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Convective drying of garlic (*Allium sativum* L.): Artificial neural networks approach for modeling the drying process

Majid Rasouli*[1]

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Abstract

In this study, artificial neural networks (ANNs) was utilized for modeling and the prediction of moisture content (MC) of garlic during drying. The application of a multi-layer perceptron (MLP) neural network entitled feed forward back propagation (FFBP) was used. The important parameters such as air drying temperature (50, 60 and 70°C), slice thickness (2, 3 and 4 mm) and time (min) were considered as the input parameters, and moisture content as the output for the artificial neural network. Experimental data obtained from a thin-layer drying process were used testing the network. The optimal topology was 3-25-5-1 with LM algorithm and TANSIG threshold function for layers. With this optimized network, R^2 and mean relative error were 0.9923 and 9.67 %, respectively. The MC (or MR) of garlic could be predicted by ANN method, with less mean relative error (MRE) and more determination coefficient compared to the mathematical model (Weibull model).

Key words: Artificial neural networks; Back propagation; Convective drying; Garlic; Moisture Content

[1]Introduction

Garlic (*Allium sativum* L.) is an important Allium spice that is a strong source of phenolic compounds, phosphorus, potassium, sulfur, zinc, selenium and vitamins A and C and lower levels of calcium, magnesium, sodium, iron, manganese and B complex vitamins elements (Brewester, 1997). It has antiseptic properties and is used in a number of medicinal preparations. Various garlic powder pills and garlic oil pills are now commercially available (Sharma & Prasad, 2006). It has been cultivated for centuries all over the world especially cultivated widely in Iran. Most of garlic has been used as a fresh vegetable without any preprocessing operation. It is also used for seasoning of foods because of its typical pungent flavor. Garlic is a semi-perishable product. Due to lack of suitable storage and transportation facilities, about 30% of fresh crop is wasted in postharvest stages by respiration and microbial spoilage (Sharma, Prasad, & Chahar, 2009). More recently, it has been used in its dried form, as an ingredient of precooked foods and instant convenience foods including sauces, gravies and soups. These lead to a sharp increasing in the demand of dried garlic. To cater the demand of dried garlic and to overcome its storage problems, it should be processed quickly and optimally to maintain the quality.

Drying is the most common food preservation method used in practice (Midilli, Kucuk, & Yapar, 2002) and dried garlic exists into different products such as powders, flakes and slices (Abbasi Souraki & Mowla, 2008). The optimization of drying operation leads to an improvement in the quality of the output product, a reduction in the cost of processing as well as the optimization of the throughput (Madamba, Driscoll, & Buckle, 1994). There are various methods for prediction of drying characteristics of agricultural products. The simplest way is to use the available empirical correlations, which based on relatively large number of experimental data to identify unknown parameters. However, this approach generally gives the most accurate results only in specific experiments and they are not valid in other conditions (Movagharnejad & Nikzad, 2007). Artificial neural network (ANN)

1. Assistant Professor, Department of Biosystem Engineering, Faculty of Agricultural Engineering, Bu-Ali Sina University, Hamedan, Iran.
(Corresponding Author Email: m.rasouli@basu.ac.ir)
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modeling is an advanced computational method that can be used to handle complicated relationships between physical properties of foods and process parameters. A major advantage of this approach is that it requires less computational time compared to the finite-element or finite-difference methods because the outputs are calculated using basic algebra. This is beneficial in the development of an on-line predictive control system (Poonnoy, Tansakul, & Chinnan, 2007). Several studies demonstrated the significance and usefulness of the artificial neural network (ANN) in modeling the drying process (Khazaei & Daneshmandi, 2007; Nazghelichi, Kianmehr, & Aghbashlo, 2010; Satish & Pydi Setty, 2005), prediction of bulk density and residual moisture content (Chegini *et al.*, 2008), temperature and moisture content prediction (Mittal & Zhang, 2000; Poonnoy *et al*., 2007), modeling of tomato drying (Movagharnejad & Nikzad, 2007), drying process of carrot (Erenturk & Erenturk, 2007), prediction of physical property changes of carrot during drying (Kerdpiboon *et al.*, 2006), energy consumption (Zhang, Yang, Mittal, & Yi, 2002) and moisture content modeling of thin-layer corn during the drying process (Trelea *et al.*, 1997).

