

Applying Artificial Neural Network for Drying Time Prediction of Green Pea in a Microwave Assisted Fluidized Bed Dryer

L. Momenzadeh¹, A. Zomorodian^{1*}, and D. Mowla²

ABSTRACT

Drying characteristics of green pea (*Pisum sativum*) with an initial moisture content of 76% (db) was studied in a fluidized bed dryer assisted by microwave heating. Four drying air temperatures (30, 40, 50 and 60°C) and five microwave powers (180, 360, 540, 720 and 900W) were adopted. Several experiments were conducted to obtain data for sample moisture content versus drying time. The results showed that increasing the drying air temperature resulted in up to 5% decrease in drying time while in the microwave-assisted fluidized bed system, the drying time decreased dramatically up to 78.8%. As a result, addition of microwave energy to the fluidized bed drying is recommended to enhance the drying rate of green pea. Furthermore, in this study, the application of Artificial Neural Network (ANN) for predicting the drying time (output parameter) was investigated. Microwave power, drying air temperature, and green pea moisture content were considered as input parameters for the model. An ANN model with 50 neurons was selected for studying the influence of transfer functions and training algorithms. The results revealed that a network with the logsig (Log sigmoid) transfer function and trainrp (Resilient back propagation; Rprop) back propagation algorithm made the most accurate predictions for the green pea drying system. In order to test the ANN model, the root mean square error (RMSE), mean absolute error (MAE), and standard error (SE) were calculated and showed that the random errors were within and acceptable range of $\pm 5\%$ with a coefficient of determination (R^2) of 98%.

Keywords: Green pea; Fluidized bed dryer; Microwave; Artificial Neural Network

INTRODUCTION

Moisture removal from agro-industrial plants by thermal drying is an integral part of food processing. In the past, continuous efforts of the food processing industry for producing dehydrated foods have been directed towards enhancing drying rate, reducing energy consumption, and minimizing thermal degradation of food constituents. Increasing mass transfer rates of water molecules with the help of using higher drying air temperature

would result in high energy cost (Tripathy and Kumar, 2008).

There are several techniques for drying process such as solar, cabinet, rotary cylindrical, column, fluidized bed, microwave, infrared drying, etc (Topuz, 2009). In fluidized bed dryers, the kernels of drying products are subjected to continuous fluidization and thoroughly mixed and uniformly exposed to drying air. A disadvantage of this technique is the long period of time required, especially in the falling rate drying period Chen *et al.* (2001). On the other hand, in microwave

¹ Department of Agricultural Machinery, College of Agriculture, Shiraz University, Shiraz, Islamic Republic of Iran.

* Corresponding author; e-mail: zomorod@shirazu.ac.ir

² Department of Chemical Engineering, College of Engineering, Shiraz University, Shiraz, Islamic Republic of Iran.



drying, the radiation energy penetrates into the object during the drying period but the products are not equally exposed to the radiation beam energy. In this drying method, although the drying duration is short, the particles are not dried uniformly and, consequently, the product quality is adversely affected by moisture stresses (Abbasi Souraki et al., 2008d). Microwave-assisted fluidized bed drying provides an effective mean to overcome the above mentioned limitations. Microwave energy penetrates into the material, facilitating rapid heating and resulting in shorter processing time compared with fluidized bed drying alone. Other advantages include space saving and high energy efficiency as most of the microwave energy is converted to heat in the drying object.

Mathematical modeling of different drying processes has been focused in numerous studies. However, such models are not widely used because of their complexity and long computing times required (Tripathy and Kumar, 2008).

In such situations, where the relationship between various variables describing the drying problem is complex and ill-defined, the widely used Artificial Neural Network (ANN) can provide a platform where these problems can be solved with reasonable accuracies and

computation times (Kalogirou, 2001).

Several studies have been conducted on the experimental investigation and modeling of fluidized bed dryers as well as experimental investigations on microwave heating of food products. This subject has been of special interest in recent years (Abid et al., 1990; Turner and Jolly, 1991; Ormos and Haidu, 1997; Stash and Pydi Setty, 2004; Chen et al., 2001; Jumah, 2005; Romano et al., 2005; Hatamipour and Mowla, 2002, 2003a, b and 2006; Abbasi Souraki and Mowla, 2008a, c).

