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STUDY OF SHELLED CORN SHRINKAGE IN A MICROWAVE-ASSISTED FLUIDIZED BED DRYER USING ARTIFICIAL NEURAL NETWORK

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Abstract- Grain drying is a vital unit operation in many processing plants. An undesirable change associated with this operation is shrinkage of dried product which results in decreased quality. Recently many attempts have been made to decrease the shrinkage of food stuff during drying. Microwave-assisted fluidized bed drying has particularly been proposed as a potentially effective method. In the present study, at each drying operating condition, the volume of shelled corn was calculated by measuring the three principal characteristic dimensions. The variation of the ratio of mean diameter of the kernel to its initial mean diameter was investigated for different operating conditions. It has been shown that employing microwave in fluidized bed drying reduces the shrinkage of particles considerably. Also, in this study, Artificial Neural Networks (ANN) analysis was employed to predict the extent of shelled corn shrinkage. In the construction of the network, three independent variables: microwave heat source, drying air temperature and moisture content were chosen as the input parameters and shrinkage of dried sample was set as the output parameter (dependent variable). The ANN model with 5 neurons was selected for studying the influence of transfer functions and training algorithms. It has been observed that back-propagation networks with logsig transfer function and trainlm algorithm were the most appropriate ANN configuration for predicting shrinkage. Results from the experiments and modeling showed good agreement. In order to test the ANN model the random errors were within an acceptable range of ±5% with a correlation coefficient (R^2) of 98%.
Keywords- Shelled corn; shrinking effect; Artificial Neural Network

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Introduction

Drying of agricultural products is an important process in terms of storing and use in the food industry and post-harvest processing [7]. Drying is a process in which moisture migrates from interior of the drying object to the surface, resulting in some changes in physical properties of the dried sample [9].

There are several types of dryers such as solar, cabinet, rotary cylindrical, fluidized bed, microwave, infrared and etc. Among them, fluidized bed dryers assisted by microwave heating sources are very efficient due to efficient mixing and high heat and mass transfer rates between hot air and drying object [21].

An undesirable change associated with moisture diffusion is shrinkage. In general, shrinkage takes place as a result of volume reduction due to evaporation of the moisture contained in the drying object. The changes in dimensions of the solid could be monitored in most cases. Many researches have focused on changes in volume, area and shape. Shrinkage during drying is important not only from the viewpoint of product end-use but also for processing simulation [4].

Shrinkage of food stuff during drying processes has been of special interest during recent decades [1, 2, 4-6, 8, 10-13, 15, 17-19]. Several methods such as mathematical modeling, regression analysis, artificial neural networks and etc. are proposed for predicting shrinkage of agricultural products. Appropriate predicting models have to be selected based on several crucial parameters including the type of material, initial moisture content of sample and the drying procedure.

Artificial Neural Networks (ANN) is effective tools for modeling, optimization and process control of several complex phenomena. It is believed that ANNs can be used to predict the shrinkage effect of drying samples in many cases [9].

In the present study, first shrinkage of corn cereal grain is measured in a fluidized bed dryer assisted by microwave. An ANN model is then developed and evaluated for the prediction of shrinkage behavior of shelled corn, based on measures of error deviation from experimental data

Materials and Methods

Specimen

Newly harvested shelled corn was used as test samples. The initial moisture content (dry basis) of shelled corn was approximately 26%.

Drying apparatus and procedures

An experimental apparatus consisting of a fluidized bed dryer assisted by a microwave energy source was designed and constructed. A cylindrical Pyrex column, 90 mm in diameter (100 mm outside diameter) and 280 mm high was used as the fluidized bed drying chamber. The chamber was placed in a domestic microwave oven (type: LG, MC- 2003TR (S)) with the frequency of 2450 MHz and approximate cavity volume of 0.075 m^3 (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 to drying object diameter is much greater than 10, the wall effect was negligible. High pressure drying air was introduced at the bottom of the Pyrex column with constant air flow rate (650 lit/min) using a porous plate as distributor and an air compressor (type: TCS-SCLL, 7 bar pressure, 15 hp), to maintain the fluidization condition in the drying chamber. The air flow rates were measured by a rotameter with an accuracy of ±10 l/min. An electrical heating unit equipped with a thermostat (±1º C) was used to maintain different levels of drying air temperature of 30, 40, 50 and 60º C. A schematic diagram of employed apparatus is shown in Fig. 1.

