Prediction of Moisture Content of Bergamot Fruit During Thin-Layer Drying Using Artificial Neural Networks

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ABSTRACT: *In this study thin-layer drying of bergamot was modelled using artificial neural network. An experimental dryer was used. Thin-layer of bergamot slices at five air temperatures (40, 50, 60, 70 & 80 ºC), one thickness (6 mm) and three air velocities (0.5, 1 & 2 m/s) were artificially dried. Initial moisture content (M.C.) during all experiments was between 5.2 to 5.8 (g.g) (d.b.). Mass of samples were recorded and saved every 5 sec. using a digital balance connected to a PC. MLP with momentum and levenberg-marquardt (LM) were used to train the ANNS. In order to develop ANN's models, temperatures, air velocity and time are used as input vectors and moisture ratio as the output. Results showed a 3-8-1 topology for thickness of 6 mm, with LM algorithm and TANSIG activation function was able to predict moisture ratio with R^2 of 0.99936. The corresponding MSE for this topology was 0.00006.*

Keywords: Bergamot, Thin-Layer, Artificial Neural Network, Levenberg-Marquardt, Momentum

Received: 17 September 2011, Revised 4 November 2011, Accepted 9 November 2011

1. Introduction

Citrus are of great important among agricultural products in the world. Iran produces 3.5 million tonnes of citrus and is ranked 22nd in the world [1]. Bergamot is an evergreen and a small tree from Rue family (Figure 1). Its fruit is pear like and bergamot oil is extracted from the skin which is used as an ingredient in perfume industries. The fruit skin with bitter and fragrant taste is used in jam production and also in pharmaceutical and medical applications. The name of the tree is citrus bergamia and belongs to bergamot family. Another citrus fruit from Rue family is citron which is called cedrate. The tree is called citrus medica and the fruit is used in jam production as well [2].

Bergamot fruit consists of flevedo, albedo and an oval shape meat. The flevedo is initially green and as the fruit ripens, becomes yellow. The albedo is white in both green and yellow stages of the flevedo and its thickness is manifold than that of the flevedo. The meat is edible and very sour and can be used in place of lemon juice or in making various pickles.

Bergamot is usually grown in south Iran like Jahrom (in Fars province). Before the yellow stage, the crop is harvested and the skin is dried. Dried skins are used in jam production in seasons that fresh fruit is not available. In addition, bergamot as dried fruit is exported to many countries [3].

Drying is defined as a process of moisture removal due to simultaneous heat and mass transfer [4]. It is also a classical method of food preservation, which provides longer shelf-life, lighter weight for transportation and smaller space for storage. Natural sun drying is prac-ticed widely in the world and also in Iran, but has some problems related to the contamination by dirt and dust and infestation by insects, rodents and other animals. Therefore, the drying process should be undertaken in closed equipments, to improve the quality of the final product.

Artificial neural networks in reality are the simplified model of man mind which is one of the tools for predicting physical phenomena, and were considered as an application on 50s of 20th century for the first time, when Frank Rosenblatt introduced Perceptron network in 1958 [5].

The smallest unit of artificial neural network is Neuron. Every network consists of one input, one output and one or several middle layers. Each layer's neurons are connected to next layer neurons by some neurons. In the network training process, these weights and the permanent amounts are added to them and named Bias idiomatically, changes continuously until the sum of the squares of error gets minimum. Weights and biases changes are on the base of learning law. For transferring every layer outcome to next layers, actuator functions are used. Sigmoid, linear, and preliminary functions can be mentioned from famous actuator functions. To build artificial neural network, data are divided to two series of instruction data and examination data. About eighty percent of data are applied to instruction and the remaining is used for examination and evaluation. In the duration of learning process, network learning level is being measured continuously by some error indices and finally, the network is being selected which has minimum error [6].

