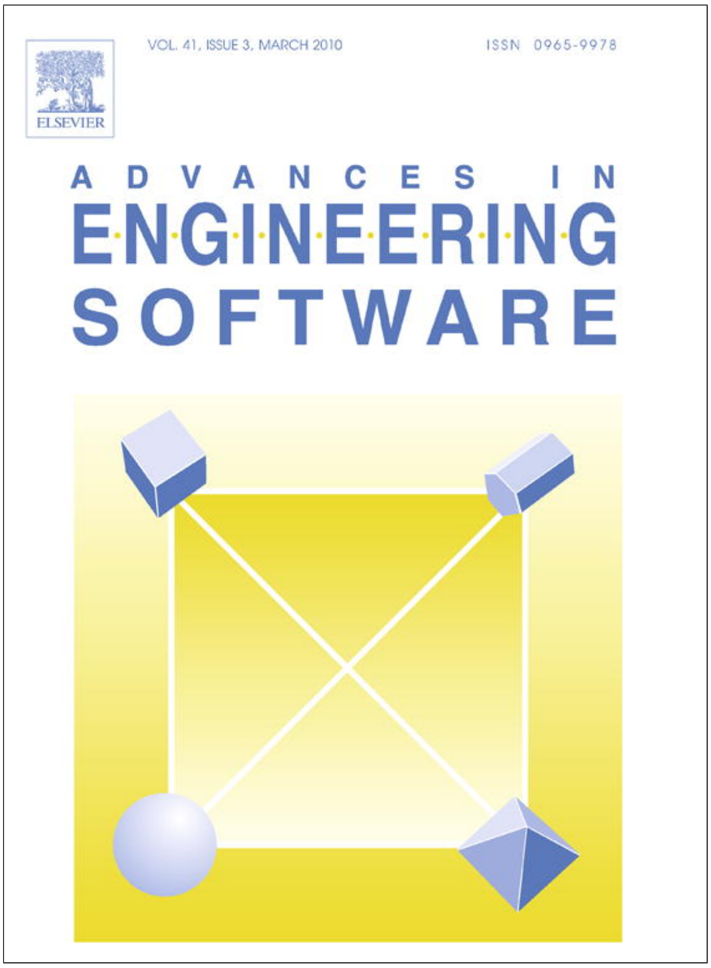
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Predicting moisture content of agricultural products using artificial neural networks

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ABSTRACT

Drying of agricultural products is a significant process to store and use them for various purposes. There are few drying methods in agricultural industry, among them fluidized bed drying is widely employed due to its several advantages over the other methods. The prediction of drying characteristics with a small number of experiments is rather efficient since because of the fact that the drying experiments is time consuming and requires tedious work for a single agricultural product. Therefore, several methods such as deterministic, stochastic, artificial intelligence have been developed in order to predict the drying characteristics based on the experimental data obtained from the lab-scale fluidized bed drying system. In this paper, the artificial neural networks (ANN) method was used to predict the drying characteristics of agricultural products such as hazelnut, bean and chickpea. The ANN was trained using experimental data for three different products through the back propagation algorithm containing double input and single output parameters. The results showed fairly good agreement between predicted results by using ANN and the measured data taken under the same modeling conditions. The mean relative error (MRE) and mean absolute error (MAE) obtained when unknown data were applied to the networks was 3.92 and 0.033, respectively, which is very satisfactory.

1. Introduction

Drying of agricultural products is very important process in terms of storing and using them in food industry. There are few techniques of drying of agricultural products such as cabin, infinite band tunnel, rotary cylindrical, fluidized bed, spray drying, etc. Among them, the fluidized bed dryers are widely used in food, chemical, pharmaceutical and metallurgical industries due to their mixing and rapid rates of heat and mass transfer between hot air and particles [1–10].

