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ORIGINAL ARTICLE

Prediction of carrot cubes drying kinetics during fluidized bed drying by artificial neural network

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Abstract This article presents static and recurrent artificial neural networks (ANNs) to predict the drying kinetics of carrot cubes during fluidized bed drying. Experiments were performed on square−cubed carrot with dimensions of 4, 7 and 10 mm, air temperatures of 50, 60 and 70°C and bed depths of 3, 6 and 9 cm. Initially, static ANN was used to correlate the outputs (moisture ratio and drying rate) to the four exogenous inputs (drying time, drying air temperature, carrot cubes size, and bed depth). In the recurrent ANNs, in addition to the four exogenous inputs, two state input and output (moisture ratio or drying rate) were applied. A number of hidden neurons and training epoch were investigated in this study. The dying kinetics was predicted with R^2 values of greater than 0.94 and 0.96 using static and recurrent ANNs, receptively.

Keywords Fluidized bed drying · Moisture ratio · Drying rate · Neural network · Carrot cubes

Nomenclatures

MR	Moisture ratio (dimensionless)
M_t	Moisture content at any time (kg water/kg dry solid)
M_e	Equilibrium moisture content (kg water/kg dry solid)
M_o	Initial moisture content (kg water/kg dry solid)
DR	Drying rate (g g-1 min-1)
M_{t+dt}	Sample moisture content at time (t+dt)
M_t	Sample moisture content at time (t)
dt	Time between two sample weighings
$R2$	Coefficient of determination
MSE	Mean square error
MAE	Mean absolute error
N	Total number of data observation
x_{pi}	Network (predicted) output from observation i
x_{di}	Experimental output from observation i
$\bar{x}$	Average value of experimental output

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Introduction

Drying is one of the oldest methods and most common form of food preservation which represents a very important aspect of food processing (Sarsavadia et al. 1999; Doymaz 2004; Doymaz et al. 2006). It makes food products easier to handle owing to volumetric shrinkage and reduction of weight after the drying process (Koyuncu et al. 2007).

Fluidized bed drying (FBD) is considered as one of the most successful drying techniques. The advantages of fluidized bed drying can be summarized as follows: 1) High heat and mass transfer rates, because of good contact between the particles and the drying gas, 2) Uniform temperature and bulk moisture content of particles, because of intensive particle mixing in the bed, 3) Excellent temperature control and operation up to the highest temperature and 4) High drying capacity due to high ratio of mass of air to mass of product (Izadifar and Mowla 2003).

The critically aspect of drying technology is the modeling of the drying process (Demir et al. 2007). The prediction of drying kinetics of agricultural products under various conditions is vital for equipment and process design, quality control, energy and fuel management, choice of appropriate storage, handling practices and etc. Several authors had attempts to propose mathematical models for the estimation of moisture ratio and drying rate of food and biological materials during drying process (Lewis 1921; Page 1949; Overhults et al. 1973; Henderson 1974; Wang and Singh 1978; Sharaf-Elden et al. 1980; Verma et al. 1985; Diamente and Munro 1991; Karathanos 1999; Midilli et al. 2002; Togrul and Pehlivan 2003; Demir et al. 2007; Guine et al. 2007; Corzo et al. 2008; Fernando et al. 2008). None of proposed models can be used over a wide range of foods, drying techniques and conditions, because the large number of theoretical assumption, condition-sensitivity and experimental errors. Thus, it is vital to researchers to find an alternative technique that incorporates a large number of variables. Among the simulation techniques, artificial neural networks (ANNs) have high learning ability and capability of identifying and modeling the complex non-linear relationships between the input and the output of a system (Hashimoto 1997). Drying is quite complex and uncertain and they can be considered as non-linear, time-varying properties and many unknown factors. This phenomenon has been modeled with different levels of complexity. ANNs permit an adequate and precise prediction of the drying process in industrial applications and have been extensively studied by many researchers (Raisul Islam et al. 2003; Hernandez-Perez et al. 2004; Martynenko and Yang 2006; Kerdpiboon et al. 2006; Erenturk and Erenturk 2007; Liu et al. 2007; Ochoa–Martinez and Ayala–Aponte 2007; Ceylan and Aktas 2008; Lertworasirikul and Tipsuwan 2008; Youssefi et al. 2009; Shafafi Zenoozian and Devahastin 2009; Omid et al. 2009; Topuz 2010).