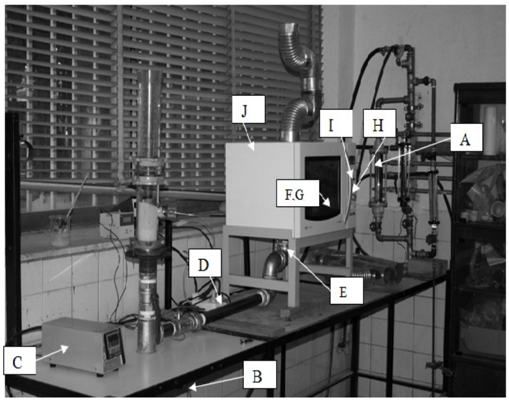

Fig. 1- Schematic diagram of the experimental apparatus

As shown in Fig. 1 three kernels of shelled corn were hung in the fluidized bed chamber as drying samples. Measurement of water loss from the samples was off-line. Sample weighting (in at most 10 seconds) was carried out using an electrical balance (balance type: MW-150t, Max weighing capacity of 150g, ±0.005g accuracy). Each sample weighting was done in triplicates and the average of the recorded weights was taken as an experimental data point.

Volume changes of shelled corn were calculated by measuring the three principal characteristic dimensions using a caliper (Mitutoyo, Japan, ±0.05mm). The geometric mean diameter was calculated using the following equation [14]:

$$D = \sqrt[3]{\frac{abc}{3}} \qquad (1)$$

Artificial Neural Networks (ANN)

The Artificial Neural Networks (ANN) are basically computational models, which simulate the function of biological neuron networks that are composed of neurons. ANN was developed using MATLAB v7.0. Each ANN has three layers of neurons: input, hidden and output (Tripathy and Kumar, 2008).

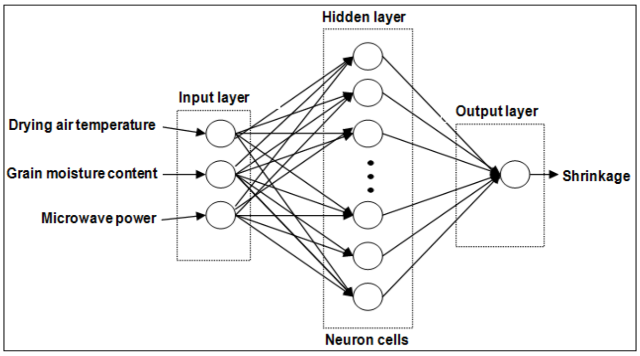

Fig. 2- Selected neural network structure

The ANN model was employed for investigating the shrinkage of shelled corn kernel. The ANN layout with three layers is shown in Fig. 2.

The input layer consists of important operating parameters namely: air drying temperature, grain moisture content and microwave power. Information from the input layer is then processed through one hidden layer with five neurons and finally the output layer shows the processing result as the value of shrinkage.

During training, weighting functions for the inputs were determined such that the predicted output data matched to the best experimental output from data set. Back propagation algorithms were used for minimizing the error of particular training pattern. A Log-Sigmoid activation function was applied and mathematical definition of the transfer function was trainlm (Levenberg–Marquardt back propagation) in the hidden layer.

Training was terminated when the Mean Absolute Error (MAE), Standard Error (SE) and Root Mean Square Error (RMSE) as given by equation 2-4 were less than ±0.05 and correlation coefficient (R^2), given by equations 5 was more than 95% [20].

