the grape *EMC*.
– The ANN model with topology of FFNN network, TANSIG-TANSIG-TANSIG transfer function, and 2-3-3-1 was the best for the prediction of the grape *EMC*.
– The relation between the moisture content and heat and entropy of sorption of the grape was a power model. The sorption entropy of the grape as a function of *EMC* was also determined by a power model.
– The grape needs less energy at a higher moisture content (above 10% d.b.) for drying and storage, but more energy at lower moisture contents.

References

Aviara N.A., Ajibola O.O. (2002): Thermodynamics of moisture sorption in melon seed and cassava. Journal of Food Engineering, **55:** 107–113.

Ayranchi E., Ayranchi G., Dogantan Z. (1990): Moisture sorption isotherms of dried apricot, fig and raisin at 20°C and 36°C. Journal of Food Scince, **55**: 1591–1593.

Bala B.K. (1997): Drying and Storage of Cereal Grains. Oxford & IBH Publishing, New Delhi.

Bala B.K., Ashraf M.A., Uddin M.A., Janjai S. (2005): Experimental and neural network prediction of the performance of the solar tunnel dryer for drying of jackfruit bulbs and jackfruit leather. Journal of Food Process Engineering, **28**: 552–566.

Blahovec J., Yanniotis S. (2009): Modified classification of sorption isotherms. Journal of Food Engineering, **91**: 72–77.

Brooker D.B., Bakker-Arkema F.W., Hall C.W. (1992): Drying and Storage of Grain and Oilseeds. AVI Publications, New York.

Cervenka L., Rezkova S., Kralovsky J. (2008): Moisture adsorption characteristics of gingerbread, a traditional bakery product in Pardubice, Czech Republic. Journal of Food Engineering, **84**: 601–607.

Chayjan R.A. (2010): Modeling of sesame seed dehydration energy requirements by a soft-computing approach. Australian Journal of Crop Science, **4**: 180-184.

Chayjan R.A., Esna-Ashari M. (2010): Modeling of heat and entropy sorption of maize (cv. Sc704): neural network method. Research in Agricultural Engineering, **56**: 69–76.

Chayjan R.A., Parian J.A., Esna-Ashari M., Peyman M.H. (2010): Mathematical modeling of thermodynamic properties of corn for estimation of desorption energy. International Agrophysics. **24**: 213–218.

Demuth H., Beale M. (2003): Neural Network Toolbox for Matlab – Users Guide Version 4.1. The Mathworks Inc., Natrick.

Gabas A.L., Telis-Romero J., Menegalli F.C. (1999): Thermodynamic models for water sorption by grape skin and pulp. Drying Technology, **17**: 961–974.

Hossain M.D., Bala B.K., Hossain M.A., Mondol M.R.A.. (2001): Sorption isotherm and heat of sorption of pineapple. Journal of Food Engineering, **48**: 103–107.

Huang B., Mujumdar A.S. (1993): Use of neural network to predict industrial dryer performance. Drying Technology, **11**: 525–541.

Jam L., Fanelli A.M. (2000): Recent Advances in Artificial Neural Networks Design and Applications. CRC Press, Boca Raton.

Janjai S., Bala B.K., Tohsing K., Mahayothee B., Heawsungcharen M., Muhlbauer W., Muller J. (2006): Equilibrium moisture content heat of sorption of longan (*Dimocarpus longan*). Drying Technology, **24**: 1691–1696.

Janjai S., Bala B.K., Tohsing K., Mahayothee B., Heawsungcharen M., Muhlbauer W., Muller J. (2007): Moisture sorption isotherms and heat of sorption of mango (*Magnifera india* cv. Nam Dok Mai). International Agricultural Engineering Journal, **16**: 159–168.

Janjai S., Bala B.K., Tohsing K., Muller J., Muhlbauer W. (2011): Moisture sorption isotherms of litchi. International Journal of Food Properties, **13**: 251–260.

Kaymak-Ertekin F., Gedik S. (2004): Sorption isotherms and isosteric heat of sorption for grapes, apricots, apples and potatoes. Lebensmittel-Wissenschaft und -Technology, **37**: 429–438.