All the pervious researchers applied static ANN models in the simulation of drying process. The static neural networks are strong tool for modeling of complex phenomena such as drying process, but they provide little insight into the following state based on current state characteristics of the dryer unit and are therefore useless for more precisely simulation of drying process. The recurrent neural networks are applicable for forecasting 'what will happen' in drying process at any following time in advance based on current data. Therefore, recurrent ANNs can describe the effects of all parameters together on drying process and develops more powerful model than the static ANNs. No research work has been found in the literature about using recurrent ANNs for modeling of fluidized bed drying.

The main objective of present study was to estimate moisture ratio and drying rate of fluidized bed drying of carrot cubes using both static and recurrent ANNs. 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. The drying rate refers to the rate of evaporation of water from the material and is the index of energy consumption during the drying process. Modeling of drying rate provides useful insight into the drying mechanisms, easy control of drying process, optimum product output and lower energy consumption.

Materials and methods

Sample

Fresh carrots (*Daucus carota* L.) were obtained from a local market in Iran and stored in a refrigerator at about 5°C. At the start of each experiment carrots were washed, peeled, and cut into cubes having dimensions of 4×4×4, 7×7×7 and 10×10×10 mm. The initial moisture content of the carrot was determined by drying of 50 g of sample in an oven at 105±2°C. Experiments were replicated three times.

Drying equipment

The drying of carrot cubes was investigated in a laboratory scale fluidized bed dryer (FBD) developed in the "Department of Agrotechnology Laboratory" of Abouraihan Campus, University of Tehran, Iran (Fig. 1).

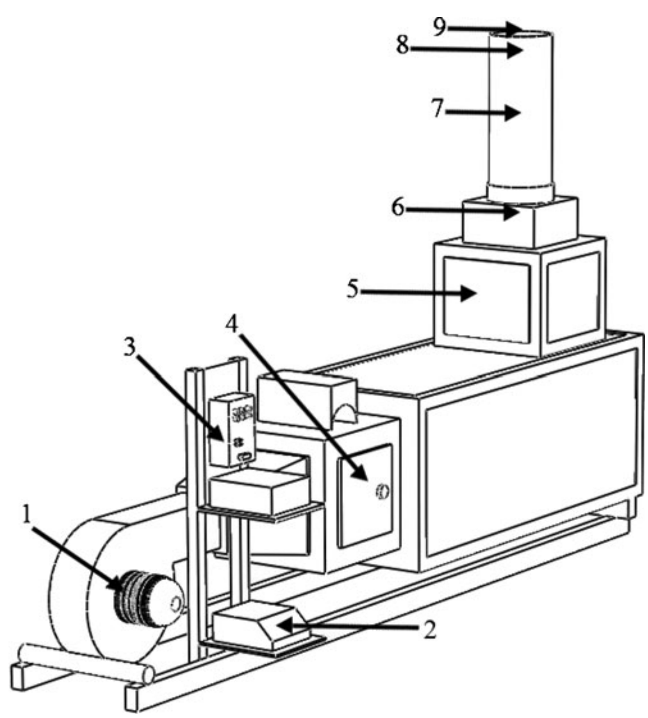

Fig. 1 Schematic view of the experimental equipment : fan (1); inverter (2); heaters control unit (3); heaters (4); chamber (5); thermocouple (6–8); fluidization cylindrical chamber(7); and anemometer (9)