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 fails for different agricultural products since such kind of correlations are not general since they are usually based on data obtained from a particular product. That is, as the products changes, the equation alternates, as same mentioned in Movagharnejad and Nikzad [11]. Therefore, several researchers used alternative techniques to obtain a general correlation which would be valid for different products. Although there are a few number of complicated models that could be used to precisely determine the drying characteristics of different agricultural product, they often require substantial expertise in handling with the transport phenomena, and computational methods for sets of non-linear partial differential equations. Recently, Hajidavalloo and Hamdullahpur [4] and Topuz et al. [10], for example, employed a set of coupled non-linear partial differential equations to accurately model the simultaneous heat and mass transfer in fluidized bed drying of large particles without using adjustable parameters. They used a three-phase model representing a bubble phase, interstitial gas phase and solid phase to describe the thermal and hydrodynamic characteristics of the bed. In another work, Babu and Setty [12] proposed to use Tanks-in-series model to predict the average moisture content of solids. However, the solutions of these analytical models are very complicated and time consuming. Consequently, researchers have been using soft computing techniques among which artificial neural networks (ANN) and genetic algorithm (GA) have received much interest due to their ability to dynamic modeling of the drying characteristic of agricultural products (Erentürk and Erentürk [13]). However, they pointed out that the ANN outperforms GA in predicting the experimental drying characteristics. In addition to that, the reasons of the use of the ANN in process modeling are listed in Ye et al. [14] as the following: First, the recent advances in computer technology and parallel processing have made the use of ANN more economically feasible. Second, since the ANN is composed of nets of non-linear basis functions, it has the ability to evolve good process models from example data and require little or no a priori knowledge of the task to be performed. Third, ANN has the potential to solve certain types of complex problems that have not been satisfactorily handled by more traditional methods.

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Nomenclature

a	parameter of the sigmoid function
b	bias parameter
c	specific heat, J/kg °C
d	particle diameter, m
de	desired or actual value
E	sum of square error
f_{act}	activation function
n	number of data
O	predicted output value
T	temperature, °C
V	weight between hidden layer and output layer
W	weight between input layer and hidden layer
X	input signal
Y	hidden unit
y	variable
x	individual factor

Greek symbol

ρ	density, kg/m^3
α	learning rate
β	momentum coefficient
s	current step

Subscripts

i	initial
p	particle

Artificial neural networks method has recently been of keen interest to researches and practitioners in the chemical and allied industries. ANN is increasingly being applied to process control as well as to a variety of other areas including the dynamic modeling of process operations, process prediction, fault diagnosis of process and parameter estimation for the design of controllers [15–17]. More specifically, ANN has been used widely in several works [18–25] for prediction of drying characteristics agricultural products due to the aforementioned reasons. These works can be summarized as: Otawara et al. [18] have modeled the non-linear hydrodynamic behavior of bubble motion and that of particle motion in a three phase fluidized bed by resorting to an artificial neural network. They have observed that the ANN was capable of predicting and modeling non-linear dynamics of three phase fluidized beds often behaving chaotically. Satish and Setty [19] have used an artificial neural network for modeling of a continuous fluidized bed dryer. Their work involved experimentation on drying of solids in a continuous fluidized bed dryer covering different variables like bed temperature, gas flow rate, solids flow rate and initial moisture content of solids. The collected data was then modeled using artificial neural networks. Their results indicated better agreement between artificial neural networks and experimental data than various mathematical models were able to achieve. Fernandez and Lona [20] have investigated the neural network applications in polymerization processes. Their paper is a brief tutorial on simple and practical procedures that can help in selecting and training neural networks and addresses complex cases where the application of neural network has been successful in the field of polymerization. Subramanian et al. [21] optimized the formulation parameters of cytarabine liposomes by using artificial neural networks (ANN) and multiple regression analysis using 3^3 factorial designs. Their study demonstrated that 3^3 factorial design and back propagation network are useful tools for understanding the effect of various formulation parameters in the preparation of cytarabine liposomes by lipid film hydration method and they predict the best composition for a particular response. Lertworasirikul and Tipsuwan [22] have proposed a multilayered feed-forward neural network in the form of non-linear-auto-regressive with exogenous input (MFNN-NARX) to predict the product quality from the dynamic drying process. The evaluation of the best MFNN-NARX model with a test data showed the good accuracy of the model. Therefore, the developed model could be used in order to determine the appropriate drying time to reach the specified moisture content. Behzadi et al. [23] have replaced three conventional components with innovative components, in a fluid bed granulator. Validation of the modified fluid bed granulator has been conducted using a generalized regression neural network (GRNN). Good correlation has been obtained between the predicted and the experimental data. They concluded that the GRNN might serve as a reliable method to validate the modified fluid bed apparatus. Kerdpiboon et al. [24] have used artificial neural network analysis to predict shrinkage and rehydration of dried carrots, based on inputs of moisture content and normalized fractal dimension analysis of the cell wall structure. They have tested the ANN models against independent data set, through which the measured values of shrinkage and rehydration have been predicted very accurately in all cases. Hernandez-Perez et al. [25] have proposed a predictive model for heat and mass transfer using artificial neural network to obtain on-line predictions of temperature and moisture kinetics during the drying of cassava and mango. They have obtained best fitting with the training dataset and claimed that the developed model could be used for on-line state estimation and control of drying processes.

