Prediction of Pistachio Thermal Conductivity Using Artificial Neural Network Approach

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ABSTRACT

One of the most important thermo-physical characteristics of pistachio is thermal conductivity, which was predicted at a range of temperatures (50 to 95°C) and moisture contents (3.8 to 52.15% dry basis; d.b.) in this species using line heat source method and artificial neural networks (ANNs). Two independent variables of temperature and moisture content were considered as inputs of ANNs and thermal conductivity was considered as an output. Radial basis function network (RBFN) with 112 entities and four neurons in second hidden layer with linear threshold function and learning rule of delta was selected to be the best ANN architecture that had the least mean square error 0.0045 and $R^2 = 0.99$. Decreasing moisture content to 10.8% (d.b.) reduced thermal conductivity, but decreasing it further to 3.8% (d.b.) caused proportionate increase in thermal conductivity of the samples. Prediction accuracy of thermal conductivity by designed ANN was 3.24% better than statistical results. Thus the RBFN is recommended for predicting the pistachio thermal conductivity.

Key Words: Pistachio; Thermal conductivity; Artificial neural networks; Radial basis function network

INTRODUCTION

Optimization of heat transfer of each food product at different stages of drying is necessary for high quality production and prediction of precise thermal values can fulfill the objectives. Pistachio is one of strategic agricultural products in Iran and contains up to 50% moisture at harvesting. Moisture content level also depends on the time of harvesting and the weather of the area (Rostami, 1998). Pistachio nuts with split shell are contaminated by aflatoxin after 48 h, whereas this period for un-split pistachio is 10 days (USDA Standard, 1990). Researchers recommend that after harvesting and dehuling of pistachio, moisture content should be decreased to lower than 7.5% on dry basis (USDA Standard, 1990). Drying of pistachio in ambient air is slow, which causes growth of mold (Hsu *et al.*, 1991). After processing, dried pistachio with 4 to 6% (d.b.) moisture content is sent to the market (Darvishian, 1999), which is according to the permissible moisture content as per recommended standard i.e., 7% (USDA Standard, 1990).

One of the most important heat properties for agricultural products is thermal conductivity. This value shows heat transfer intensity in unit area from unit thickness in unit time to change solid temperature 1°C (Incropera & De Witt, 1996). Thermal conductivity of materials depends on chemical composition, physical construction, state of pressure and temperature. Solids with lower porosity have lower thermal conductivity. Also heat conductivity of solids increases with moisture content (Denizel, 1977). Line heat source method was used for measuring thermal conductivity of some materials. In most cases, the measured values by this method were more precise than the other methods (Nix *et al.*, 1969).

Rao *et al.* (1975) derived the thermal conductivity of potato by Ingersol seri. Tagawa and Murata (1995) determined thermo-physical properties of bean by using Ingersol seri relationship and derived thermal conductivity by nonlinear least square method. Karatas and Battalbey (1991) studied the moisture distribution of pistachio along with the drying time. They exposed a single pistachio nut in the fixed environmental moisture and temperature condition and modeled the drying and moisture distribution in a single nut.

Yanniotis and Zarmboutis (1996) studied the moisture absorption rate in pistachio nuts. They measured the absorption and desorption of pistachio nuts at 15, 25 and 40°C. According to the results, dried pistachio with moisture content less than 6% (d.b.) is to be kept in environment with relative humidity less than 60% and at 20°C. Hsu *et al.* (1991) measured and calculated the pistachio thermophysical properties at room temperature with moisture content of 5 to 40% (w.b.) by linear heat source method.

Farkas *et al.* (2000) used the ANNs for an agricultural fixed bed dryer and showed that the ANN could be used for modeling drying grains. For prediction of moisture evaporation process in a fluidized bed dryer, an ANN model

was proposed by Zbicincski *et al.* (1996). Studies on prediction of thermal conductivity of different materials, the input/output dimensionless parameters (Reynolds number, Archimedes & ratio of bed height to average diameter of grains as inputs & Nusselt number as an output) for training and testing of ANN were used (Zbicincski & Ciesielski, 2000). Results showed that, this method increases the instability of ANN training and the average errors, but calculated mean standard error was in the permissible limit of 4%. Islam *et al.* (2003) used back propagation algorithm (BPA) for prediction of drying rate of potato pieces. BPA predicted the page equation coefficients. The objective of this research was to introduce a suitable ANN for prediction of thermal conductivity of pistachio finding its practicability.