Labuza T.P. (1975): Water relations of foods. London Academic Press, London: 155–172.

Lahsasni N., Kouhila M., Mahrouz M. (2004): Adsorpion-desorption isotherms and heat of sorption of pickly pear fruit (*Opuntia ficus-india*). Energy Conversion and Management, **45**: 249–261.

Lertworasirikul S., Tipsuwan Y. (2008): Moisture content and water activity prediction of semi-finished cassava crackers from drying process with artificial neural network. Journal of Food Engineering, **84**: 65–74.

Madamba P.S., Driscoll R.H., Buckle K.A. (1996): Enthalpy-entropy compensation models for sorption and browning of garlic. Journal of Food Engineering, **28**: 109–119.

McMinn W.A.M., Al-Muhtaseb A.H., Magee T.R.A. (2004): Moisture sorption characteristics of starch gels. part ii: thermodynamic properties. Journal of Food Process Engineering, **27**: 213–227.

Mcminn W.A.M., Magee T.R.A. (2003): Thermodynamic properties of moisture sorption of potatoes. Journal of Food Engineering, **60**: 157–165.

Movagharnejad K., Nikzad M. (2007): Modeling of tomato drying using artificial neural network. Computer and Electronics in Agriculture, **59**: 78–85.

Pahlevanzadeh H., Basiri A.R., Zarrabi M. (2000): The determination of the parameters and pretreatment solution on grape drying. Drying Technology, **19**: 217–226.

Palipane K.B., Driscroll R.H. (1992): Moisture sorption characteristics of in-shell macadamia nut. Journal of Food Engineering, **18**: 63–76.

Pancharyia P.C., Popovic D., Sharma A.L. (2002): Desorption isotherm modeling of black tea using artificial neural networks. Drying Technology, **20**: 351–362.

Peng G., Chen X., Wu W., Jiang X. (2007): Modeling of water sorption isotherm for corn starch. Journal of Food Engineering, **80**: 562–567.

Phomkong W., Srzednichi G., Driscoll R.H. (2006): Desorption isotherms of stone fruit. Drying Technology, **24**: 201–210.

Poonnoy P., Tansakul A., Chinnan M. (2007): Artificial neural network modeling for temperature and moisture content prediction in tomato slices undergoing microvave-vacum drying. Journal of Food Science, **72**: 42–47.

Rao M.A., Rizvi S.S.H. (1995): Engineering Properties of Foods. 2nd Ed. Marcel Dekker Inc., New York.

Reddy B.S., Chakraverty A. (2004): Equilibrium moisture characteristics of raw and parboiled paddy, brown rice and bran. Drying Technology, **22**: 837–851.

Simal S., Femenia A., Castell-Palou A., Rosselló C. (2007): Water desorption thermodynamic properties of pineapple. Journal of Food Engineering, **8**: 1293–1301.

Spiess W.E.L., Wolf W. (1983): Physical Properties of Foods. Applied Science Publisher, London, 65–86.

Veltchev, Z.N., Menkov N.D. (2000): Desorption isotherm of apples at several temperatures. Drying Technology, **18**: 1127–1137.

Tsami E.D. (1994): Net isosteric heat of sorption in dried fruit. Journal of Food Engineering, **4**: 327–335.

Wang N., Brennan J.G. (1991): Moisture sorption isotherm characteristics of potatoes at four temperatures. Journal of Food Engineering, **14**: 269–282.

Yanniotis S., Blahovec J. (2009): Model analysis of sorption isotherms. LWT-Food Science and Technology, **42**: 1688–1695.

Received for publication December 7, 2009
Accepted after corrections August 7, 2010

Corresponding author:

Dr. Reza Amiri Chayjan**,** Bu-Ali Sina University, Faculty of Agriculture, Department of Agricultural Machinery Engineering, 6517833131, Hamedan, Iran
tel.: + 98 8114238193, e-mail: amirireza@basu.ac.ir