It can be concluded from the above literature review that the ANN method was used to predict the characteristics of drying process, however most of these works [11,13,22,24] use tray dryer as the dryer technology. It is presented in [18,19] that fluidized bed dryer could be modeled by using ANN, but these two works did not investigate any particular agricultural product. In this work, we investigate the use of ANN to predict the fluidized bed drying characteristics of agricultural products. To validate the prediction capability of the ANN model constructed, a laboratory scaled fluidized bed dryer was facilitated and used for the drying of hazelnut, bean and chickpea. In the present experiments, the effect of inlet air temperature on the drying characteristics of three distinct granular products have been investigated, whereas the effect of inlet air velocity was not considered since the inlet air velocity was set to the minimum fluidization velocity during the whole experimentation. It was also observed that the changes in the air velocity could slightly affect the drying rate of the product, which could be disregarded for practical applications. In order to predict drying performance characteristics of fluidized bed system, an optimized ANN model has been constructed and tested against the test data obtained by using three different granular products, namely hazelnut, bean and chickpea. The proposed ANN model was then shown to be fairly good agreement with the measured data, and it was concluded that the ANN model could be safely utilized as a predictive tool for fluidized bed drying of granular agricultural products, as long as it was properly constructed and optimized.

2. Artificial neural networks: a brief overview

The artificial neural networks are basically computational models, which simulate the function biological networks, composed of neurons. In the literature most papers on the use of 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.

The system has three layers of neurons: input layer, a hidden layer and an output layer. The neurons or units of the network are connected by the weights. The input layer consists of all the input factors, information from the input layer is then processed through one hidden layer, and following output vector is computed in the final (output) layer. The scheme of ANN used in this work is shown in Fig. 1. Back propagation (BP), which is one of the most famous training algorithms for multi-layer perceptions, is a gradient descent technique to minimize the error for particular training pattern. Although BP training algorithm has some drawbacks, this method was preferred due to its simplicity and reliability. Since the ANN technique is a relatively newer one over the existing traditional modeling methods relying upon physical conservation laws, it would be worth to briefly introduce some important aspects of the neural network from the completeness of the present paper point of view. 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.

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

where W_{ij} is the weight of the connection from the ith input unit to the jth hidden unit, b_j is the weight of bias connection for jth 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.

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

where V_{jk} is the weight of the connection from the jth hidden unit to the kth output unit. The parameter of bias (b) in Eqs. (1) and (2), also called the threshold value, is permanently set to 1 in hidden layer as well as output layer so that corresponding weight shifts the activation function along the X axis. The activation function used in this study is a logistic sigmoid function defined as

$$f_{act}(x) = \frac{1}{1+e^{-x}} \tag{3}$$

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

$$E = \frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{K}(de_{pk} - O_{pk})^2 \tag{4}$$

where de_{pk} is the desired or actual output, O_{pk} is the predicted output for the p_k^{th} pattern. During training, an ANN is the presented with the data for thousands of times, which is referred to as cycles. After each cycle the error between the ANN output and desired values are propagated backward to adjust the weight in a manner mathematically guarantied to converge. Adjustment of the weights ΔW_{ij} can be calculated as

$$\Delta W_{ij} = -\alpha\frac{\partial E}{\partial W_{ij}} + \beta\Delta W_{ij}(s-1) \tag{5}$$

where α is the learning rate, β is the momentum coefficient and s is the current step. Detailed description of the mathematical formulation of the BP can be found in [26]. 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's state of knowledge [27].