One of the important usages of artificial neural network is training and predicting outcome with new data. In FFBP1 network, with BP2 learning algorithm, at first, outcome layer weights are compared with optimum values. If error is excessive, outcome layers weights will be modified on the basis of updating rules and if training error is less than predefined error, learning process will finish. Also, CFBP3 network uses BP algorithm for weight correction like FFBP network. But the main property of that network is every layer's neurons are connected to all of the neurons of previous layers [7]. Used training algorithms for updating applied network weights are: Momentum algorithm and Levenberg-Marquardt (LM) algorithm. Whereas for instructing neural network on the base of LM algorithm, computations are done in parallel mode, that is known for one of the fastest methods for instructing back propagation neural network with less than one hundred weight connection. LM algorithm mainly is on the base of Hessian Matrix that is used for nonlinear optimization on the base of minimum squares [4].

Many researchers have used artificial neural networks for predicting desirable parameters in dryers. [8] used a multilayer feed-forward neural network (MFNN) for drying kinetics of pistachio nuts (Akbari v.). Experiments were performed at five drying air temperatures (ranging from 40 to 80 ºC) and four input air flow velocities (ranging from 0.5 to 2 m/s) with three replicates in a thin-layer dryer. The (3-8-5-1)-MLP is the best-suited model estimating the moisture content of the pistachio nuts at all drying runs. For this topology, R2 and MSE values were 0.9989 and 4.20E-06, respectively [8].

[9] compared the use of genetic algorithm and ANN approaches to study the drying of carrots. They demonstrated that the proposed neural network model not only minimized the R2 of the predicted results but also removed the predictive dependency on the mathematical models (Newton, Page, modified Page, Henderson-Pabis). They also suggested that the application of the artificial neural networks could be used for the on-line state estimation and control of the drying process [9].

[10] did a research about comparison of dynamic drying estimation of plant Acenasea Angostifulia (a plant with more medical usage) by regression analysis and neural network. In this research, thin layer dynamic drying of this plant and its comparison in a regression analysis and neural network. Experiments was done in three thermal levels 15, 30 and 45 degrees of centigrade and air velocity in three levels 0.3, 0.7 and 1.1 meters per second and sample length in three measures less than 3 millimeters, 3 up to 6 millimeters and more than 6 millimeters. 150 grams of samples was put under mentioned cures in dryer after exit of refrigerator. Regression analysis was done with four models of Newton, Henderson and Pubis, page, and modified page and in the same time, analysis was done in neural network and two-layer optimized network with one hidden layer and 30 neurons was resulted. Gotten results indicate neural network model estimated moisture capacity with 0.1 percent better precision than modified page model [10].

[11] did a research about predicting drying velocity by neural network. This research was done on the layers of tomato. Cures included air velocity in range of 0.5 up to 2 meters per second, dryer air temperature in the range of 40 up to 55 degrees of centigrade, air relative moisture in the range of 5 up to 50 percent, and sample plates thickness in the range of 3 up to 10 millimeter. In this research, page drying model was used thus this model analyzed in neural network [11].

[12] used multilayer ANN models with three inputs (concentration of osmotic solution, temperature, and contact time) to predict five outputs (drying time, color, texture, rehydration ratio, and hardness) during osmo-convective drying of blueberries. The optimal configuration of the neural network consisted of one hidden layer with 10 neurons. The predictability of the ANN models was compared with that of multiple regression models [12].

The results confirmed that ANN models had much better performance than the conventional empirical or semiempirical mathematical models. The effects of different drying conditions (temperature, air velocity, drying time, and sample thickness) and different osmotic treatments (use of sorbitol, glucose, and sucrose solutions) on the drying time and quality of osmotically dried pumpkins through the application of ANNs and image analysis was predicted [13]. Optimum artificial neural network (ANN) models were developed based on one to two hidden layers and 10-20 neurons per hidden layer [14]. [15] presented a comparative study among mechanistic and empirical models to estimate dynamic drying behavior of semifinished cassava crackers using a hot air dryer [15]. The prediction performance of different approaches such as the diffusion model, Newton model, Page model, modified Page model, Henderson and Pabis model, ANN model, and Adaptive-Network-Based Fuzzy Inference System (ANFIS) in modeling the drying processes of semifinished cassava crackers under different drying air temperatures was investigated. Overall, the ANN model performed superior to the diffusion model but was marginally better than ANFIS and modified Page models.

