Comparison between artificial neural networks and mathematical models for estimating equilibrium moisture content in raisin

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Abstract: Empirical models and Artificial Neural Networks (ANNs) were utilized for the prediction of Equilibrium Moisture Content (EMC) in raisin. Six empirical models including GAB, Smith, Henderson, Oswin, Halsey and D’Arsy-watt were applied for this estimation. Two types of Multi Layer Perceptron (MLP) neural networks entitled Feed Forward Back Propagation (FFBP) and Cascade Forward Back Propagation (CFBP) were used. In order to train the input patterns, two training algorithms consist of Levenberg-Marquardt (LM) and Bayesian regularization (BR) were used. Thermal and relative humidity limits were 30-80℃ and 10.51%-83.62%, respectively. The best result for mathematical models belonged to D’Arsy-Watt with R^2 and the mean relative error of 0.9943% and 10.84%, respectively. The best outcome for the use of ANN also appertained to FFBP network with LM training algorithm, topology of 2-3-3-1 and threshold function order of TANSIG-TANSIG-PURELIN. With this optimized network, R^2 and the mean relative error was 0.9969% and 8.32%, respectively. These results show the supremacy of ANN, in comparison with empirical models. In order to predict the EMC in raisins, empirical models can therefore be replaced with the ANN.

Keywords: ANN, back propagation, sorption isotherm, EMC, Iran

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1 Introduction

Raisin (Dried Grape) is one of the most important Iranian horticultural products with high export value for the country. Standard process of post harvest, such as drying, packaging and storage of grapes would guarantee the quality of raisin and increases its export value as well as producers income.

Water activity and environmental air temperature affect the Equilibrium Moisture Content (EMC) x=f (aw, T). EMC is a durability criterion and any change in quality of food and agricultural products during storage and packaging is crucially important (Veltchev and Menkov, 2000). Fundamental relationship between EMC and relative humidity of food products is known as sorption isotherms (Palipane and Driscoll, 1992). Sorption characteristics of food and agricultural products are used for designing, modeling and optimizing some processes such as drying, aeration and storage (Labuza, 1975; Bala, 1997).

Aeration which relates the air relative humidity and moisture content is essential for optimizing raisin quality. Zarabi (2000) investigated moisture sorption isotherms of grape (Thompson Seedless cultivar) at low temperatures. In his research, sorption isotherms of grape have been determined in temperatures between 20 to 40℃ and Halsey model giving the best result for the prediction of EMC.

Gabas et al (1999) proposed a model for water absorption of Italian grape cultivars. They determined moisture sorption isotherm for the temperatures between 35 to 75℃ and found that GAB model was the best for EMC prediction.

Artificial neural networks have been used for some

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industrial applications such as modeling the moisture content of thin layer corn during drying process for wet milling quality at constant air flow rate, absolute humidity and variable temperatures (Trelea, Countrios and Trystram, 1997) and sorption isotherm of black tea (Panchariya et al., 2002).

Many researchers have investigated the EMC of food and agricultural products which include: moisture sorption characteristics of starch gels (McMinn, Al-Muhtaseb and Magee, 2004), moisture adsorption isotherms of almond at different temperature and water activity levels for nut and almond powder (Pahlevanzadeh and Yazdani, 2005) and hysteresis phenomenon in foods (Caurie, 2007).

Equilibrium moisture characteristics play a very important role in postharvest stage. Mathematical models are the most common methods for estimating equilibrium moisture content. These models which are fitted to experimental data have many problems, such as reduction of computation velocity and accuracy of processing control systems as well as production of numerous equations. The precise prediction of EMC not only decreases the storage losses of raisin but also affects processing systems. Upon mathematical model or ANNs determination through their programming into a control system, it could be possible to predict EMC, if aeration will dry or wet the mass of raisin at a safe level.

The objective of the present study was to apply empirical models and artificial neural networks for predicting EMC of raisin in order to simulate sorption isotherm at thermal boundary of 30-80℃ and 10.51% - 83.62% of relative humidity. In other words, a two dimensional mapping was created for EMC prediction using temperature and relative humidity. To attain this purpose, moisture sorption isotherm was obtained by standard static gravimetric method and then predicted by mathematical model and neural networks. Various topologies were used to predict EMC, followed by comparison of optimized cases of the two methods, and finally the best approach was proposed.