The major objectives of the present study were to study the drying behavior of green pea in a microwave-assisted fluidized bed dryer at different microwave energy levels and the drying air temperatures and also to develop and evaluate ANN model of this drying configuration to predict the green pea drying time based on measures of error deviation from experimental data.

MATERIALS AND METHODS

Experimental Apparatus

A schematic diagram of this apparatus is illustrated in Figure 1. Freshly harvested green pea (*Pisum sativum*) with an average

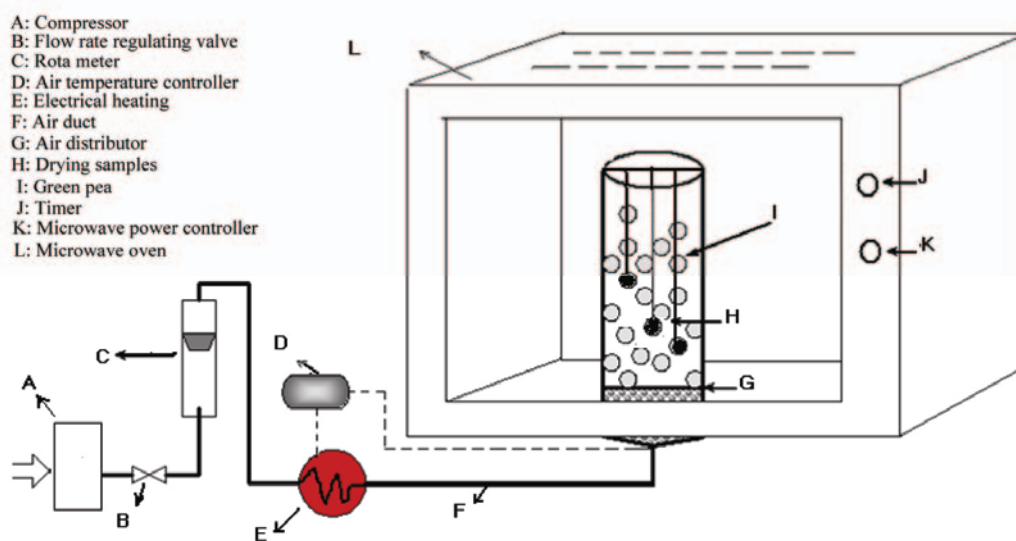


Figure 1. Schematic diagram of the experimental apparatus.

initial moisture content of 76% (db) was chosen as the drying material to be dried by this combined dryer.

A cylindrical Pyrex column of 90 mm diameter (100 mm outside diameter) and 280 mm height was used as the fluidized bed drying chamber. The chamber was placed in a domestic microwave oven (LG, MC-2003TR(S)) with the frequency of 2450 MHz and approximate cavity volume of 0.075 m³ (outside dimensions of 574 mm × 376 mm × 505 mm). This oven was equipped with 5 power level settings of Low (180W), Medium low (360W), Medium (540W), Medium high (720W) and High (900W). Since the ratio of cylinder diameter of the fluidized bed to the average diameter of the green pea was greater than 10, the wall effect was negligible. A porous plate was placed at the bottom of the cylinder to act as air distributor and supporting floor for the drying objects. High pressure drying air was introduced at the bottom of the Pyrex column with a constant flow rate of 650 lit/min to maintain the fluidization condition in the chamber. An air compressor (type: TCS-SCLL, 7 bar pressure, 15 hp) was employed to supply high pressure and constant air flow rate. Air flow rates were measured by a rotameter with an accuracy of ±10 l/min. An electrical heating unit equipped with a thermostat (±1° C) was provided to maintain different levels of drying air temperature of 30, 40, 50 and 60° C.