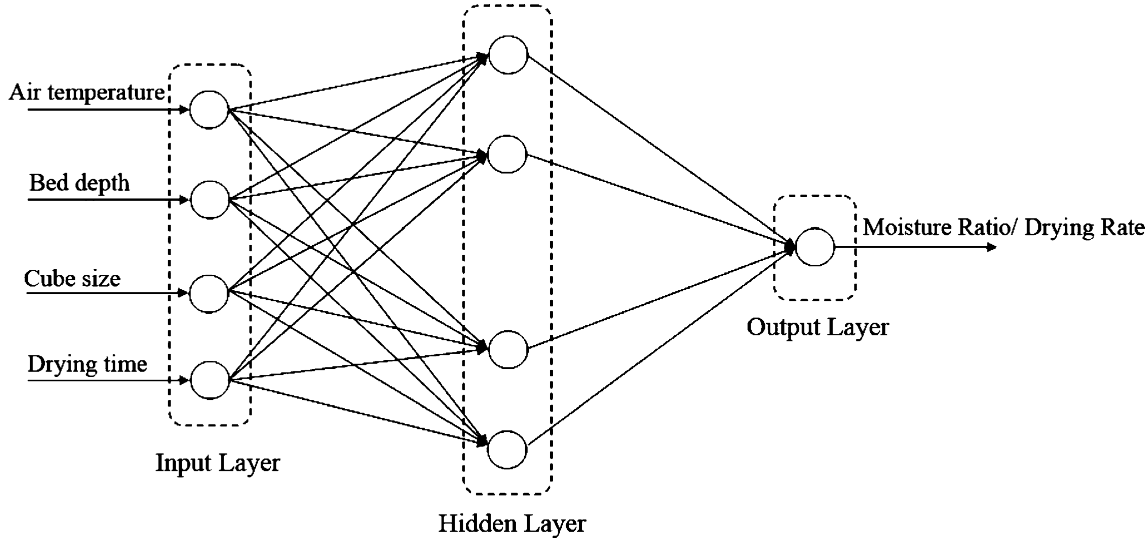

Fig. 2 Structure of static ANNs

The Plexiglas cylindrical chamber was 15 cm in diameter and 30 cm in height. A centrifugal fan provided an air supply, drawn from ambient air. In order to supply the required airflow rate for fluidization of carrot cubes, the fan speed was changed by an inverter which operated directly on the blower motor. The dryer had an automatic temperature controller with an accuracy of ±1°C. Air velocity was measured using an anemometer (*PROVA AVM-07 TES*, Co., Taipei, Taiwan) with an accuracy of ±0.05 m/s. Weighing was made at every 5 min with a digital balance with an accuracy of ±0.1 gr (*Mahak*, Co., Iran). During the experiments, drying air velocity, ambient temperature, relative humidity, and inlet and outlet temperatures of drying air in dryer chamber were recorded.

Experimental procedure

Before each experiment, the cylindrical drying chamber was filled with square−cubed carrots to a chosen height, and then the samples were taken out from the cylinder to determine the initial weight. After the dryer is reached at steady state conditions for operation temperature and fluidization velocity,