2 Materials and methods

2.1 Mathematical sorption isotherm models

The most common physical models for deriving EMC of agricultural products include the models of GAB, Smit, Henderson, Oswin, Halsey and D'Arsy-Watt. These models have been proposed and tested for the relationship between the EMC and water activity (Bassal, Vasseur and Lebert, 1993; Zomorodian, 2001; San M. et al., 2001; Garcia-Alvarado et al., 1995; Sanny et al., 1997). Formulas of the models are shown in Table 1.

Table 1 Selected isotherm equations for fitting tested data

Model	Formula	Formula No.
GAB	$\begin{cases} EMC = \dfrac{X_m.k.c.a_w}{(1-k.a_w)(1-k.a_w+k.c.a_w)} \\ X_m = A.\exp\left(\dfrac{h}{R.T}\right) \\ k = B.\exp\left(\dfrac{h_1}{R.T}\right) \\ c = C.\exp\left(\dfrac{h_2}{R.T}\right) \end{cases}$	(1)
Smith	$EMC = a - b.\ln(1-a_w)$	(2)
Henderson	$EMC = \left[\dfrac{-1}{a.T}\ln(1-a_w)\right]^{\left(\frac{1}{b}\right)}$	(3)
Oswin	$EMC = a.\left[\dfrac{a_w}{1-a_w}\right]^{b}$	(4)
Halsey	$EMC = \left[\dfrac{-a}{T.\ln(a_w)}\right]^{\left(\frac{1}{b}\right)}$	(5)
D'Arsy-Watt	$EMC = \dfrac{a.b.a_w}{1+a.a_w} + c.a_w + \dfrac{d.e.a_w}{1-d.a_w}$	(6)

Where a_w is water activity in decimal; EMC the equilibrium moisture content in % d.b., T the environmental absolute temperature in K, and R the universal gas constant (8.314 J mol^{-1} K^{-1}). X_m, k, a, b, c, d, e, A, B, C, h, h_1 and h_2 are constants for different materials calculated by using an experimental method. Supremacy of each model for prediction of EMC is expressed by two indices of coefficient of determination (R^2) and mean relative error (E_m). The fitting was performed by non-linear regression based on the minimization of the square sum by means of the software Statgraphics plus 4.1.

2.2 Artificial neural networks

An artificial neural network consists of neurons, which have been related with special arrangement. Neurons are in layers and every network includes some neurons in input layer, one or more neurons in output layer and neurons in one or more hidden layers. Algorithms and architectures of artificial neural networks are different through variation in neuron model and relationship between neurons, and their weights. The learning purpose in artificial neural networks is to update weights, so that with presenting set of inputs, desired outputs are obtained. The most common types of artificial neural networks include: feed forward, feed back and competitive (Menhaj, 1998; Jam and Fanelli, 2000). Training is a process that finally results in learning. Each network is trained with presented patterns. During this process, the connection weights between layers are changed until the differences between predicted values and the target (experimental) is reduced to the permissible limit. Weights interpret the memory and knowledge of network. With the aforementioned conditions, learning process take place. Trained ANN can be used for prediction of outputs of new unknown patterns (Heristev, 1998). The advantages of using ANN are: high computation rate, learning ability through pattern presentation, prediction of unknown pattern and flexibility affront the noisy patterns. In this research, feed and cascade forward networks as well as several learning algorithms were utilized.

Feed Forward Back Propagation (FFBP) consists of one input layer, one or several hidden layers and one output layer. For learning this network, back propagation (BP) learning algorithm is usually used. In the case of BP algorithm, the first output layer weights were updated. A desired value exists for each neuron of output layer. The weight coefficient was updated by this value and learning rules. BP algorithm presents suitable results for subsequent problems but for the other problems it gives an improper result. In some cases, the learning process was upset due to local minimum. This happens because of lying the answer at the smooth part of threshold function.

During training this network, calculations were carried out from input of network toward output and values of error were then propagated to prior layers. Output calculations were conducted layer to layer so that the output of each layer was the input of next one.

Cascade Forward Back Propagation (CFBP) is similar to FFBP network in using the BP algorithm for weights updating, but the main symptom of this network is that each layer neurons are related to all previous layer neurons.