Experimental Procedure

A bulk of green pea was dried in the fluidized bed chamber. In this bed, three kernels of green pea were randomly marked in the bulk and were hung over the bed using very thin strings (Figure 1). These kernels were thoroughly mixed in the fluidized bed and could be easily traced for any moisture content reductions during the drying processes. All experiments were carried out in triplicates. Sample weighing was

undertaken no longer than 10-seconds intervals using an electrical balance (MW-150t, max weighing capacity of 150g, ±0.005g accuracy). The accuracy of this method for generating reproducible drying curves has been demonstrated by previous studies (Zhou *et al.*, 1998; Ajibola, 1989).

Several sets of the experiment were conducted to obtain data for drying sample moisture contents versus time. At the end of each drying period, when the moisture content of the green pea reached the equilibrium stage (no appreciable changes in three successive samples' weighing), the exit air temperature profile remained at a nearly constant level. This temperature leveling phenomenon showed that, in this stage of drying, the absorbed energy was balanced by the surface convective cooling and represented the end of the drying process.

Artificial Neural Network Modeling (ANN)

Artificial Neural Networks have been successfully used in the prediction and optimization problems in bioprocess and chemical engineering. ANN has been developed as a generalization of mathematical models of human cognition and neural biology (Satish and Pydi Setty, 2004).

In this technique, the available data set was divided into two parts: one was used to train the network and the other to validate the model. The network consists of an input layer, an output layer and a number of hidden layers. At each node in a layer, the information is received, stored, processed, and communicated further to nodes in the next layer. All the weights are initialized to small random numeric values at the beginning of training. These weights are updated or modified iteratively using the generalized delta rule or the steepest-gradient descent principle. The training process converges when no considerable change is observed in the values associated with the connection links or when a



termination criterion is satisfied (Erenturk and Erenturk, 2007).

In this study, the ANN model was trained using 120 randomly selected data points and the remaining 30 data points were utilized to test the network performance. MATLAB 7.0 was used for training and testing of neural network.

The methodology used for the assessment of network performance involves obtaining the minimum statistical measures of error between experimental and predicted transient time predicted by the model. In this study, statistical parameters, namely, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Standard Error (SE) and coefficient of determination (R^2) represented by equations 1 to 4 were computed to check the performance of the developed model (Tripathy and Kumar, 2008).

$$MAE = \frac{1}{N} \sum_{i=1}^N |\bar{D}_{p,exp,i} - \bar{D}_{p,cal,i}| \quad (1)$$

$$RMSE = \left[\frac{1}{N} \sum_{i=1}^N (\bar{D}_{p,exp,i} - \bar{D}_{p,cal,i})^2 \right]^{1/2} \quad (2)$$

$$SE = \frac{\sqrt{\sum_{i=1}^N (D_{p,exp,i} - D_{p,cal,i})^2}}{N - 1} \quad (3)$$

$$R^2 = \frac{\sum_{i=1}^N (D_{p,exp,i} - \bar{D}_{p,exp,i})^2 - \sum_{i=1}^N (D_{p,exp,i} - D_{p,cal,i})^2}{\sum_{i=1}^N (D_{p,exp,i} - \bar{D}_{p,exp,i})^2} \quad (4)$$

A well-trained ANN model should produce small MAE, RMSE and SE with large R^2 values (Tripathy and Kumar, 2008). The ANN model was trained with varying numbers of neurons and randomly chosen logsig (Log sigmoid) transfer functions and Trainrp (Resilient back propagation; Rprop) algorithm

for hidden layer, Table 1. The procedure started with a minimum of 1 neuron and increasing the network size in steps by adding a neuron each time. Errors increased rapidly when the number of neurons was less than 40. The predictions were highly sensitive to the number of neurons. The lowest error was obtained with 50 hidden neurons. The values of error were essentially constant between 50 and 70 neurons. Thus the ANN model with 50 neurons was selected for studying the influence of transfer functions and training algorithms on model prediction capability.

Microwave power (6 levels), drying air temperature (4 levels), and grain moisture content in each time were chosen as input layers and the appropriate drying time in each step was set as the output layer. Figure 2 depicts the schematic structure of the applied neural network. This function takes the input (which may have any value between plus and minus infinity) and the output value into the range 0 to +1 (Farkes et al., 2000).

$$\log sig(n) = \frac{1}{(1 + \exp(-n))} \quad (5)$$

$a = \text{logsig}(n)$

In order to study the effect of different parameters on network performance, the model was run with changing parameter.