The objective of the present study was to build up and evaluate the predictive performance of an ANN model to approximate a nonlinear function relating moisture content of garlic during the drying process under different drying conditions. The prediction of moisture ratio in the drying systems is helpful to find out the optimum drying time to reach optional moisture content in the final product.

Materials and methods

Fresh garlic (*Allium sativum* L.) bulbs were obtained from a field located in Azarshahr (East Azarbaijan Province), Iran; and stored in a refrigerator at 4°C until experiments started. After 2h stabilization period at the ambient temperature, the bulbs by uniform size were selected and separated into cloves and peeled, then were cut using a rotating disc slicer into 2, 3 and 4 mm thickness (L) mm.

The initial moisture content of pre-treated garlic was determined using a mechanical convection oven at 102±1°C until constant weight was attained (AOAC, 1990). The initial moisture content of pre-treated garlic was 2.03 (g_{water}. $g_{dry\ solid}^{-1}$). The samples weight was measured by an electronic balance with a sensitivity of 0.001 g. Four replications were conducted to obtain a reasonable average.

Drying equipment

Drying experiments were performed in a pilot plant tray- dryer. A schematic view of the dryer is shown in Figure 1. The dryer mainly consists of three basic units, a fan providing desired drying air velocity, electrical heaters controlling the temperature of drying air and drying chamber. The dryer was equipped with a data acquisition system and a controlling unit of temperature, air flow velocity and relative humidity. Air was flowed by an axial flow blower (90 W) and the velocity of air flow was controlled by changing the rotating speed of fan (SPC1-35, Autonics, Taiwan) and measured using a vane probe type anemometer (AM-4202, Lutron, Taiwan) with an accuracy of ± 0.1 $m.s^{-1}$. Air was heated, while flowing through three spiral type electrical heaters, having 5, 5 and 2 kW capacity. These electrical heaters turned off or on separately via a temperature control unit (TZ4ST-Autonics, Taiwan) depending on the changes in the temperature, to stabilize a constant air temperature during each experiment with an accuracy of ±0.1°C. The weighing system consisted of an electronic balance (AND GF3000, Japan) having an accuracy of ±0.01 g. During the drying process, the air temperature and relative humidity in the drying chamber were logged on a data acquisition system (Delta T, England).

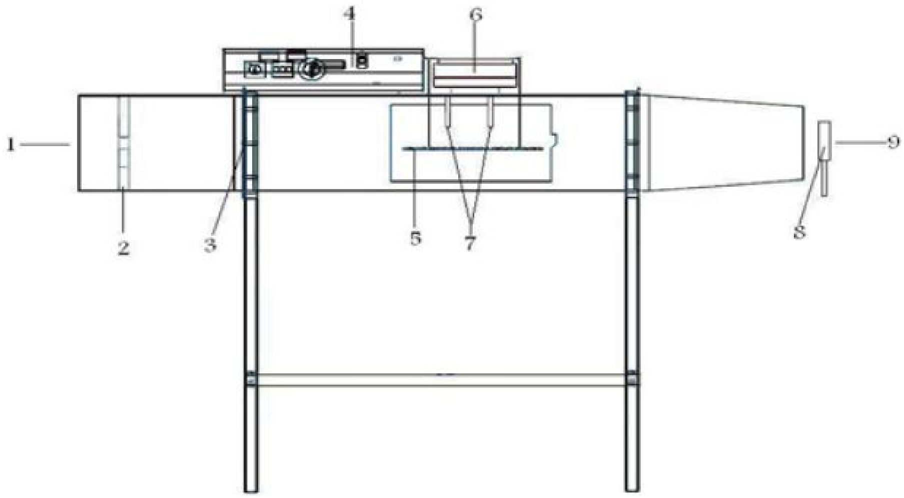

Fig. 1. Schematic diagram of the convectional drying equipment (1) Air inlet; (2) Fan; (3) Heaters; (4) Temperature and air flow velocity controlling; (5) Perforated tray; (6) Digital balance; (7) Relative humidity sensor and thermocouple to data logger; (8) Digital anemometer; (9) Air outlet.