Two training algorithms including Levenberg-Marquardt and Bayesian regulation back propagation algorithms were used for updating network weights.

Gradient-based training algorithms, such as back propagation, are most commonly used by researchers. They are not efficient because the gradient vanishes at the solution. Hessian based algorithms allow the network to learn features of a complicated mapping more suitable. The training process converges quickly, as the solution is approached, because the Hessian does not vanish at the solution. To benefit the advantages of Hessian based training, Levenberg-Marquardt algorithm was used. The LM algorithm is a Hessian based algorithm for non-linear least squares optimization (Hagan and Menhaj, 1994).

Bayesian Regularization (BR) algorithm is a training process of back propagation which is initialized with random distribution of initial weights and biases. After presentation of input patterns to the networks, updating initial weight begins to obtain final distribution using algorithm. This procedure is robust to a high noise level and has a good approximation with arbitrary accuracy of training and it can improve generalization performance. In this algorithm, instead of the Sum of Squared Error (SSE) on the training set, a cost function, which is the SSE plus a penalty term, is automatically adjusted (Girosi et al., 1995).

Structural learning with forgetting is the main technique used for regularization (Girosi, Jones and Poggio, 1995; Kozma et al., 1996). It has a good approximation with arbitrary accuracy of training and can also improve generalization performance.

2.3 Experiments

Raisin samples supplied from Qazvin Province, Iran. Moisture content of raisin was about 15%(d.b.). Salt saturated solutions including lithium chloride, potassium acetate, magnesium chloride, potassium carbonate, magnesium nitrate, sodium nitrate and potassium chloride (all made by MERK Company) were used to provide needed relative humidity.

One of the most common methods used for EMC determination is gravimetric; as it has high precision and dose not need a complex implement (Spiess and Wolf, 1983). After separating the raisins' tails, they were fragmented into pieces of 1 to 2 mm in size. Fifty grams of such raisins pieces were placed into two Petri dishes (90 mm in diameter). Dishes were then transferred into a decicator and kept for 15 days while they were weighted every single day. Equilibrium was derived when the difference of any successive weighing was lower than 0.001 g (Gabas, Telis-Romero and F. C. Menegalli, 1999; Ayranchi et al., 1990; Tsami, Marinos-Koris and Maroulis, 1990).

To establish a fixed relative humidity at water activity domain of 0.11-0.84, eight salt saturated solutions were utilized. Creation of such relative humidity by the saturated solutions has been reported through the literature (Rahman, 1995). In order to control the saturation of solutions, they were covered and placed in an oven of 80℃ for 6 h, the period of time that should not be longer; otherwise, salt crystals appear in the solutions.

The temperature needed for the experiment was provided by using an incubator. After 15 days, weighting was done in three days interval. Three to four weeks were needed for the samples to reach the equilibrium.

Lower relative humidity and upper experimental temperature cause a decrease in the time required for the equilibrium. In order to determine the final moisture content, the equilibrated samples were placed in a vacuum oven [(70 ±1)℃ and 150 mbar] for 6 h (Tsami et al., 1990). All the experiments were conducted in three replications. *EMC* of samples was determined as follows:

$$EMC = \frac{M_w - M_d}{M_d} \times 100\% \qquad (7)$$

Where: M_w and M_d are the weight of wet and dry samples, respectively.

2.4 Designing the ANNs

Considering and applying the two inputs in all experiments, the EMC value derived for different conditions. Networks with two neurons in input layer (Relative humidity and temperature) and one neuron in output layer (EMC) were designed. Figure 1 shows the considered neural network topology and input and output parameters. Boundaries and levels of input parameters are shown in Table 2. Neural network toolbox (ver. 4.1) of MATLAB software was used in this study.