Figure 1. Bergamot Fruit

2. Material and Methods

2.1Thin-layer drying equipment

Figure 2 shows a schematic diagram of a dryer used for experimental work. It consists of a fan, heaters, drying chamber and instruments for measurement. The airflow rate was adjusted by the fan speed control. The heating system consisted of an electric 2000 W heater placed inside the duct. The drying chamber temperature was adjusted by the heater power control. Two drying trays were placed inside the drying chamber. In the measurements of temperatures, thermocouples were used with a digital thermometer (LM35), with reading accuracy of 0.1ºC. A thermo hygrometer (capacitive, Philippine made) was used to measure humidity levels at various locations of the system. The velocity of air passing through the system was measured by a hot wire (Testo, 405 V1, Germany) with 0.01 meters per second sensitivity was used and a digital scale with 0.01 gram sensitivity and capacity of 3100 grams.

To do the algorithm of controlling and monitoring information, an application has designed in visual basic 6 environment that demonstrates information related to temperature and moisture sensors and also being on or off of every heaters every time [16].

Drying mechanism is in this way that circulated air in channel by blower, passes heater and after getting warm, leads to bergamot slices by channel. Airflow absorbs bergamot moisture when it passes slices and makes it getting warm. So temperature increase speeds up water exit from sample tissue and resulted product dryness. 165 grams of bergamot thin layer was flatten on two grid square aluminium dishes with 25 centimeters side length in a way that on every dish one layer of product was put.

2.2 Sample Preparation Method

After washing bergamot surface, bergamot layers with thickness 6 millimetres prepared by cutter device. Drying experiments in five temperature levels 40, 50, 60, 70 and 80 degrees of centigrade and input air flow velocity in three levels 0.5, 1 and 2 meters per

[1]Feed-Forward Back Propagation
[2]Error Back Propagation
[3]Cascade-Forward Back Propagation

second in three repetitions was done. While drying, layers weights were being recorded by a digital scale connected to computer and dryer air temperature and moisture was being measured and registered every 5 seconds. Drying continued up to the time that bergamot thin layer weights, approximately would not change (sample weight changes approximately reached zero). Then samples were put on oven with temperature 105°C and after getting dried during 24 hours, samples dry weights were gained [17].

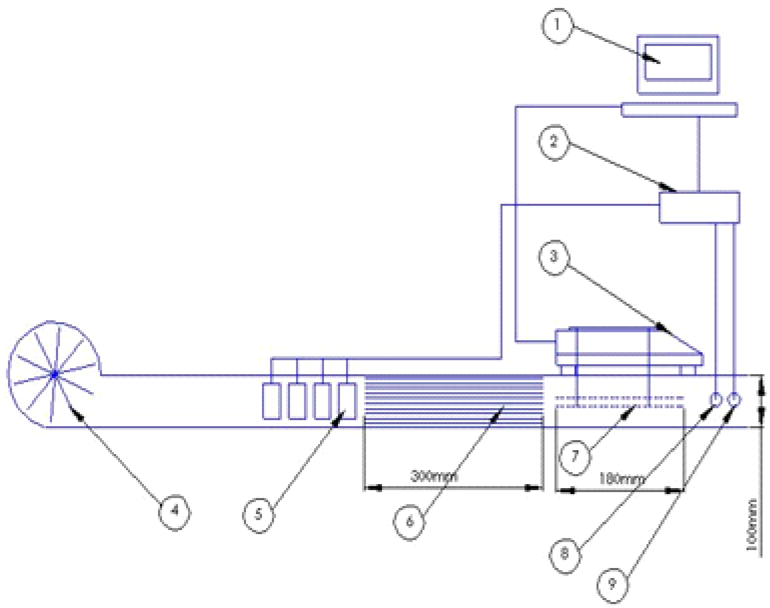


Figure 2. Schematic of thin-layer drying equipment used in this work
1. Computer 2. Microcontroler 3. Digital balance 4. Fan 5. Heaters
6. Straightener 7. Tray 8. Temperature sensor 9. Humidity sensor

2.3 Designing Artificial Neural Network

By imaging three input factors applied in all of thin layer drying experiments, the moisture ratio of bergamot slices was gained in one thickness. Artificial neural network with three neurons input layer (drying time, dryer temperature and velocity) and one neuron output layer (moisture ratio) was designed (Figure 3). The software Neurosolutions version 5 was used in this study. To achieve proper answer, Feed-Forward Back Propagation network was used. Training process by mentioned network is a repetitive process includes weights changes between different layers and gets gradually to stability of these weights during training, as the error between desired amounts and predicted amounts gets minimum.