MATERIALS AND METHODS

Measurement instruments. For measuring thermal conductivity of pistachio, linear heat source method was used. It is a fast and precise method. Used instrument was a drum made from galvanized steel with thickness of 0.055 mm, diameter of 200 mm and height of 40 mm. A 300 W electrical heat element with 180 mm length was installed in the center of the drum (Koochak-zadeh, 2000). To control of the electrical heat element, a 1 KW-A adjustable feed source was used. It could change 110 to 220 V input voltage to output of 250 V. A wattmeter of Lutron D.W. 6060 was used for measuring heat line source. Also two thermocouples TP-01 were placed at distances of 18 and 40 mm from linear heat source. Digital thermometer of Lutron TM-915 was used to change the thermocouple signal and temperature monitoring. Thermometer output was connected to computer. Given information, was registered by SW-U001 (Ver. 1.3) software. One Samsung microwave oven M945 was used for preparing the pistachio samples (Koochak-zadeh, 2000).

Sample preparation. Abbas-Ali variety of pistachio was used for performing experiments, which was bold in size and its slot nuts percentage was too high. For preparing of the samples with assumed moisture content, first it was washed and cheap nuts were separated, then samples were placed in the microwave oven. With variation of in time and radiation conditions 150 g samples were dried to appropriate moisture content. Microwave with short wave radiation was adjusted to 2450 MHz and 500 W for 1 to 30 min. In this way, 5 moisture content levels were created. Then the samples were placed into the refrigerator for a week to have samples with uniform moisture content at each level. For measuring average moisture content of pistachio samples, about 150 g of pistachio was placed in the oven for 6 h at $130 \pm 3°C$.

After the pistachio samples were prepared for each moisture content level, they were poured into the drum container until it was filled up. In all the experiments, the temperature of number 1 thermocouple was recorded from the beginning of experiments and continued to reach temperature of 95°C. For measuring of real power of heat line element, output wires of transducer was connected to wattmeter and then connected to heat element. By tuning the output voltage of transducer, the power of line element was adjusted and then recorded. Each time before apparatus power measurement, wattmeter was calibrated in state of un-loading and transducer was adjusted. Furthermore, it was tried to fix the real power of heat linear element.

Mathematical model. For calculation of pistachio thermal conductivity, equation (1) was used (Hsu *et al.*, 1991):

$$K = \frac{Q}{4\pi(T_2 - T_1)} Ln(\frac{\theta_2 + \theta_0}{\theta_1 + \theta_0}) \qquad (1)$$

Where Q: linear heat source power (W/m), T_1: temperature at the beginning of experiment (°C), T_2: mean secondary temperature for all data recorded at the considered time intervals (°C), θ_0: time correction parameter (S), θ_1: initial time equal to 0.785S for all moisture content levels and θ_2: required time for temperature of T_2.

To determine θ_0, the equation between temperature and time for each experiment data was proposed by Sutter *et al.* (1975):

$$T = A + B \times Ln(\theta + \theta_0) \qquad (2)$$

Where, A and B: constants that are used for adaptation of time-temperature curves in natural logarithm form.

Artificial neural networks (ANNs). ANN is one of the computing methods. It uses simple processing elements named neuron. ANNs discovers the inherent relationship between parameters through learning process and creates a mapping between input space (input layer) and target space (output layer). Hidden layer/layers process the input data from input layer and produce answer in output layer. Each network is trained with presented patterns. During this process, the connection weights between layers is changed until the differences between predicted values and the target (experimental) is reduce to permissible limits. With the aforementioned conditions, learning process takes place. Trained ANN can be used for prediction of outputs of new un-known patterns (Dayhoff, 1990).

An ANN has special characteristics such as: (1) high processing rate due to parallel processing construction, (2) learning ability through pattern presentation, (3) prediction of un-known pattern at desired precision, after learning, (4) flexibility at un-desired errors of input training pattern (noise) and (5) if a part of network connections is damaged, created error is not notable (Khanna, 1990). Architectures of an ANN can be changed by varying single neuron model, interconnection between neurons and weight of these connections. In this study, feed forward neural network was used for function approximation and pattern classification (Khanna, 1990). The multilayer perceptron (MLP) and

radial basis function (RBF) networks are the most commonly used feed forward ANNs. Either of two networks has layered structure. In a MLP network, neurons of hidden layer have output as follow (Dayhoff, 1990; Khanna, 1990):

$$h_j = f'(s_j) = f(\sum_{K=1}^{N} W_{jk} x_k) \qquad (3)$$

And an output layer neuron generates as output:

$$y_i = f'(s_i^*) = f(\sum_{j=1}^{m} W_{ij} h_j) \qquad (4)$$

Where h_j: output of *j*th neuron in hidden layer, s_j: weighted sum of *j*th neuron in hidden layer, x_k: input of *k*th neuron in input layer, y_i: output of *i*th neuron in output layer and s_i^*: weighted sum of *i*th neuron in the output layer.