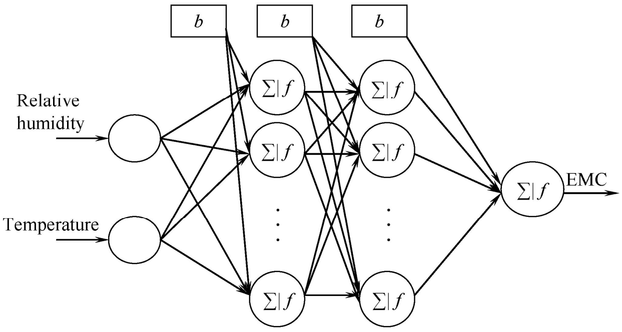


Figure 1 Topological structure of artificial neural network

Table 2 Input parameters for ANNs and their boundaries

Parameters	Minimum	Maximum	No. of Levels
Air Temperature/℃	30	80	5
Relative Humidity/%	10.51	83.62	8

In order to obtain desired answer, two networks of FFBP and CFBP were utilized. Training process by these networks is iterative. When the error between desired and predicted values is minimum, training process meets the stability. The increasing method was used for selection layers and neurons for evaluation of various topologies. By this method, when the network is trapped into the local minimum, new neurons are gradually added to the network. This method has more practical potential to detect the optimum size of the network. The increasing method has some advantages as follows: a) the network complexity gradually increases with increasing neurons; b) the optimum size of the network always obtains by adjustments and c) monitoring and evaluation of local minimum carry out during the training process. Various threshold functions were used to reach the optimized status (Demuth & Beale, 2003):

$$Y_j = \frac{1}{1+\exp(-X_j)} \qquad \text{(LOGSIG)} \qquad (8)$$

$$Y_j = \frac{2}{(1+\exp(-2X_j))-1} \qquad \text{(TANSIG)} \qquad (9)$$

$$Y_j = X_j \qquad \text{(PURELIN)} \qquad (10)$$

In which X_j is the sum of weighed inputs for each neuron in j^{th} layer and computed as below:

$$X_j = \sum_{i=1}^{m} W_{ij} \times Y_i + b_j \tag{11}$$

Where: m is the number of output layer neurons; W_{ij} the weight of between ith and jth layers; Y_i the ith neuron output and b_j: bias of jth neuron for FFBP and CFBP networks. About 75% of all data were randomly selected for training network with suitable topology and training algorithm (Figure 2).

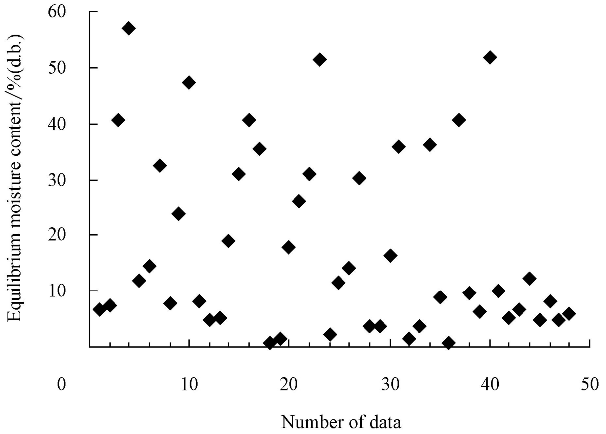


Figure 2 Distribution of training and testing data set

The following criterion of root mean square error has defined to minimize the training error (Demuth and Beale, 2003):

$$MSE = \sum_{p=1}^{M} \sum_{i=1}^{N} (S_{ip} - T_{ip})^2 \tag{12}$$

Where: MSE is the mean square error; S_{ip} the network output in ith neuron and pth pattern; T_{ip} the target output at ith neuron and pth pattern; N the number of output neurons and M the number of training patterns. To optimize the selected network from prior stage, the secondary criteria was used as follows:

$$R^2 = 1 - \frac{\sum_{k=1}^{n} [S_k - T_k]}{\sum_{k=1}^{n} [S_k - \frac{\sum_{k=1}^{n} S_k}{n}]} \tag{13}$$

$$E_{mr} = \frac{100}{n} \sum_{k=1}^{n} \left| \frac{S_k - T_k}{T_k} \right| \tag{14}$$

$$SD_{mr} = \sqrt{\frac{\sum_{k=1}^{n} \left(\left| \frac{S_k - T_k}{T_k} \right| - \overline{\left| \frac{S_k - T_k}{T_k} \right|} \right)}{n-1}} \tag{15}$$