RESULTS AND DISCUSSIONS

In order to show the effects of various drying parameters on drying time of green pea, the drying processes was continued until the final moisture content of the grain

Table 1. List of transfer functions and back propagation training algorithms used in ANN training.

Transfer function	Training algorithms
Logsig (Log sigmoid)	scg (Scaled conjugate gradient back propagation)
Tansig (Hyperbolic tangent sigmoid)	cgp (Polak–Ribiere conjugate gradient back propagation)
Poslin (Positive linear)	bfg (BFGS quasi-Newton back propagation)
Satlin (Saturating linear)	lm (Levenberg–Marquardt back propagation)
	rp (Resilient back propagation; Rprop)

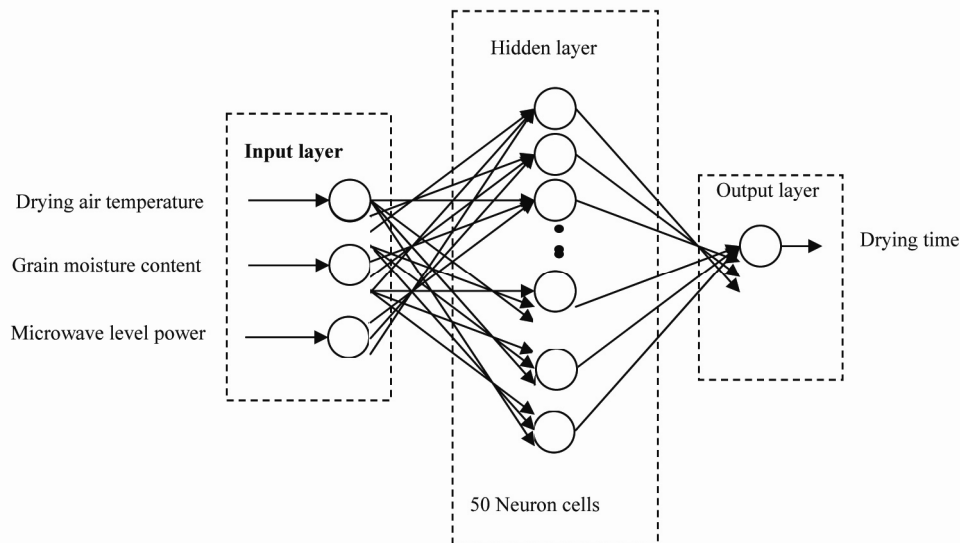


Figure 2. Selected artificial neural network structure.

reached a safe moisture content of 25% (db) (Tavakolipour, 1997). The drying process was terminated when the dry bulb temperature of exit air was nearly equal to the drying air temperature.

The effects of air temperature and microwave power on green pea drying time were studied at four levels of air temperature (30, 40, 50 and 60° C) and six levels of microwave power (0, 180, 360, 540, 720 and

900 W). MSTAT-C (version 2.10) statistical package was used for statistical analysis. The results are presented in Table 2.

Effects of Drying Air Temperature and Microwave Power on Drying Time

Figures 3 and 4 show the variations of

Table 2. Results of statistical analysis.

Variables	Sum of squares	Degree of freedom	F value
Air drying temperature (A)	6512.2	3	107.3**
Microwave power levels (B)	93245.7	5	1435.9**
A×B	6348.2	15	28.4**
Error	89.7	69	

** Significant at $p=0.01$

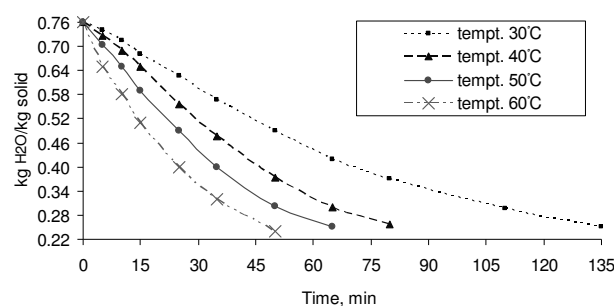


Figure 3. Effect of drying air temperature on drying time of green pea without microwave radiation