In this study, the available data set is partitioned into two parts, one corresponding to training and the other corresponding to validation of the model. Using experimental data in the fluidized bed dryer, an optimized ANN model was developed to predict the outlet moisture content of the granular products. All simulations were performed in the MATLAB environment using its ANN toolbox. In order to facilitate the comparisons between predicted values for different network parameters (learning rate, momentum coefficient and neuron number in hidden layer) and desired values, there is a need for error evaluation. Mean relative error (MRE) and mean absolute error (MAE) were calculated following expression,

$$\text{MRE}\ (\%) = \frac{1}{n}\sum_{i=1}^{n}\frac{|de_i - O_i|}{de_i} \times 100 \tag{6}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|de_i - O_i| \tag{7}$$

where de_i is desired or actual value, O_i the predicted output value and n is the number of data. The experimental data sets consist of 99 groups (total 198 for time and moisture content) of which 66 were used for training the network and 33 were selected randomly to test the performance of the trained network. The learning rate and momentum coefficient were both initially set to 0.1 then incremented to 0.9. In order to clarify how the ANN was optimized, some of the results which were obtained during the learning and testing were given in Table 1.

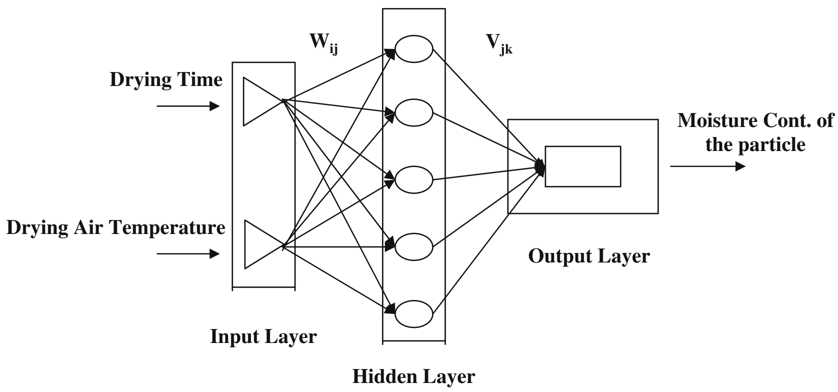

Fig. 1. The scheme of ANN.

Table 1
Some selected results during the training.

Learning rate	Momentum coefficient	Hidden neuron number	MRE (learning)	MRE (test)	MAE (learning)	MAE (test)
0.2	0.4	5	5.9	11.16	0.044	0.112
0.5	0.4	5	5.32	13.91	0.053	0.132
0.8	0.4	5	6.12	12.12	0.077	0.161
0.2	0.4	2	7.35	11.05	0.052	0.083
0.2	0.4	4	6.02	11.21	0.044	0.085
0.2	0.1	3	6.35	11.97	0.042	0.083
0.2	0.7	4	6.46	11.83	0.050	0.097
0.5	0.7	2	7.35	11.05	0.076	0.121
0.5	0.1	5	5.46	13.54	0.048	0.124
0.8	0.7	5	5.09	7.71	0.072	0.118

3. Experimental study

3.1. Physical properties of materials

Hazelnut, bean and chickpea were used as drying material and their shapes were assumed to be spherical with an average diameter of 16 mm, 9 mm and 7 mm, respectively. The initial moisture contents of hazelnut, bean and chickpea are in the range of 8%, 10.74% and 9.81% on a dry basis, respectively. Other properties of the particles can be found in Table 2.