The used activation function to find out optimized condition is: [7]

(1). hyperbolic tangent function[4]

$$Y_j = \frac{2}{\left(1+\exp\left(-2X_j\right)\right)} - 1 \tag{1}$$

where X_j is the sum of with weight inputs of every neurons of layer j and is calculated by below equation:

$$X_j = \sum_{i=1}^{m} W_{ij} \times Y_i + b_j \tag{2}$$

where *m* is the number of output layer neurons, W_{ij} is the weight between layer *i* and layer *j*, Y_i is neuron *i* output and b_j is the bias amount of layer *j* neuron.

[4]TANSIG

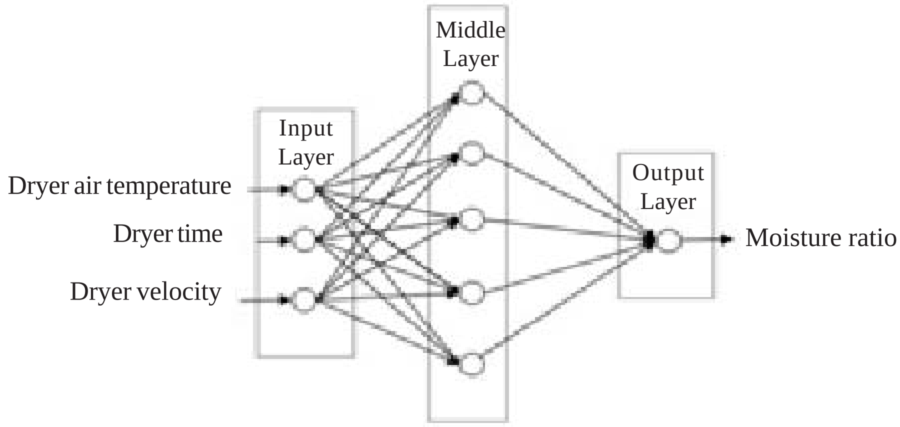


Figure 3. A schematic of designed artificial neural network

About %60 of data for training, %15 for validity evaluation and %25 randomly for evaluating trained network were used. For finding a network with proper topology by training algorithms, mean square error criterion has been used while the purpose is to get minimized mentioned error and is defined by equation (3): [6, 7]

$$MSE = \frac{\sum_{p=1}^{M}\sum_{i=1}^{N}\left(S_{ip} - T_{ip}\right)^2}{NP} \qquad (3)$$

where *MSE* is mean square error in training step, S_{ip} is network output in neuron *i* and pattern *p*, T_{ip} is desirable output in neuron *i* and pattern *p*, *N* is number of output neurons and M is number of training patterns.

3. Result and Discussion

Table 1 present error amount simulated by artificial neural network method, with number of neurons and different hidden layers in thickness 6 mm of bergamot thin layer. According to tables 1, when Levenberg-Marquardt algorithm has been used, in thickness 6 mm when 1 hidden layer with 8 neurons, the best answer has been presented.

Figure 4 demonstrates modeling error reduction procedure of thin layer bergamot drying with thickness 6 mm in velocities and temperature of dryer, by epoch increase.