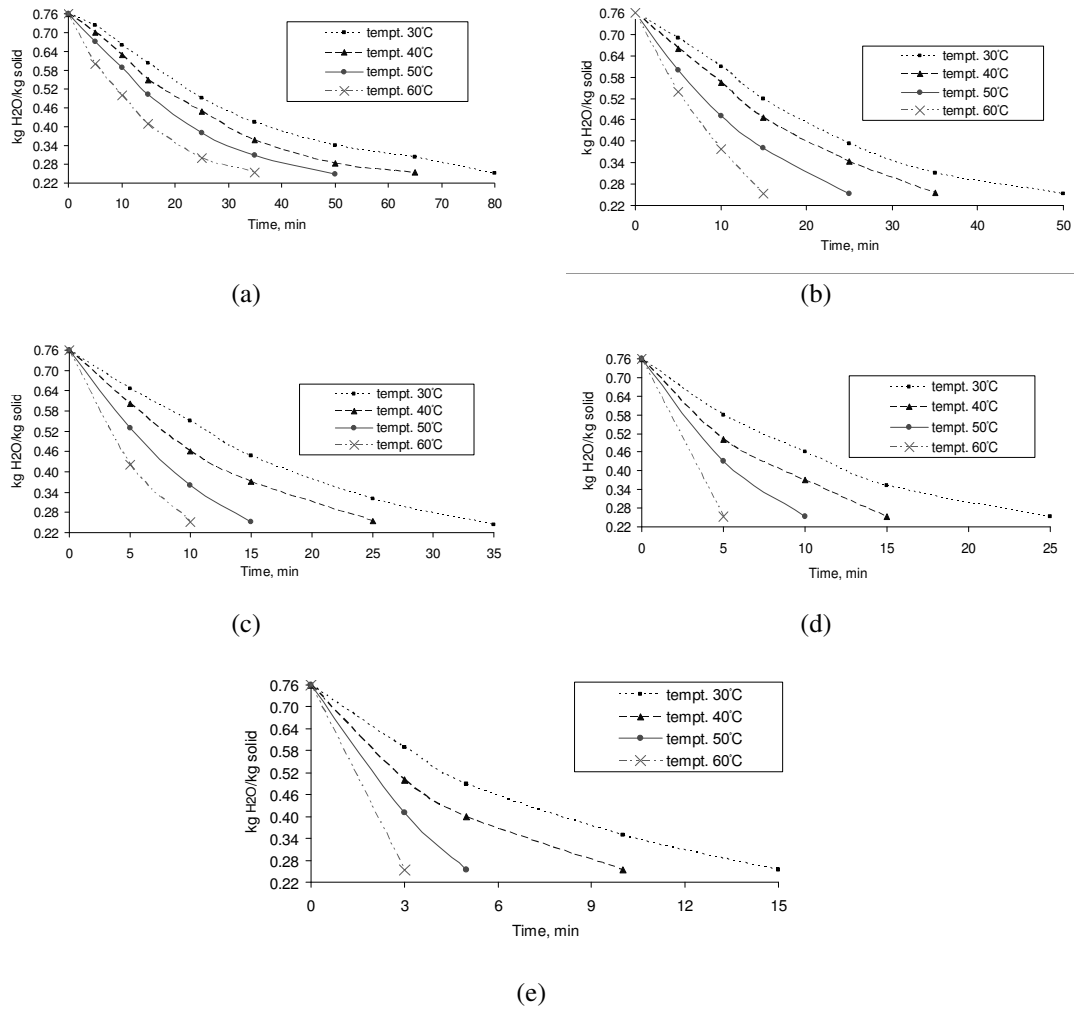


Figure 4. Effect of drying air temperature on drying time of green pea at different microwave power levels (a: 180, b: 360, c: 540, d: 720 and e: 900W).

Table 3. Drying time reduction at different microwave energies and drying air temperatures with respect to zero microwave power.