3.2. Experimental setup

To investigate the drying characteristics of the particles, a laboratory scale fluidized bed was designed and constructed as shown in Fig. 2. The bed column was made of Plexiglas with an inner diameter of 196 mm, height of 1000 mm, and wall thickness of 2 mm. A perforated distributor plate with 2 mm thickness, and 15 mm holes was provided to obtain uniform distribution of the fluidizing air. The air heater consists of four strip electric elements which have 2000 W total power. The air was supplied by a centrifugal blower. The temperature distribution through the bed was measured by a thermometer (Testo 905-T1, Type K thermocouple, 0.1 °C resolution) at different heights above the distributor plate (40, 80, 120 mm above the distributor plate). The pressure difference between the two sides of distributor plate and the distributor plate and fluidized bed height was measured with an electronic pressure cell (Testo 505-P1, 1 mm H_2O resolution). Air velocity was measured and determined with a static pitot tube (chromium-plated brass, 350 mm length, 7 mm diameter) and an electronic pressure transducer. Inlet and outlet humidity of the air were measured using a humidity measurement stick (Testo 605-H1, 125 mm length, 12 mm diameter, 5–95% RH, 0.1% RH resolution).

The moisture content of the particles was observed by making use of a moisture analyzer (Sartorius MA30). Moisture analysis was based on infrared drying. In this process, the moisture was removed from the sample by heating. The difference between the initial weight and the final weight yielded the moisture content of a sample. Before each experiment, the unit was run in the absence of particles for about 2 h to reach thermally steady state conditions. After the bed reached the required temperature and stabilized, the air supply and electric heater were turned off, and the

Table 2
Physical properties of the particles (Ref. [9] and literature).

Particle	Property	Value	Unit
Hazelnut	d_p	16	mm
	c_p	1650	J/kg K
	ρ_p	795	kg/m^3
Bean	d_p	9	mm
	c_p	1300	J/kg K
	ρ_p	1230	kg/m^3
Chickpea	d_p	7	mm
	c_p	1980	J/kg K
	ρ_p	1380	kg/m^3

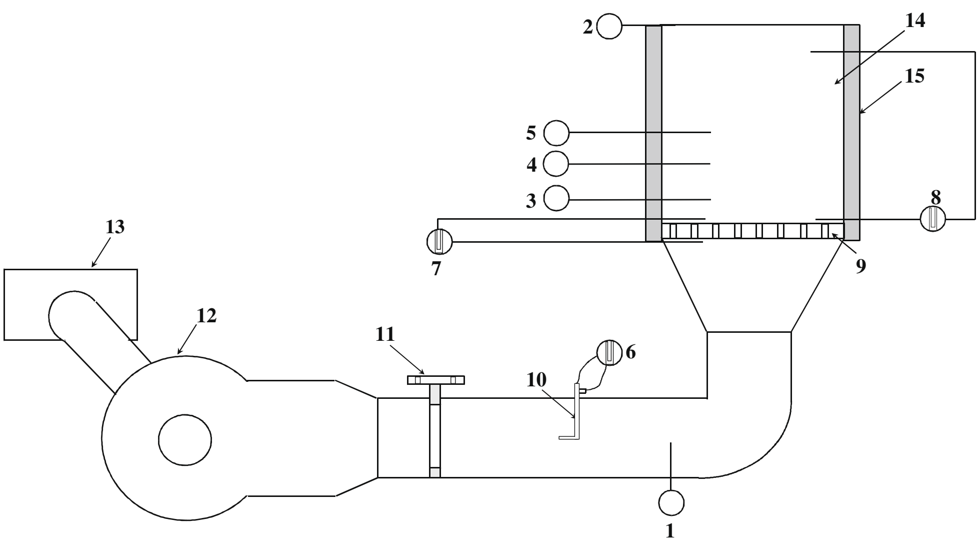

Fig. 2. Schematic diagram of experimental setup. (1, 2: Humidity stick [for measurement of inlet and outlet air humidity], 3–5: Thermometers [for measurement of fluidized bed air temperature at 4,8,12 cm of bed, respectively], 6–8: Pressure cell [for measurement pressure drop. 6: to observe inlet air velocity with pitot tube, 7, 8: to measure distributor plate and fluidized bed pressure drop, respectively], 9: Perforated plate, 10: Pitot tube, 11: Valve, 12: Fan, 13: Climate center, 14: Plexiglas bed column, 15: Insulation.)