Experimental procedure

The dryer was adjusted to the selected temperature for about half an hour before starting of the experiments in order to achieve steady state conditions. Then, the samples (about 120 g) were spread in a single layer on a tray that connected to the balance in the dryer. Weight loss of samples was measured and recorded every 120 s. Drying time was defined as the time required to reduce the moisture content of samples to 0.09 (g_{water}. $g_{dry\ solid}^{-1}$) (equilibrium moisture content). Additional samples (180g) were put on a separate tray within drying chamber without connecting to the balance. These samples were used to observe and measure the color changes of garlic slices during and at the end of drying process when the moisture content of samples fell to 1.06, 0.43, 0.13 and 0.09 (g_{water}. $g_{dry\ solid}^{-1}$). Drying experiments were performed at the drying air temperatures of 50, 60 and 70°C, a constant air flow rate of 1.5 $m.s^{-1}$ using garlic slices with different thickness, 2, 3 and 4 mm. Each experiment was repeated three times. The moisture content data obtained at different drying air temperatures and slice thicknesses during drying process were converted to the moisture ratio (MR). However, the MR was simplified to M/M_i instead of the $(M - M_e)/(M_i - M_e)$, because the values of the M_e are relatively small compared to M or M_i. Hence the error involved in the simplification is negligible (Ertekin & Yaldiz, 2004; Rasouli *et al*., 2011).

Artificial neural networks (ANNs)

The artificial neural networks are basically computational models, which simulate the function of biological networks, composed of neurons. Most research studies using artificial neural networks apply a multilayered, feed forward, fully connected network of perceptions. Among the reasons for using this kind of ANN is the simplicity of its theory, ease of programming and good results. If topology of the network is allowed to vary freely, it can take the shape of any broken curve (Topuz, 2010). The network had three layers; input, hidden and output. The numbers of neurons in the input layer and the output layer were equal to the number of input and output parameters, respectively. Each input unit of the input layer receives input signal X_i and broadcasts this signal to all units in the hidden layer. Each hidden unit Y_j sums its weighted input signal and applies its activation function to compute output signal as identified in Equal (1):

$$Y_j = f_{act}\left(\sum_{i=1} W_{ij} X_i + b_j\right) \tag{1}$$

where W_{ij} is the weight of the connection from the i^{th} input unit to the j^{th} hidden unit, b_j is the weight of bias connection for j^{th} hidden unit. The output signal of the hidden unit Y_j is sent to all units in the output layer. Each output unit O_k sums its weighted input signal and applies its activation function to compute its output signal as identified in equal (2):

$$O_k = f_{act}\left(\sum_{j=1} V_{jk} Y_j + b_k\right) \tag{2}$$

Where V_{jk} is the weight of the connection from the j^{th} hidden unit to the k^{th} output unit. The parameter of bias (b) in Equals. (1) and (2), also called the threshold value, is permanently set to 1 in the hidden layer as well as in the output layer, so that corresponding weight shifts the activation function along the x axis. The activation functions used in this study were tangent sigmoid and logistic sigmoid that are defined respectively as:

$$f_{act}(x) = \frac{1}{1+\exp(x)} \tag{3}$$

$$f_{act}(x) = \frac{2}{\left(1+\exp(-2x)\right)-1} \tag{4}$$

(Demuth & Beale, 2003; Erenturk & Erenturk, 2007).

The BP training algorithm is an iterative gradient descent algorithm, designed to minimize the mean of square error (MSE) which is averaged over all patterns and is calculated as follows:

$$MSE = \frac{\sum_{p=1}^{m}\sum_{i=1}^{n}\left(S_{ip} - T_{ip}\right)^2}{n_p n_0} \tag{5}$$

Where S_{ip} is the desired or actual output, T_{ip} is the predicted output for the pattern, n_0 is the number of neurons in the output layer, and n_p is the number of patterns.