Drying air temperature	Microwave power W	% of decrease in drying time	Drying air temperature	Microwave power W	% of decrease in drying time
30° C Average time reduction=70.3%	180	42	50° C Average time reduction=74.8%	180	44
	360	64		360	69
	540	75		540	81
	720	82		720	87
	900	89		900	93
40° C Average time reduction=73%	180	43	60° C Average time reduction=78.8%	180	46
	360	68		360	76
	540	77		540	84
	720	86		720	92
	900	91		900	96

sample moisture content in fluidized bed and microwave-assisted fluidized bed dryers, respectively. As expected, increasing the air temperature resulted in increase in the drying rate. This effect can be attributed to the controlled rate of water vapor transfer inside the drying sample due to moisture diffusion towards the surface. Therefore, the water vapor concentration on the outer surface of the drying object reached the equilibrium conditions more rapidly at higher drying air temperature. Similar results were reported by other researchers (Feng *et al.*, 2001, for drying of apple; Sanga *et al.*, 2002, for carrot; Jumah, 2005, for corn, Abbasi Souraki and Mowla, 2008b, for green beans). The combined effect of microwave power and drying air temperature on drying time are shown in Figure 4. The results indicated that by increasing the drying air temperature and using microwave energy power as an assisting heat source, the values of drying rate or moisture diffusivity increased, probably due to the penetration of microwave energy into the sample and also due to the creation of a large vapor pressure difference between the center and the surface of the grain. Similar results were reported by other researchers, (Abbasi Souraki and Mowla, 2008c).

The results showed that increasing the drying air temperature (30°C to 60°C) resulted in up to 5% decrease in drying time, while increasing the microwave energy level (180 W to 900W) in the microwave-assisted fluidized bed system, the drying time decreased dramatically up to 78.8%. The results of this investigation, as presented in Table 3, show a very good agreement with the work of Abbasi Souraki and Mowla (2008c).

The data set was normalized. Network performance was evaluated by plotting the ANN model output against the experimental data and analyzing the percentage error between the predicted and the measured values i.e. experimental data. A comparison between the experimental moisture content versus predicted moisture content by ANN is shown in Figure 5.

The ANN model with 50 neurons was selected for studying the influence of transfer functions and training algorithms. The results revealed that a network with the logsig (Log sigmoid) transfer function and trainrp (Resilient back propagation; Rprop) back propagation algorithm made the most accurate predictions for the green pea drying system, Table 1.

The effect of uncertainty in the output experimental and ANN prediction values on root mean square error (RMSE) was studied by introducing small random errors within a range of $\pm 5\%$ (Tripathy and Kumar, 2008). Table 4 represents the results of sensitivity analysis on green pea experimental data. It can be seen that the ANN prediction results have a very strong dependence on input parameters. The results of the present work are consistent with those of Satish and Pydi Setty (2004) and Tripathy and Kumar (2008).

CONCLUSIONS

The results showed that increasing the drying air temperature (30°C to 60°C) resulted in up to 5% decrease in drying time while increasing the microwave energy level (180 W to 900W) in the microwave-assisted fluidized bed system, the drying time decreased dramatically up to 78.8% and based on error analysis results, it was

Table 4. Results of the measures of error in drying time prediction results of ANN model considering Logsig transfer function and trainrp algorithm for 50 neurons.

Source of error	Measures of error
Mean absolute error (MAE)	0.436
Root mean square error (RMSE)	0.586
Standard error (SE)	0.105
Correlation coefficient (R^2)	0.981



found that the neural network with 50 neurons and Logsig transfer function with trainrp back propagation algorithm was the most appropriate ANN configuration for drying time predicting for green pea.

ACKNOWLEDGEMENT

The authors wish to thank Dr. A. Tahavvor for his comments regarding the Artificial Neural Network technique and Eng. Ostvar for his comments on improving English structure of the manuscript.