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\overline{D}_{p,\exp,i} - \overline{D}_{p,cal,i}| \qquad (2)$$

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

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(\overline{D}_{p,\exp,i} - \overline{D}_{p,cal,i})^2\right]^{1/2} \qquad (4)$$

$$R^2 = \sqrt{\frac{\sum_{i=1}^{N}(D_{p,\exp,i} - \overline{D}_{p,\exp,i})^2 - \sum_{i=1}^{N}(D_{p,\exp,i} - D_{p,cal,i})^2}{\sum_{i=1}^{N}(D_{p,\exp,i} - \overline{D}_{p,\exp,i})^2}} \qquad (5)$$

In this study, the available experimental data was partitioned into two parts, 120 data points for training and 30 data points for validation of the model.

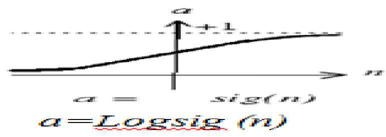

Fig. 3- Log-Sigmoid Transfer Function

The Log-sigmoid (logsig) activation function is shown in Fig. 3. This function takes the input (which may have any value between plus and minus infinity) and determines the value of output inside the range 0 to +1, as given equation 6 [3].

$\text{logsig}(n) = 1 / (1 + \exp(-n))$

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

In order to study the effects of different parameters on network performance, the model was run with changing an important parameter while keeping the others constant.

Results and Discussion

Shrinkage Effect

In order to show the effects of various parameters on the rate of shrinkage of shelled corn, several experiments were carried out under different operating conditions. In each experiment, the ratio of initial geometric mean diameter (D_0) to the geometric mean diameter of the kernel at a given condition (D) was determined and plotted verses grain moisture content, as shown in Figs. 4 and 5.

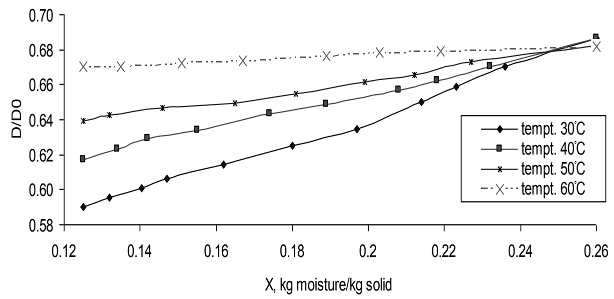

Fig. 4- Variation of D/D0 with drying sample moisture content for different air temperatures without microwave assisted.

It was concluded that drying air temperature and microwave power level were the main factors that showed significant effects on the grain shrinkage during the drying process. Analysis of the experimental data revealed that the variations of D/D_0 for the samples in a fluidized bed in both cases of drying with and without microwave heat source were well correlated as linear functions of the moisture content of drying samples.

As it was expected, increasing of the heating air temperature and microwave power resulted in decreasing of the shrinkage of the kernels. Indeed by increasing these parameters, the water vapor concentration on outer surface of the drying sample reached the equilibrium condition more rapidly. This shrinkage reduction can be interpreted in terms of a decrease in drying time so that the kernel could not find enough time to be shrunk. Similar results were reported by other researchers such as [6, 15 and 16].

The combined effect of microwave power and drying air temperature on shrinkage are showed in Fig. 5. The results indicated that by increasing the drying air temperature and using microwave energy power as an assisting heat source, the values of shrinkage increased. This increase can be due to the penetration of microwave energy into the sample and creation of a large vapor pressure difference between the core and the surface of grain.