In order to facilitate the comparisons between predicted values for different network parameters (learning rate, momentum coefficient and neuron number in hidden layer, different activation functions and the training algorithm) and desired values, there is a need for secondary criteria which were used as follow:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left[S_{ip} - T_{ip}\right]}{\sum_{i=1}^{n}\left[S_{ip} - \frac{\sum_{i=1}^{n} S_{ip}}{n}\right]} \tag{6}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|S_{ip} - T_{ip}\right| \tag{7}$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{S_{ip} - T_{ip}}{S_{ip}}\right| \times 100 \tag{8}$$

During training, an ANN is the presented with the data for thousands of times, which is referred to as epochs. After each epoch the error between the ANN output and the desired values is propagated backward to adjust the weight in a manner mathematically guaranteed to converge. Adjustment of the weights ΔW_{ij} can be calculated as:

$$\Delta W_{ij} = -\alpha \frac{\partial E}{\partial W_{ij}} + \beta \Delta W_{ij}\left(s-1\right) \tag{9}$$

(Topuz, 2010).

Where α is the learning rate, β is the momentum coefficient and s is the current step. Training is the act of continuously adjusting the connection weights until they reach unique values that allow the network to produce outputs that are close enough to actual desired outputs. The accuracy of the developed model, therefore, depends on these weights. Once optimum weights are reached, the weights and biased values encode the network state of knowledge (Topuz, 2010).

Considering and applying the tree inputs in all experiments, the MC value was derived for different conditions. Networks with tree neurons in input layer (drying air temperature (°C), thickness of slices (mm) and time (s)) and one neuron in output layer (MC) were designed. Figure 2 shows the considered neural network topology and input and output parameters. Boundaries and levels of input parameters are shown in Table 1. Using experimental data obtained in the thin-layer dryer, an optimized ANN model was developed to predict the outlet moisture content of the garlic. In order to determine the optimal number of hidden units of the proposed neural network architecture, pilot experiments were done. In order to avoid over fitting, two common methods were used. These were: (i) early stopping; and (ii) minimizing the number of hidden units (Erenturk & Erenturk, 2007). In this study, Back propagation (BP) algorithm, which is one of the most famous training algorithms for multi-layer perceptions, was implemented using the neural network toolbox of MATLAB (R2009a) software. The available data set was partitioned into three parts, 70% for training, 20% for test and 10% corresponding to the validation of the model. The training process was carried on until a minimum of the error was reached in the second (validation) partition. The estimation of the performance of the trained network was based on the accuracy of the network on the test partition (Erenturk & Erenturk, 2007).

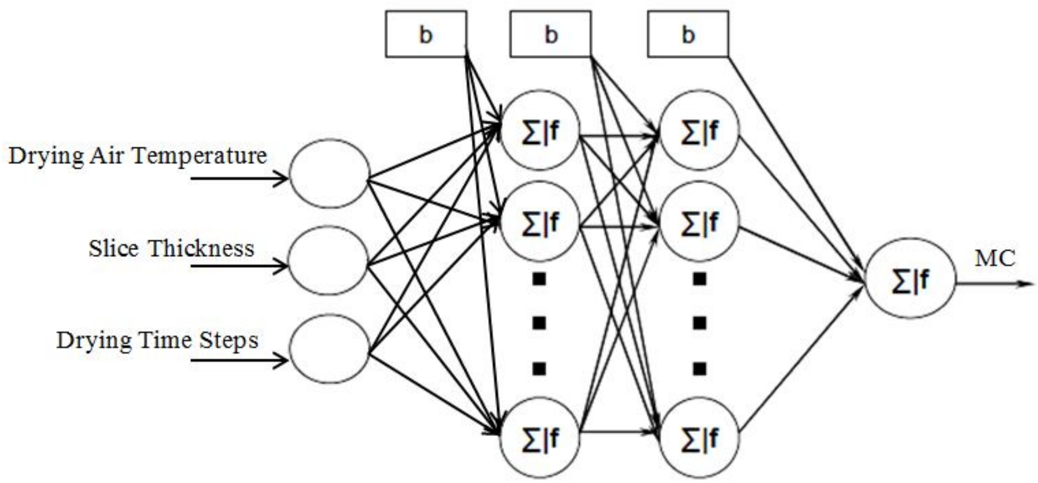

Fig. 2. Artificial neural network topology used for predicting the moisture content.