Nomenclature

MAE	Mean absolute error
N	Number of observations
R ²	Coefficient of determination
RMSE	Root mean square error
SE	Standard error
T _{p, exp, i}	Average experimental drying time for the ith observation
T _{p, cal, i}	Calculated drying time for the ith observation

REFERENCES

1. Abbasi Souraki, B. and Mowla, D. 2008a. Experimental and Theoretical Investigation of Drying Behavior of Garlic in an Inert Medium Fluidized Bed Assisted by Microwave, *J. Food Eng.*, **88** (4): 438-449.
2. Abbasi Souraki, B. and Mowla, D. 2008b. Axial and Radial Moisture Diffusivity in Cylindrical Fresh Green Beans in a Fluidized Bed Dryer with Energy Carrier: Modeling With and Without Shrinkage. *J. Food Eng.*, **88**: 9-19.
3. Abbasi Souraki, B. and Mowla D. 2008c. Simulation of Drying Behavior of a Small Spherical Foodstuff in a Microwave Assisted Fluidized Bed of Inert Particles, *Food Res. Int.*, **41**(3): 255-265.
4. Abbasi Souraki, B. Andrés, A. and Mowla, D. 2008d. Mathematical Modeling of Microwave-Assisted Inert Medium Fluidized Bed Drying of Cylindrical Carrot Samples. *Chem. Eng. and Processing: Process Intensification*, **48**: 296-305.
5. Abid, M., Gibert, R. and Laguerie, C. 1990. An Experimental and Theoretical Analysis of the Mechanisms of Heat and Mass Transfer during the Drying of Corn Grains in a Fluidized Bed. *Int. Chem. Eng.*, **30**: 632-642.
6. Ajibola, O.O. 1989. Thin-layer Drying of Melon Seed. *J. Food Eng.*, **9**: 305-320.
7. Chen, G., Wang W. and Mujumdar, A.S. 2001. Theoretical Study of Microwave Heating Patterns on Batch Fluidized Bed Drying of Porous Materials. *Chem. Eng. Sci.*, **56**(24): 6823-6835.
8. Erenturk, S. and Erenturk, K. 2007. Comparison of Genetic Algorithm and Neural Network Approaches for the Drying Process of Carrot. *J. Food. Eng.*, **78**: 905-912.
9. Farkes, I., Remenyi, P. and Biro, A. 2000. Modeling Aspects of Grain Drying with a Neural Network. *Comp Elect Agri*, **29**: 99-113.
10. Feng, H. Tang, J., and Cavalieri, R. P. 2001. Dielectric Properties of Dehydrated Apples as Affected by Moisture and Temperature Transaction of ASAE, **45**(1): 129 - 135.
11. Hatamipour, M.S. and Mowla, D. 2002. Experimental Investigation of Heat Transfer in an Air Duct with an Inclined Heating Surface. *Chem. Eng. Comm.*, (In press).
12. Hatamipour, M. S. and Mowla, D. 2003a. Experimental Investigation of Drying of Carrots in a Fluidized Bed with Energy Carrier. *Chem. Eng. Tech.*, **26**: 43-49.
13. Hatamipour, M. S. and Mowla, D. 2003b. Experimental and Theoretical Investigation of Drying of Carrots in a Fluidized Bed with Energy Carrier. *Drying Tech.*, **21**(1): 83-101.
14. Hatamipour, M. S. and Mowla, D. 2006. Drying Behavior of Maize and Green Peas Immersed in Fluidized Bed of Inert Energy Carrier Particles. *Food Bio. Proc.*, (Trans IChemE), **84**(C3): 1-7.
15. Izadifar, M. and Mowla, D. 2003. Simulation of Cross-Flow Continuous Fluidized Bed Dryer for Paddy Rice. *J. Food Eng.*, **58**: 325-329.
16. Jumah, R. 2005. Modeling and Simulation of Continuous and Intermittent Radio Frequency-Assisted Fluidized Bed Drying of Grains. *Food Bio. Proc.*, (Trans IChemE), **83**(C3): 203-210.
17. Kalgoriou, S. A. 2001. Artificial Neural Network in Renewable Energy Systems