RBF network is similar to MLP network, but the computation done by neurons of hidden layer. Hidden layer neurons have outputs as (Broomhead & Lowe, 1988):

$$h_j = exp(-\frac{\|x_i - c_j\|^2}{\sigma_{ij}^2}) \qquad (5)$$

Where x_i: vector of input pattern, σ_{ij}^2: variance of gaussian kernel and c_j is the center of gaussian kernel.

Designing the ANNs. Experiments were carried out in three replications for all moisture content levels. Regarding to two input factors of initial moisture content and temperature, 224 number of thermal conductivity for pistachio were derived at temperatures of 50 to 95°C and initial moisture content of 3.8 to 54.15% (d.b.). An ANN with two neurons in input layer (temperature & moisture content) and one neuron in output layer (thermal conductivity) was designed. Fig. 1 depicts typical neural network topology, also input and output experimental parameters are shown in this figure. Optimum numbers of neurons in hidden layer/layers were derived by trial and error. Software package of Neural Works Professional 11/PLUS (Ver. 5.23) was used for this research.

In order to train the designed ANN, several networks were used, two of which are: multi layer perceptron (MLP) with back propagation algorithm (BPA) and Radial basis function network (RBFN). Training process for these algorithms iterative, then conclude of weight changing between different layers along with training time, became stable and difference between real values (experimental) are predicted and minimized. Several threshold functions were used for evaluation of ANNs and finding the best one. These functions are (Dayhoff, 1990; Khanna, 1990):

$$Y_j = Sin(X_j) \qquad (6)$$

$$Y_j = \frac{1}{1 + exp(-X_j)} \qquad (7)$$

$$Y_j = X_j \qquad (8)$$

$$Y_j = tanh(X_j) \qquad (9)$$

X_j: sum of weighted inputs of *j*th layer and is calculated as follows:

$$X_j = \sum_{i=1}^{m} W_{ij} \times Y_i + b_j \qquad (10)$$

For MLP network, *m*: number of output layer neurons, W_{ij}: weight of connections between layers of i and j, Y_i: output of *i*th neuron and b_j: bias neuron of *j*th layer. For RBF network *m*: number of output layer neurons, W_{ij}: weight of connected to *j*th output neuron, b_j: bias neuron of *j*th layer and Y_i: function of input vector as (Broomhead & Lowe, 1988):

$$Y_i = -exp(-\sum_{i=1}^{n} \frac{\|x_i - c_j\|^2}{2\sigma_{ij}^2}) \qquad (11)$$

Where, *n*: number of neurons in hidden layer.

Several Learning rules were used for training process, such as: Delta Rule, Norm-Cum-Delta, Ext DBD, Quick Prop, Max Prop and Delta-Bar-Delta. In each of the training algorithms, the aim was reducing the root mean square error (RMSE), which defines as:

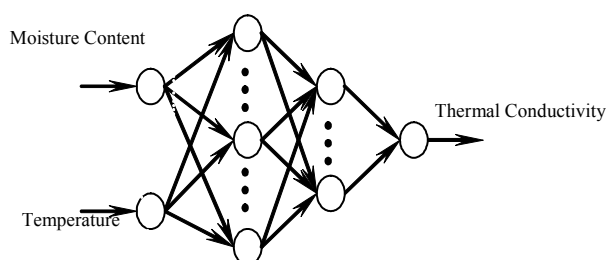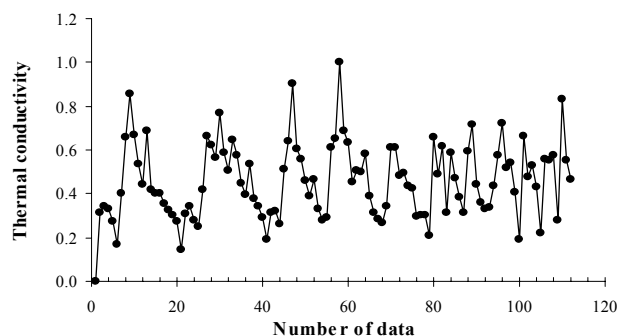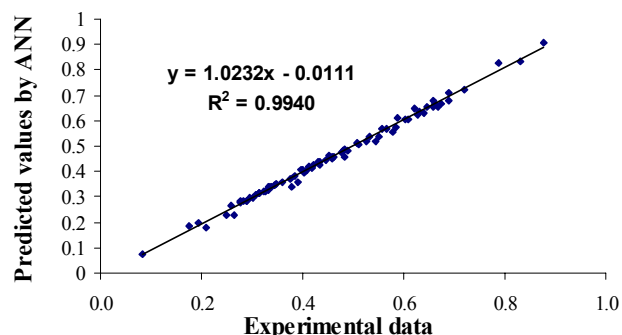$$RMSE = \frac{1}{2P} \sum_{P=1}^{N} \sum_{K=0}^{M} (y_{kP} - t_{kP})^2 \qquad (12)$$

Where *P*: total number of training patterns, *M*: total number of output neurons, y_{kP}: network output at the *k*th output neuron and t_{kP}: target output at the *k*th output neuron.