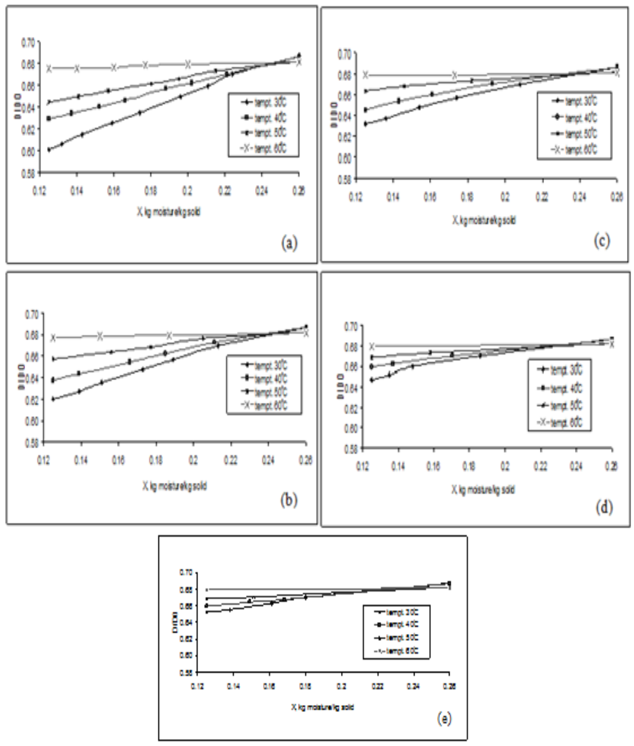

Fig. 5- Variation of D/D0 with drying sample moisture content for different air temperatures and different microwave power (a: 180, b: 360, c: 540, d: 720 and e: 900W).

Sensitive analysis in ANN prediction

In this Artificial Neural Network (ANN) model, three independent variables: level of microwave heat source (zero to 900 W), drying air temperature (30 to 60°C) and grain moisture content (26% to 12.5%) were chosen as the input parameters, and shrinkage of drying sample was regarded as the output parameter (dependent variable).

In order to determine the optimum structure of ANN, the rate of error convergence was checked by changing the number of hidden neurons (ANN with 1 to 10 neurons in hidden layer was tested) and adjusting the training algorithm. The data set was first normalized and then divided into two parts; one part was used for training the networks and the other for testing.

One of the most difficult tasks in ANN model development is to find the optimal network architecture. This network architecture can be selected among several network configurations containing the combination of various model parameters namely, the number of neurons in the hidden layers, different transfer functions and the training algorithms. A list of different transfer functions and training algorithms investigated during training network is summarized in Table 1 [20]. Table 2 represents the results of sensitivity analysis on shelled corn shrinkage experimental data. It can be seen that the ANN prediction results have a very strong dependence on input parameters. The present work showed a good agreement with the works of [9 and 18].

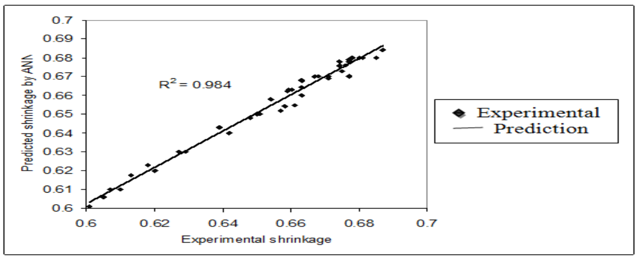

Fig. 6- Comparison of the experimental and predicting shrinkage values given by the proposed ANN model.

The accuracy of various proposed prediction models was checked by comparing of the predicted and the experimental drying sample shrinkage data. This comparison, showed a very good agreement, as shown in Fig. 6.

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)

Table 2- Measures of error in percent of shrinkage using the ANN model considering Logsig transfer function and trainlm algorithm for 5 neurons.

Source of error	Measures of error
Mean Absolute Error (MAE)	0.432
Root Mean Square Error (RMSE)	0.589
Standard Error (SE)	0.11
Correlation coefficient (R^2)	0.984

Conclusions

- Shrinkage of shelled corn could be well correlated to the moisture content by linear equations. It is shown that in fluidized bed dryer assisted by microwave system, the shrinking was less than the corresponding shrinking values in fluidized bed drying system alone.
- Applicability of Artificial Neural Networks (ANN) in predicting the shrinkage of shelled corn was well accepted. It was observed that back-propagation networks with logsig transfer function and trainlm algorithm were the most appropriate ANN configuration for prediction capability of shrinkage.

Nomenclature

a, b, c	Maximum, intermediate, minimum diameter (mm)
D	Geometrical mean diameter at any time (mm)
D_0	Initial geometrical mean diameter (mm)
MAE	Mean absolute error
X	Moisture content
N	Number of observations
R^2	Correlation coefficient
RMSE	Root mean square error
SE	Standard error
$D_{p, exp, i}$	Average experimental drying time for the ith observation
$D_{p, cal, i}$	Calculated drying time for the ith observation

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