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

3 Results and discussion

3.1 Sorption curves

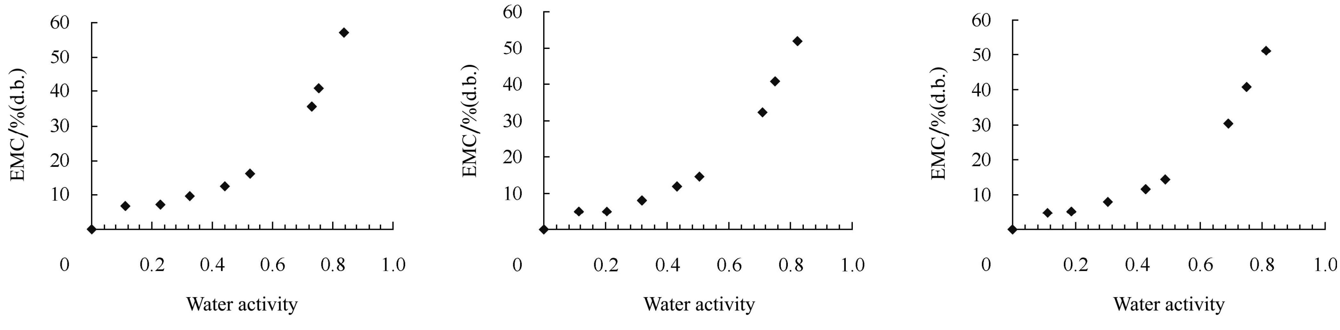
The averages of EMC in three replications as well as water activities of salt solutions are shown in Figure 3. These curves are the moisture adsorption isotherm of raisin. Increasing temperature in a water activity decreased the EMC. Increasing in water activity caused an increase in raisin EMC of all temperatures. The changes in water activity more than 0.5 are quite obvious. (In the temperature above 60℃ with low water activity, the EMC value has also no significant change.)

Raisin like other high glucose dried fruits absorbs less moisture in low water activity, but more in high water activity. Because of moisture absorbing properties of biopolymers in all food materials, curve slope increases and this phenomenon is also seen in raisin because of its high absorbing moisture rate which is in turn related to glucose. In low water activity, physical properties of glucose, do not have significant effect on moisture absorption. No shaped glucose, absorbed more moisture compared with crystal glucose.

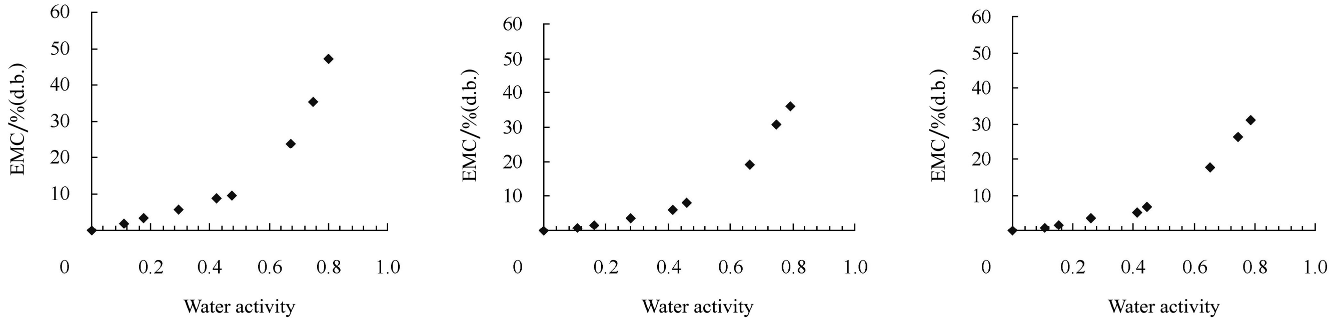
3.2 Mathematical models

Mathematical models of GAB, Smith, Henderson, Oswin, Halsey and D’Arsy-Watt used for raisins EMC empirical data fitting. Non linear regression method with software was used for fitting the data. Three indices of variation coefficient (R^2), mean square error (MSE) and mean relative error (E_{mr}) were utilized for appropriate fitness determination.