According to equation (2), weight matrixes for input layer to hidden layer for optimized topology in thickness 6 mm of bergamot is:

$$\begin{bmatrix} -0.89 & 2.66 & 0.15 \\ 9.79 & 4.67 & 1.29 \\ 2.58 & -0.12 & -0.14 \\ -7.49 & 1.68 & -0.04 \\ 0.06 & 0.03 & 0.06 \end{bmatrix}$$

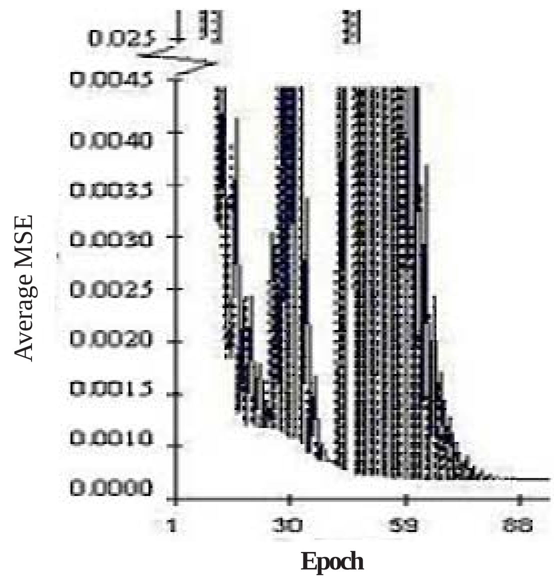
Weight matrixes for hidden layer to output layer for optimized topology in thickness 6 mm of bergamot is:

$$[-4.78 \quad 0.05 \quad 3.60 \quad 0.75 \quad -0.55]$$

Bias matrixes for input layer to hidden layer for optimized topology in thickness 6 mm of bergamot is:

Bias matrixes for hidden layer to output layer for optimized topology in thickness 6 mm of bergamot is: [4.49].

In figure 5 as a sample, a comparison between experimental moisture ratio and modeling on the base of artificial neural network method in air velocity 1 meter per second and thickness 6 mm of bergamot layer has been made.



Thickness = 6mm

Figure 4. Modeling error reduction procedure of bergamot thin layer drying by epoch increase

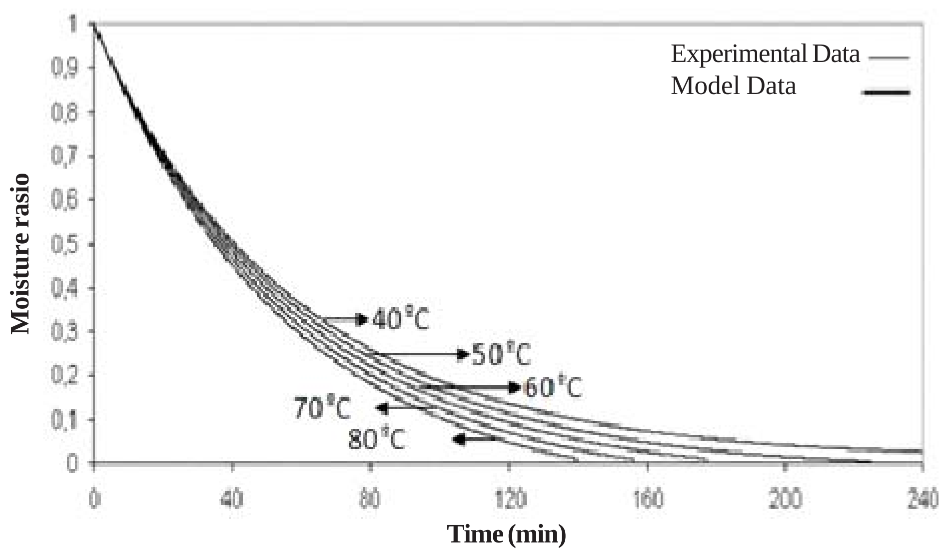


Figure 5. A comparison between experimental moisture ratio and modeling on the base of ANN method in velocity 1 m/s and thickness 6 mm

4. Conclusions

Results of this research show that:

1- Artificial neural network predicts moisture ratio of bergamot thin layers by three input parameters time, drying air velocities and dryer temperatures. The best neural network for instructing data is Feed-Forward Back Propagation network with Levenberg-Marquardt training algorithm and TANSIG activation function for layers with topology 3-8-1 and coefficients of determination 0.99936 for thickness 6 mm of bergamot layers in different situations of thin layer drying.

2- Finally it can be concluded that artificial neural network is a much proper tool to predict moisture ratio in the field of thin layer drying of agricultural products.

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