For training, the data were divided into three sections, randomly. Half of the data (112 patterns) were used for training the designed networks, 80 patterns for test and 32 data sets for evaluation of ANNs (Fig. 2).

To increase the precision and velocity of ANN process, all data were normalized by the following relationship:

$$X_n = \frac{X(B_U - B_L) + X_{max}B_L - X_{min}B_U}{X_{max} - X_{min}} \qquad (13)$$

Where X: experimental data, X_{min} and X_{max}: minimum and maximum data, respectively, B_L and B_U: lower and upper boundaries, respectively and X_n: normalized data which is between B_L and B_U.

Fig. 1. Used ANN topology

Fig. 2. Distribution of training data set

Fig. 3. Predicted values of thermal conductivity for testing of optimized ANN (80 data set)
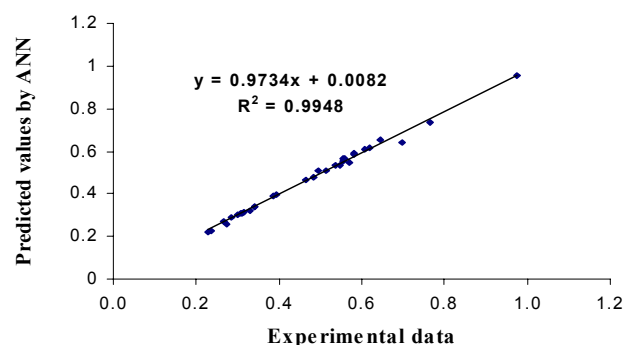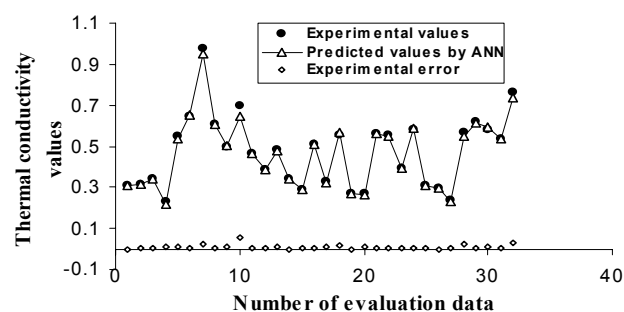

$$y = 1.0232x - 0.0111$$
$$R^2 = 0.9940$$

RESULTS AND DISCUSSION

Analysis of designed networks. In this research work, the Different combinations of networks, threshold functions and learning rules were tested. Learning rule of delta with linear threshold function was found to be the best case in the combination of RBF network. The MLP network with one and two hidden layers was used. RMSE was calculated for each network. Results revealed that RBF network contains the least RMSE values. Furthermore this network was selected and optimized (Table I). For increasing the RBFN prediction ability, of the neural works software, an additional hidden layer was used, Furthermore, all topologies of RBFN used in Table I are four layer. In this software, recommended that it is better the number of entities be the near of training pattern numbers. The number of neurons for hidden layer was determined by trial and error. After selecting of suit threshold function, learning rule, hidden layer and their neurons, then was optimum epochs, learning rate and momentum should be selected by

Table I. Learning criteria values for different values in layer and neuron numbers for several examined ANNs