- Application: A Review, *Renew. Sustain. Energy Rev.*, **5**: 373-401.
18. Ormos, Z. and Haidu, R. 1997. Study of rotary fluidized bed dryers, 1. Drying of Suspensions and Pastes. *Hungarian J. Ind. Chem.*, **25(1)**: 41-45.
 19. Romano, V. R., Marra, F. and Tamarro, U. 2005. Modeling of Microwave Heating of Foodstuff: Study on the Influence of Sample Dimensions with A FEM Approach. *J. Food Eng.*, **71**: 233-241.
 20. Satish, S. and Pydi Setty, Y. 2004. Modeling of a Continuous Fluidized Bed Dryer Using Artificial Neural Networks. *Int. Comm. Heat and Mass Transfer*, **32**: 539-547.
 21. Sanga, E. C. M., Mujumdar, A. S. and Raghavan, G. S. V. 2002. Simulation of Convection-Microwave Drying for a Shrinking Material. *Chem. Eng. Proc.*, **41**: 487-499.
 22. Tavaklipour, H. 1386. Principles of Drying of Food Materials and Agricultural Products. Ayish, second edition, Tehran, Iran.
 23. Tripathy, P.P. and Kumar S. 2008. Neural Network Approach for Food Temperature Prediction During Solar Drying. *Int. J. Thermal Sci.*, **48**: 1452-1459.
 24. Topuz, A., 2009. Predicting Moisture Content of Agricultural Products Using Artificial Neural Networks. *Adv. Eng. Software*, **41(3)**: 464-470.
 25. Turner, I.W. and Jolly, P.G. 1991. Combined Microwave and Convective Drying of a Porous Material. *Drying Tech.*, **9(5)**: 1209-1269.
 26. Zhou, S. J.; Mowla, D.; Wang, F. Y. and Rudolph, V., 1998. Experimental Investigation of food Drying Processes in Dense Phase Fluidized Bed with Energy Carrier. CHEMECA 98, Port Doulas, North Queensland, Australia.

بکار گیری شبکه عصبی مصنوعی برای پیش بینی زمان خشک شدن نخود سبز در یک خشک کن بستر سیالی با کمک ماکروویو

ل. مؤمن زاده، ع. زمردیان و د. مولا

چکیده

خواص خشک شدن نخود سبز (*Pisum satium*) با رطوبت اولیه ۷۶٪ بر پایه خشک (d. b) در یک خشک کن بستر سیالی با کمک ماکروویو مورد مطالعه قرار گرفت. چهار سطح دمای هوای خشک کننده (۳۰، ۴۰، ۵۰ و ۶۰ درجه سانتیگراد) و پنج سطح توان ماکروویو جزء پارامترهای مورد مطالعه قرار گرفت. آزمایشات زیادی در جهت یافتن محتوای رطوبت نمونه مورد نظر و مدت زمان خشک شدن آن صورت گرفت که نتایج نشان با افزایش درجه حرارت در یک توان مشخص در نهایت تنها ۵٪ مدت زمان خشک شدن را کاهش می دهد که این در حالی است که با اضافه شدن توان ماکروویو به این سامانه مدت زمان خشک شدن تا ۷۸٪ کاهش میابد. در نهایت می توان نتیجه گرفت که با افزایش توان ماکروویو و دمای هوای خشک کننده نرخ خروج رطوبت افزایش میابد. در ادامه این تحقیق با استفاده از شبکه عصبی مصنوعی مدل مناسبی برای یافتن مدت زمان خشک شدن (پارامتر خروجی شبکه) ارائه گردید. توان ماکروویو، دمای هوای خشک کننده و محتوای رطوبت دانه به عنوان پارامترهای ورودی مدل می باشد. نتیجه نشان داد که شبکه عصبی مورد استفاده با ۵۰ نرون و



تابع (Log sigmoid) و الگوریتم پس انتشار (Resilient back propagation; Rprop) trainrp (Log sigmoid) تابع
برای (Rprop) بهینه حالت ممکن برای پیش بینی مدت زمان خشک شدن می باشد. برای
اعتبار سنجی مدل از (RMSE) root mean square error، (MAE) mean absolute error و (SE) standard error استفاده شد و نتایج نشان داد که این مقادیر کمتر از ۵٪ می باشد
این در حالی است که ضریب تبیین (R^2) بیشتر از ۹۸٪ می باشد.