material was charged into the bed as quickly as possible. The air supply and heater power were then reinstated. All experiments were conducted under batch fluidization. During the experiments, temperature distribution through the bed and bed pressure drop were measured. As fluidization continued, solid samples were removed from the column at different times and were analyzed for their moisture content.

Errors and uncertainties are inherent in both the instrument and the process of making the measurement, and too much reliance should not be placed on any single reading from one affected by the environment. Final accuracy depends on a sound program on correct methods for taking readings on proper instruments. When readings are repeated, they tend to produce a band of results rather than a point or a line. Errors and uncertainties in the experiments can arise from instrument selection, instrument condition, instrument calibration, environment, observation, reading and test planning (Holman [28], Akpınar [29]). In the fluidized bed drying experiments the temperature, velocity, pressure difference, relative humidity of drying air and weight loss of particles were measured with appropriate instruments. During the measurements of the parameters, uncertainties occurring are presented in Table 3. Considering the relative errors in the individual factors denoted by x_n, the error estimation was made using the following equation (Holman [28]);

$$W = [(x_1)^2 + (x_2)^2 + \cdots + (x_n)^2]^{1/2} \tag{8}$$

Table 3
Uncertainties of the parameters during fluidized bed drying of particles.

Parameter	Unit	Comment
Temperature through the bed	°C	±0.1
Bed inlet and outlet temperature	°C	±0.3
Relative humidity of inlet and outlet bed air	RH	±0.02
Pressure difference	hPa	±0.03
Air velocity	m/s	±0.018
Moisture quantity	g	±0.01
Measurement time of mass loss values	min	±0.1
Measurement time of temperature values	min	±0.1

4. Results and discussion

Three different temperatures of the bed air were used in the experiments for the hazelnut and then, as seen in Fig. 3, the drying rate was accelerated with an increase in temperature. As for the inlet air temperature, both bean and chickpea particles were exhibited nearly the same drying behavior as shown in Figs. 4 and 5. Recent papers by the present first author [8,9] demonstrated that, if the inlet air velocity was over the minimum fluidization velocity, the changes in air velocity were observed to slightly affect the drying rate of the products.

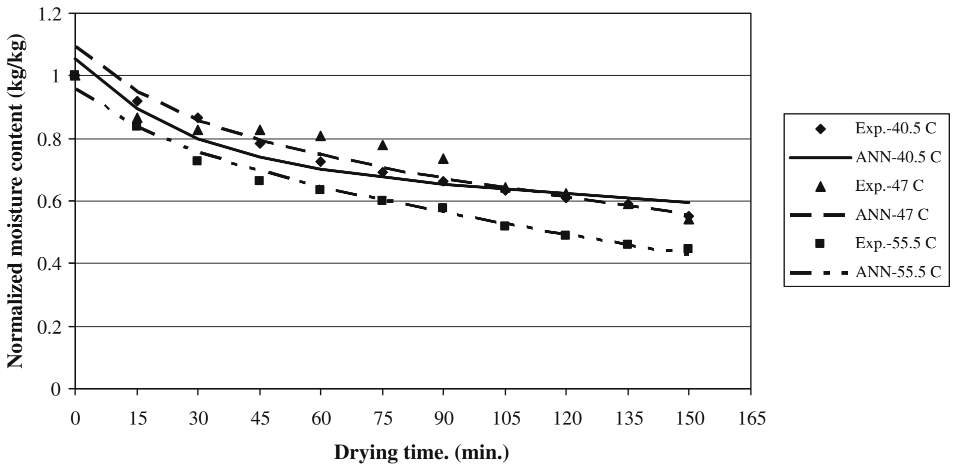

Fig. 3. Comparison of ANN prediction and experimental data: normalized moisture content of the hazelnut vs. drying time with T_i = 40.5 °C, 47 °C and 55.5 °C.