Table 1- Input parameters for ANNs and their boundaries

Parameters	Minimum	Maximum	No. of Levels
Air Temperature (° C)	50	70	3
Slice Thickness (mm)	2	4	3
Time Steps (min)	45	249	-

Result and discussion

In present ANN model, three independent variables, such as drying time, drying air temperature and slice thickness have been chosen as input parameters, and moisture content (dependent variable) of products has been regarded as the output parameter. In order to obtain the optimum structure of FFBP neural network, the ANN model was trained with varying number of neurons in hidden layer, TANSIG and LOGSIG threshold function and LM, CGF and OSS learning algorithms. Several topologies were tested and the best results which used from each training algorithm and Threshold function are represented in Table 2. Minimization of error was accomplished using the Levenberg–Marquardt (LM) algorithm. Training was completed after 200 epochs. The numbers of neurons in hidden layers were varied from 5 to 30. The networks were simulated with the learning rate equal to 0.05.

The best results for FFBP network with LM algorithm belonged to TANSIG threshold function and 3-25-5-1 topology. This composition produced *MSE*=0.00131, R^2=0.9923 and *MRE* =9.67 and converged in 200 epochs.

The best results for FFBP network with CGF algorithm belonged to LOGSIG threshold function and 3-3-2-1 topology. This composition produced *MSE*=0.00399, R^2=0.9901 and *MRE* =12.27 and converged in 200 epochs.

The best results for FFBP network with OSS algorithm belonged to TANSIG threshold function and 3-25-5-1 topology. This composition produced *MSE*= 0.00399, R^2=0.9919 and *MRE* =11.34 and converged in 200 epochs.

Finally, application of LM algorithm has better result than CGF and OSS algorithms because it produced less *MRE* and more R^2 values. The results are presented in table 2. Experimental and predicted data set are shown in figure 3 and *MSE* for training patterns in figure 4. Results showed that *MRE* is the least value for this network, so this network selected as an optimized one.

Besides, in order to compare the results against the existing predictive models, a thin layer drying mathematical model was selected from the literature. Rasouli *et al*. (2011) used a nine thin layer drying models to describe the drying characteristics of garlic were evaluated according to the statistical criteria such as R^2, RMSE and SSE. The Weibull model was selected as a suitable model to represent the thin layer drying behavior of garlic slices.

The coefficients of the accepted model and the final MR equation of thin layer drying of garlic slices were as follows (Rasouli *et al*., 2011):

$$k_1 = 5.994251 \times L^{-0.164} \exp\left(\frac{-516.322}{T_{abs}}\right)$$

$$\overline{R}^2 = 0.8128 \qquad (10)$$

$$k_2 = 6.02554 \times 10^{-6} \times L^{1.065} \exp\left(\frac{3429.964}{T_{abs}}\right)$$

$$\overline{R}^2 = 0.9721 \qquad (11)$$

$$MR = f(T, L, t) = \exp\left(-\left(\frac{t}{k_2}\right)^{k_1}\right) \qquad (12)$$