Network	Threshold function	Learning rule	Number of layers and neurons	RMSE	R^2
	Linear	Delta	2-112-2-1	0.0097	0.9945
	Linear	Delta	2-112-3-1	0.009	0.9924
	Linear	Delta	2-112-4-1	0.0045	0.9940
	Linear	Delta	2-112-6-1	0.0064	0.9909
	Linear	Norm-Cum-Delta	2-112-4-1	0.0121	0.9611
	Linear	Ext DBD	2-112-2-1	0.0169	0.9868
	Linear	Ext DBD	2-112-4-1	0.0124	0.9404
	TanH	Delta	2-112-2-1	0.0119	0.9913
RBF	TanH	Delta	2-112-3-1	0.0126	0.9909
	TanH	Delta	2-112-4-1	0.0085	0.9744
	TanH	Delta	2-112-5-1	0.0141	0.9927
	TanH	Delta	2-112-6-1	0.0121	0.9900
	TanH	Norm-Cum-Delta	2-112-4-1	0.0196	0.9669
	TanH	Ext DBD	2-112-2-1	0.0172	0.9869
	TanH	Ext DBD	2-112-4-1	0.0150	0.9460
	TanH	Delta-Bar-Delta	2-112-2-1	0.0596	0.9185
	Sigmoid	Delta	2-112-4-1	0.0236	0.9915
	Sin	Delta	2-112-3-1	0.0132	0.9905
	Sin	Delta	2-112-4-1	0.0052	0.9703
	Sin	Delta	2-112-5-1	0.0109	0.9932
	Sin	Delta	2-112-6-1	0.0120	0.9893
	TanH	Ext DBD	2-6-1	0.0456	0.9754
	Sigmoid	Delta	2-4-1	0.0389	0.8950
	Sigmoid	Ext DBD	2-5-1	0.0372	0.8950
	Sigmoid	Ext DBD	2-6-1	0.0269	0.8900
	Sin	Delta	2-4-6-1	0.0243	0.8900
MLP	Sin	Delta	2-4-2-1	0.0295	0.8920
	Sin	Delta	2-6-5-1	0.0290	0.8890
	Sin	Delta	2-5-6-1	0.0271	0.9926
	Sin	Delta	2-5-2-1	0.0276	0.9925
	Sin	Ext DBD	2-5-4-1	0.0289	0.9926
	TanH	Delta	2-6-4-1	0.0275	0.9903
	TanH	Delta	2-6-6-1	0.0270	0.9831
	TanH	Delta	2-3-5-1	0.0286	0.9916
	TanH	Delta	2-7-3-1	0.0266	0.9845

trial and error. The values 0.3, 0.25 and 0.15 obtained for input layer, second hidden layer and output layer, respectively. Also, values for optimum momentum and epoch obtained were 0.4 and 20000, respectively by the same method. Results of training error for several networks with different number of layers and neurons for each layer have been shown in the Table I. The RMSE was the least (0.0045) for RBF network with linear threshold function, learning rule of delta, four neurons in second hidden layer and 112 patterns. With this RMSE value, $R^2 = 0.994$, was calculated for fitness of experimental values with predicted ones for testing data (Fig. 3). Fig. 4 shows the predicted and target values of 32 independent experimental data sets for evaluating designed network. The real error values of evaluation data set revealed that the network training was done without any over-training (Fig. 5). Sablani and Rahman (2003) predicted the heat conductivity of food by three input factor of moisture content, temperature and apparent porosity. They derived precision about 95% by using of back propagation algorithm. In another research, Sablani *et al*. (2001) used the ANN approach to model the bakery products as a function of product moisture content,

Fig. 4. Experimental and predicted values for evaluation of optimized ANN by independent data set

$$y = 0.9734x + 0.0082$$
$$R^2 = 0.9948$$

Fig. 5. Predicted values and real errors of designed ANN for evaluation data

temperature and apparent density. The best ANN topology was capable to predict thermal conductivity of those products by about 98% with back propagation algorithm.

Statistical model. A statistical model for prediction of pistachio thermal conductivity for all used data at the considered limits of temperature and initial moisture content, was proposed by Koochak-zadeh (2000):

$$K = -8.066769M + 0.05493t - 8.595M^2 - 0.001284t^2 + 0.271137M \times t + 0.622738M^3 + (7.590181\times10^{-6}) \times t^3 - 0.037529M^2 \times t - 0.001569M \times t \quad R^2 = 96.17 \quad (14)$$

Where t: temperature (°C) and M: initial moisture content. Comparison between proposed equation and designed ANN results predictions appears that ANN can increase the prediction precision by 3.25%.

Comparison between results showed that because of special distribution of patterns in thermal conductivity problems, the RBFN was a better choice between networks for more precise prediction of thermal conductivity.

CONCLUSION

As the precise simulation of thermal conductivity of pistachio in drying, transportation and storage, in this paper a novel approach based on the ANN method has been used as an suitable method for finding the relationship between input and output variables and nonlinear mapping. So, thermal conductivity of pistachio was predicted by two independent parameters of temperature and initial moisture content, which were then compared with the proposed statistical model. The best ANN architecture for training of database was RBF network with delta learning rule, linear threshold function, 4 neurons in second hidden layer and 112 pattern set, because of the best RMSE (= 0.0045) and R^2(=0.994). Also the results showed that using this methodology the precision of prediction of output values increases by 3.25%, which was better than statistical method results.

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