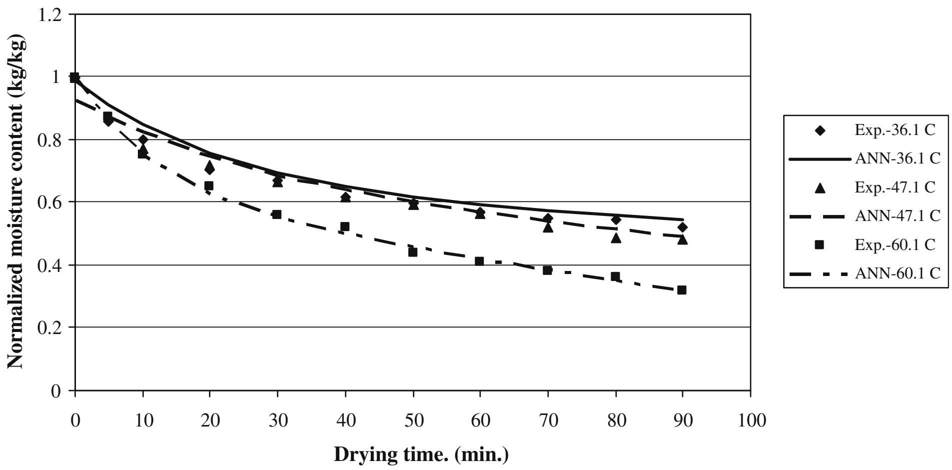

Fig. 4. Comparison of ANN prediction and experimental data: normalized moisture content of the chickpea vs. drying time with T_i = 36.1 °C, 47.1 °C and 60.1 °C.

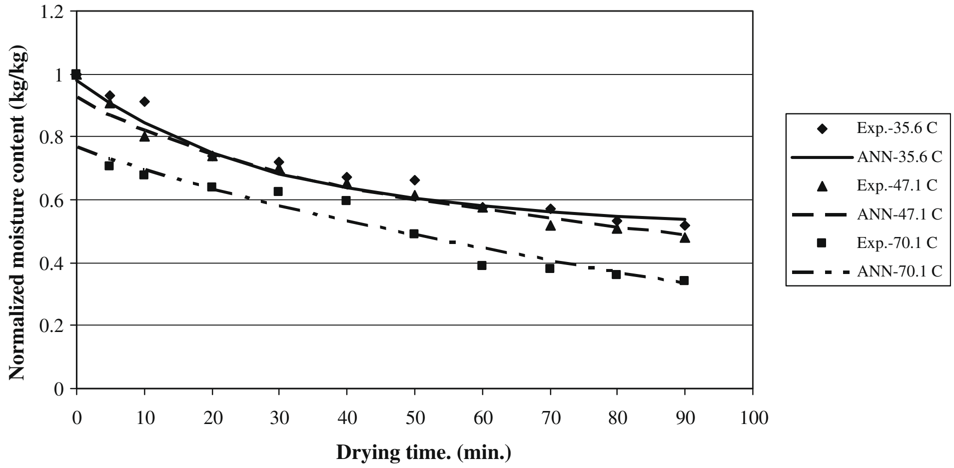

Fig. 5. Comparison of ANN prediction and experimental data: normalized moisture content of the bean vs. drying time with T_i = 35.6 °C, 47.1 °C and 70.1 °C.

In this present ANN model, two independent variables, i.e., drying time and inlet air temperature have been chosen as the input parameters, and moisture content of products has been regarded as the output parameter (dependent variable). In order to decide the optimum structure of neural network, the rate of error convergence was checked by changing the number of hidden neurons and adjusting the learning rate and momentum coefficient. The networks were trained up to cycles where the level of MRE is satisfactory and further cycles had no significant effect on error reduction. In order to explain how the ANN was optimized, some of the results obtained during the learning and testing were given in Table 1. It can be seen in Table 1 that, learning rate, momentum coefficient and hidden neuron number were changed and, MRE and MAE coefficients were determined for learning and test data. Optimum learning rate and momentum coefficient values determined in each network for fastest convergence are given in Table 4. Results obtained from ANN were compared with experimental data. As shown in Figs. 3–5, the results are very close to the experimental data.