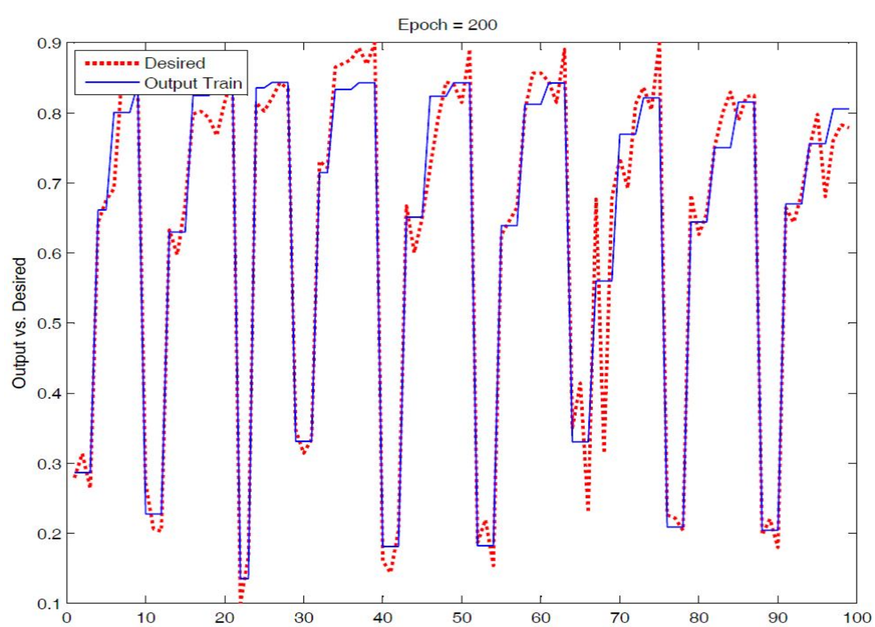

Fig. 3. Predicted Values of MR using ANNs versus experimental values

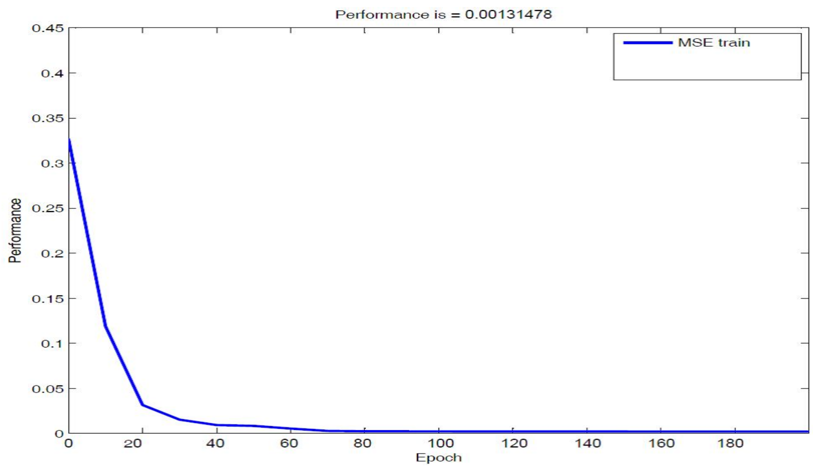

Fig. 4. Mean square error of training patterns for the best ANN

Table 2. Training algorithm for different neurons and hidden layers at the uniform threshold function for layers

Training Algorithm	Threshold Function	No. of Layers and Neurons	MSE	R^2	MRE	MAE
LM	TANSIG	3-3-2-1	0.00174	0.9912	10.76	0.054
		3-4-2-1	0.00127	0.9898	13.12	0.059
		3-10-5-1	0.00145	0.9901	11.18	0.044
		3-15-5-1	0.00227	0.9912	11.37	0.077
		3-20-5-1	0.00169	0.9854	13.87	0.073
		3-25-5-1	**0.00131**	**0.9923**	**9.67**	**0.041**
	LOGSIG	3-3-2-1	0.00123	0.9863	14.33	0.065
		3-4-2-1	0.00135	0.9899	12.57	0.064
		3-10-5-1	0.00314	0.9889	17.89	0.065
		3-15-5-1	0.00237	0.9866	16.56	0.140
		3-20-5-1	0.00278	0.9854	14.48	0.097
		3-25-5-1	0.00199	0.9911	10.25	0.076
CGF	TANSIG	3-3-2-1	0.00346	0.9822	18.74	0.023
		3-4-2-1	0.00447	0.9876	15.55	0.035
		3-10-5-1	0.00463	0.9791	16.79	0.040
		3-15-5-1	0.00681	0.9889	17.72	0.034
		3-20-5-1	0.00572	0.9831	21.34	0.165
		3-25-5-1	0.00519	0.9890	14.22	0.118
	LOGSIG	**3-3-2-1**	**0.00399**	**0.9901**	**12.27**	**0.087**
		3-4-2-1	0.00456	0.9827	16.55	0.061
		3-10-5-1	0.00423	0.9826	22.78	0.067
		3-15-5-1	0.00884	0.9766	15.67	0.091
		3-20-5-1	0.00727	0.9731	13.39	0.096
		3-25-5-1	0.00663	0.9890	17.92	0.074
OSS	TANSIG	3-3-2-1	0.00403	0.9913	12.34	0.063
		3-4-2-1	0.00289	0.9897	11.89	0.094
		3-10-5-1	0.00321	0.9799	13.67	0.083
		3-15-5-1	0.00462	0.9899	13.78	0.087
		3-20-5-1	0.00284	0.9905	11.91	0.077
		3-25-5-1	**0.00213**	**0.9919**	**11.34**	**0.059**
	LOGSIG	3-3-2-1	0.00236	0.9905	13.88	0.067
		3-4-2-1	0.00147	0.9908	13.11	0.017
		3-10-5-1	0.00755	0.9867	12.33	0.079
		3-15-5-1	0.00537	0.9897	16.69	0.089
		3-20-5-1	0.00574	0.9888	14.22	0.125
		3-25-5-1	0.00262	0.9877	11.37	0.083