Results of empirical models fitting at temperatures between 30 to 80℃ are shown in Table 3. For this temperature range, D’Arsy-Watt model produced the best results where R^2 = 0.9943 and E_{mr}=10.84%. Therefore this model produced the best results for six temperature levels that could be used for the estimation of raisins EMC at various temperatures and water activities. Any of empirical models has an equation with constants. The values have been depicted in Table 3.



a. 30℃ b. 40℃ c. 50℃



d. 60℃ e. 70℃ f. 80℃

Figure 3 EMC of raisin at different water activities and temperatures

Table 3 Coefficients and outputs of mathematical models

Model	a	b	c	d or k	e or X_m	MSE	R^2	E_{mr}
SMITH	-3.24	27.57	-	-	-	7.28	0.9708	37.38
OSWIN	15.50	0.818	-	-	-	1.60	0.9929	13.00
GAB	-	-	1.157	0.719	128.92	1.40	0.9946	12.78
HALSEY	7.97	1.11	-	-	-	2.02	0.9911	17.90
DARCY-WATT	-0.7748	-10.36	-4.39	0.7877	9.04	1.43	0.9943	10.84
HENDERSON	-0.121	0.716	-	-	-	2.30	0.9910	16.83

3.3 ANNs approach

FFBP and CFBP networks were used for mapping between inputs and outputs of patterns. Two strategies were utilized to investigate different threshold functions affecting network optimization that include similar and various threshold functions for all layers (Table 4). Both strategies together with learning algorithms of LM and BR were used for FFBP and CFBP networks. Several topologies were tested and the best results which used from each network, training algorithm and Threshold function/functions, are represented in Table 4.

The best results for FFBP network with LM algorithm in the first strategy belonged to TANSIG threshold function and 2-3-3-1 topology. This composition produced MSE=0.00015, R^2=0.9946 and E_{mr} =10.67 and converged in 16 epochs. The best result for the second strategy of FFBP network with LM algorithm is belonged to 2-3-3-1 topology and TANSIG–TANSIG–PURELIN threshold functions, and produced MSE=0.00016, E_{mr} =8.32 and R^2=0.9969.

The best results for FFBP network with BR algorithm and the first strategy is belonged to TANSIG threshold function and 2-4-2-1 topology. This composition produced MSE=0.00059, R^2=0.9892 and E_{mr} =26.20 and converged at 13 epochs. Also for FFBP network, BR algorithm and the second strategy, the best topology was 2-4-2-1 with LOGSIG–TANSIG–PURELIN threshold functions. This composition produced E_{mr}=11.72, R^2= 0.9930 at 27 epochs. In addition, for FFBP network, LM algorithm presented the better result than BR algorithm.

Table 4 Training algorithm for different neurons and hidden layers for several networks at the uniform threshold function for layers

Network	Training algorithm	Threshold function	No. of Layers and Neurons	*MSE*	R^2	E_{mr}	SD_{EMR}	Epoch
FFBP	LM	TANSIG	2-3-3-1	0.00015	0.9946	10.67	9.43	16
		LOGSIG	2-4-2-1	0.00019	0.9874	15.11	23.39	14
		LOGSIG–TANSIG–LOGSIG	2-3-3-1	0.00017	0.9873	15.98	19.51	29
		TANSIG–TANSIG–PURELIN	2-3-3-1	0.00016	0.9969	8.32	10.21	48
	BR	TANSIG	2-4-2-1	0.00059	0.9892	26.20	42.23	13
		LOGSIG	2-4-2-1	0.00050	0.9876	26.97	48.55	24
		LOGSIG–TANSIG–LOGSIG	2-4-2-1	0.00056	0.9855	31.12	57.96	20
		TANSIG–TANSIG–PURELIN	2-4-2-1	0.00083	0.9930	11.72	15.44	27
CFBP	LM	TANSIG	2-2-2-1	0.00021	0.9927	12.76	10.84	18
		LOGSIG	2-3-3-1	0.00015	0.9926	16.85	24.97	14
		LOGSIG–TANSIG–LOGSIG	2-3-3-1	0.00022	0.9925	15.61	23.77	12
		TANSIG–TANSIG–PURELIN	2-3-3-1	0.00011	0.9957	11.87	12.30	21
	BR	TANSIG	2-3-2-1	0.050	0.8074	143.39	313.50	21
		LOGSIG	2-4-2-1	0.0046	0.9886	44.40	74.96	24
		LOGSIG–TANSIG–LOGSIG	2-4-2-1	0.0015	0.9886	18.95	20.97	24
		TANSIG–TANSIG–PURELIN	2-4-2-1	0.00076	0.9899	13.59	15.42	37

Furthermore, in this stage, application of LM algorithm has better result than BR algorithm because it produced less E_{mr} and more R^2 values.