Table 4
Network details and testing results of individual neural networks.

Network parameters	Output parameters
	Moisture content of the hazelnut, bean and chickpea
Hidden neuron number–Iteration numbers	5–2000
Learning rate–Momentum coefficient	0.2–0.6
MRE (test)	3.92
MAE (test)	0.033

Besides, in order to compare the results against the existing predictive models, a fluidized bed drying mathematical model was selected from the literature. Hajidavalloo and Hamdullahpur [4] and Topuz [9] used a three-phase model representing a bubble phase, interstitial gas phase and solid phase to describe the thermal and hydrodynamic characteristics of the bed. Detailed information about this model can be found in Topuz et al. [10]. They have used this model to predict the drying characteristics of hazelnut. It can be seen in Fig. 6 that, ANN results exhibit a good agreement with experimental results rather than mathematical model ones for hazelnut.

These findings demonstrate that artificial neural networks produce better prediction and more useful results.

5. Conclusions

The main purpose of the present study is to investigate applicability of artificial neural networks in predicting the fluidized bed

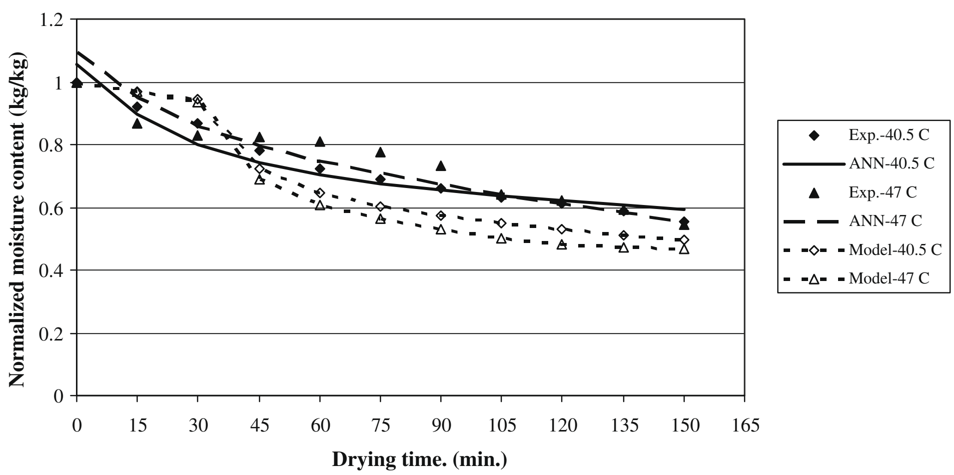

Fig. 6. Comparison of ANN and model prediction: normalized moisture content of the hazelnut vs. drying time with T_i = 40.5 °C and 47 °C.

drying characteristics of agricultural products. Fluidized bed drying data were acquired by conducting drying tests on a specially designed and fabricated fluidized bed test facility. Since traditional predictive correlations existing in the literature were generally based upon some prescribed products, they show significant departures from the experimental observations. This is primarily due to the fact that they are curve-fitted correlations in nature, and their accuracy is usually restricted by the physical properties of product and test conditions. Although there are some more complicated and general models taken physical conservation laws as the basis, they require substantial expertise in the mathematical behavior of non-linear partial differential equations, and are of marginal significance from a practical point of view. As an alternative to the present situation, an attempt has been made to model the drying characteristics of granular agricultural product employing feed forward artificial neural networks. For this purpose an optimum neural network has been constructed and its predictions were compared with the existing experimental data. The results showed very good agreement with the experimental data and it has been concluded that the ANN model can be effectively utilized as a prediction tool for such a purpose.

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