Detailed information about this model can be found in (Rasouli *et al*., 2011). They have used this model to predict the drying characteristics of garlic. The ANN results exhibit a good agreement with experimental results rather than mathematical model ones for garlic. These findings demonstrate that artificial neural networks produce better prediction and more useful results.

Conclusions

In this study, the drying behavior of the garlic slices as a thin layer was investigated experimentally. It was observed that the ANN model can be used to predict the drying characteristics of garlic undergoing different thin-layer drying conditions.

The best ANN for data training was FFBP with LM algorithm and TANSIG threshold function for layers, 25 neurons for the first hidden layer and 5 for the second one. With this optimized network, R^2 and mean relative error were 0.9923 and 9.67 %, respectively. The optimal models can predict the moisture content with high values of R^2.

The MC (or MR) of garlic could be predicted by ANN method, with less mean relative error (MRE) and more determination coefficient compared to the mathematical models (Weibull model). The methodology in this paper could be applied for other products as well. In addition, the developed ANN models are useful tool for estimating the on-line states and for controlling the drying process in industrial operations.

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نشریه پژوهشهای علوم و صنایع غذایی ایران
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خشک شدن همرفتی سیر(*Allium sativum L.*) : رویکرد شبکه های عصبی مصنوعی برای مدل‌سازی فرآیند خشک کردن

مجید رسولی[*1]

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چکیده

در این مطالعه، شبکه عصبی مصنوعی برای مدل‌سازی و پیش‌بینی میزان رطوبت سیر در طی خشک کردن سیر استفاده شد. برای این منظور شبکه عصبی مصنوعی پرسپترون چند لایه تحت عنوان پس انتشار پیشرو به‌کار گرفته شد. پارامترهای مهم از جمله دمای هوای خشک کردن (50، 60 و 70 درجه سانتی‌گراد)، ضخامت ورقه‌ها (2، 3 و 4 میلی‌متر) و زمان خشک کردن به‌عنوان ورودی و محتوای رطوبت به‌عنوان خروجی شبکه در نظر گرفته شد. داده‌های آزمایشگاهی به‌دست آمده از فرآیند خشک کردن لایه نازک سیر برای آموزش و تست شبکه استفاده شد. توپولوژی بهینه 3-25-5-1 با الگوریتم LM و تابع آستانه TANSIG برای لایه‌ها بود. با این شبکه بهینه، مقدار R^2 و خطای نسبی به‌ترتیب 0/9923 و 9/67 درصد بود. مقدار MC برای سیر را می‌توان با استفاده از شبکه عصبی، با میانگین خطای متوسط کمتر و ضریب تبیین بیشتر نسبت به مدل ریاضی ویبل پیش‌بینی کرد.

واژه‌های کلیدی: شبکه‌های عصبی مصنوعی، انتشار اولیه، خشک کردن همرفتی، سیر، محتوای رطوبت.

1- استادیار، گروه مهندسی بیوسیستم، دانشگاه بوعلی سینا.
(*- نویسنده مسئول: Email: m.rasouli@basu.ac.ir)