The best results for CFBP network in the first strategy and LM algorithm belonged to 2-2-2-1 topology. This composition produced E_{mr} =12.76 and R^2=0.9927 at 18 training epochs. CFBP network for the second strategy and LM algorithm for 2-3-3-1 topology and threshold functions of TANSIG–TANSIG–PURELIN showed the *MSE*=0.00011, E_{mr} =11.84 and R^2=0.9957.

The best results for CFBP network in the first strategy with BR algorithm and 2-4-2-1 topology produced *MSE*=0.0046, E_{mr} = 44.40 and R^2=0.9880 at 22 epoch. The best result for CFBP network with BR algorithm and the second strategy was related to LOGSIG–TANSIG–PURELIN threshold function and 3-5-5-1 topology. This composition produced *MSE*=0.00076, E_{mr} =13.56 and R^2=0.9899.

With regard to the results, the second strategy of FFBP network, LM algorithm with LOGSIG–TANSIG–PURELIN threshold functions and 2-3-3-1 topology showed the best performance. These findings showed that, the best result in all cases belonged to second strategy. This is because topology of the second strategy, E_{mr} and R^2 have the better values. Experimental and predicted data set and their error are shown in Figure 4 and MSE for training and testing patterns in Figure 5. Results showed that E_{mr} is the least value for this network, so this network selected as an optimized one. MATLAB software output demonstration for optimized network is shown in Figure 6.

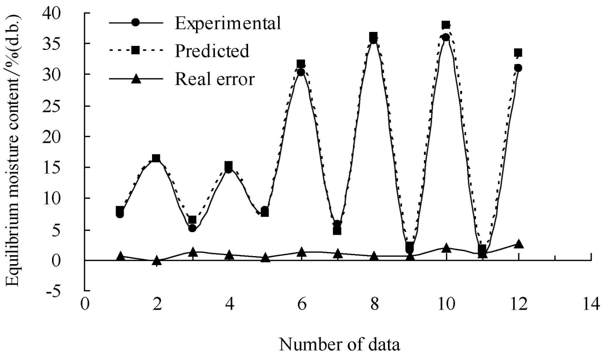


Figure 4 Predicted values of EMC using ANNs versus experimental values and real error

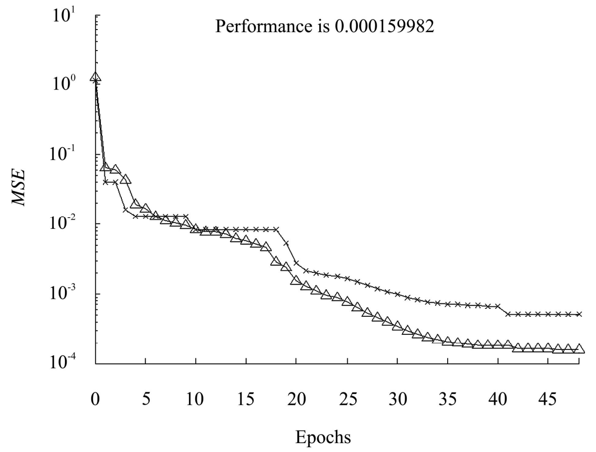


Figure 5 Mean square error of training and testing patterns for the best ANN

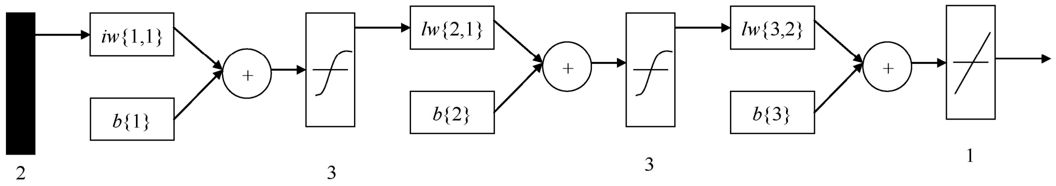


Figure 6 Matlab software output demonstration for optimized network (IW and LW are weight matrix, b is bias matrix)

Values of weight matrix between layers and biases are:

(Weight matrix between input layer and layer1)

$$IW\{1,\ 1\}=\begin{bmatrix}-7.18 & 2.01\\ 6.52 & 0.23\\ 0.13 & -1.99\end{bmatrix}$$

(Weight matrix between layers 1 and 2)

$$LW\{2,\ 1\}=\begin{bmatrix}0.02 & -0.02 & -2.05\\ -2.48 & 1.11 & -1.43\\ -0.53 & -0.14 & 2.70\end{bmatrix}$$

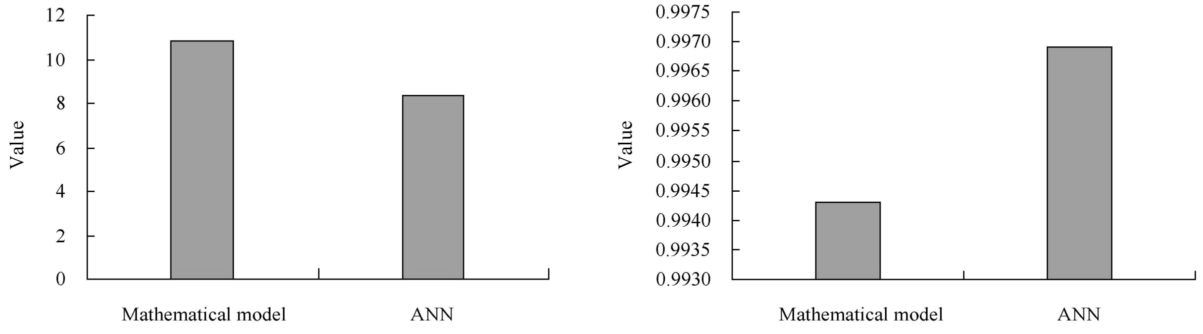
(Weight matrix between layers 2 and 3)

$$LW\{3,\ 2\}=\begin{bmatrix}1.07 & 0.02 & -1.76\end{bmatrix}$$

(Bias to layer 1) $b\{1\}=\begin{bmatrix}4.24\\ -2.02\\ 2.70\end{bmatrix}$; (Bias to layer 2) $b\{2\}=\begin{bmatrix}2.07\\ -0.11\\ 0.04\end{bmatrix}$; (Bias to layer 1) $b\{3\}=[1.75]$

The average value of indices for mathematical model and optimized ANNs are shown in Figure 7. Mathematical model and ANNs have a significant difference in producing R^2 having the average value for mathematical model of 0.9943 and for optimized ANN of 0.9969 (Figure 7a). The relative error produced by ANNs (8.32%) is less than that of mathematical model (10.84 in Figure 7a).

Modeling and afterwards choosing a model that fits the experimental data using E_{mr}, for practical purposes, should always be lower than 10% (Mohapatra and Rao, 2005); therefore, none of the mathematical models are reliable to predict EMC values for entire temperature range. But ANN method is suitable, as ANN model can predict the EMC of raisin with an acceptable accuracy, also the ANN models could predict the EMC of raisin with SD_{EMR} around the E_{mr} values. These results show that the overtraining for the presented models does not happen and E_{mr} with SD_{EMR} are the suitable indices for comparing of two methods. E_{mr} and SD_{EMR} also have the controlling role for MSE and R^2.



a. Mean relative error

b. Coefficient of determination

Figure 7 Average values of indices for mathematical models and optimized ANN

4 Conclusions

An artificial neural network is used as a new method for nonlinear mapping to predict EMC of raisin (black currant) through two independent parameters including air temperature and relative humidity. The following conclusions can be drawn from the experiments:

Raisin like other high glucose dried fruits absorbs less moisture in low water activity but more in high water activity. This is because in low water activity, glucose has not significant effect on moisture absorption.

The best result for mathematical model belonged to D'Arsy-Watt model at temperature with R^2 and mean relative error of 0.9943 and 10.84%, respectively.

The best ANN for data training was FFBP with LM algorithm and TANSIG–TANSIG–PURELIN threshold functions for layers, three neurons for the first hidden layer and three for the second one. With this optimized network, R^2 and mean relative error were 0.9969 and 8.32%, respectively.

The EMC of raisin could be predicted by ANN method, with less mean relative error and more determination coefficient compared to the mathematical models.

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