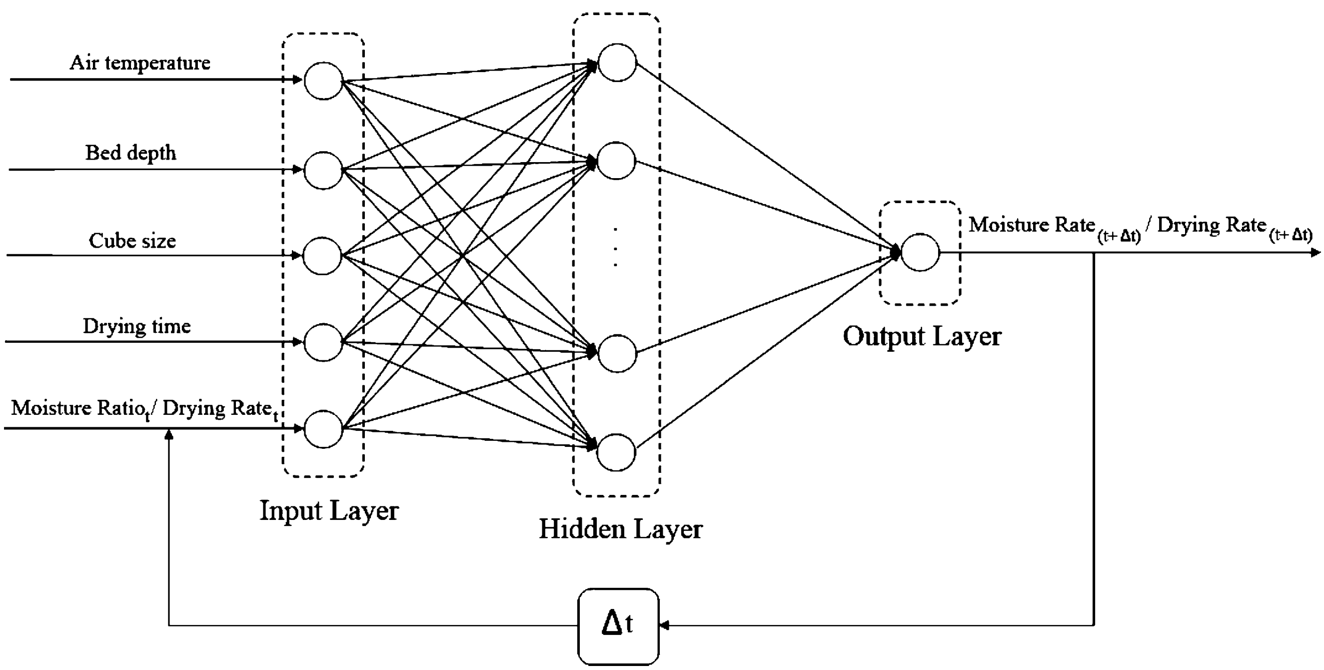

Fig. 3 Structure of recurrent ANNs

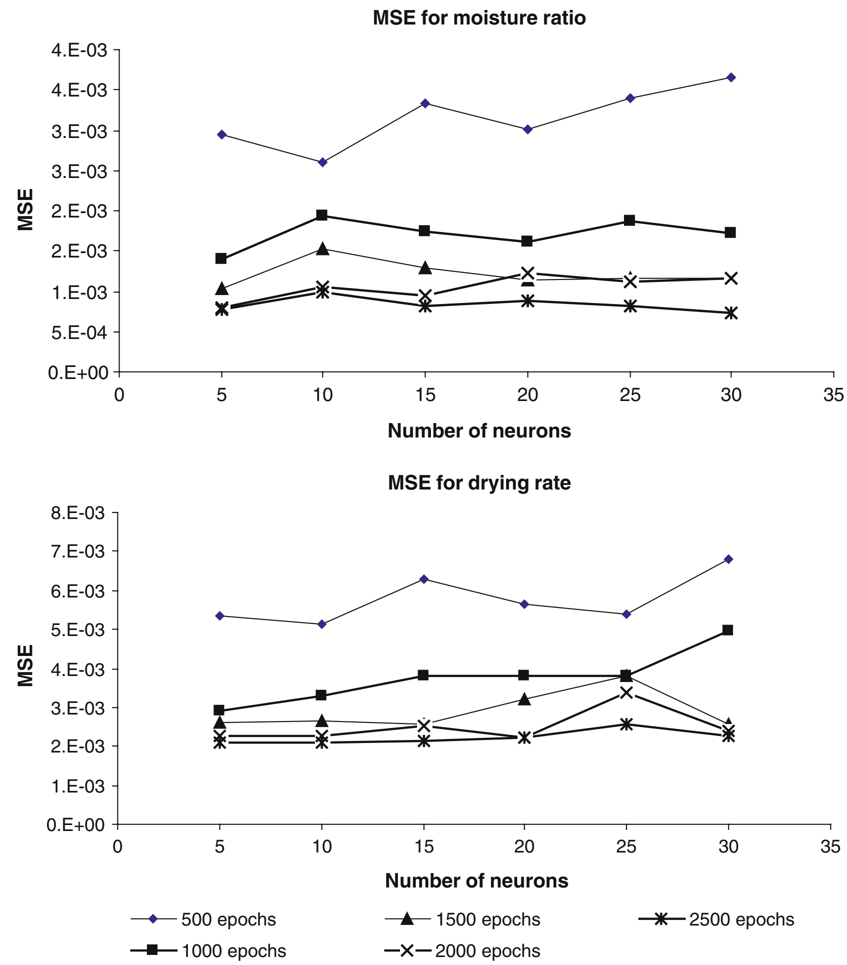

Fig. 4 MSE of various MLFF ANN versus the number of hidden layer for different number of neurons and training epochs using static network

the carrot cubes were put in the drying chamber and dried there. Experiments were conducted at inlet air temperatures of 50, 60 and 70°C, initial bed heights of 3, 6 and 9 cm and carrot cube dimensions of 4×4×4, 7×7×7 and 10×10×10 mm. Each set of conditions was tested three times.

Mathematical formulation

The moisture ratio of drying material can be obtained using following equation (Doymaz 2004).

$$MR = \frac{M_t - M_e}{M_o - M_e} \quad (1)$$

Where MR is the moisture ratio (dimensionless), M_t is the moisture content an any time (kg water/kg dry solid), M_e is the equilibrium moisture content (kg water/kg dry solid) and M_o is the initial moisture content (kg water/kg dry solid).

The drying rate for carrot cubes was obtained (g g^{-1} min^{-1}) using the following equation (Kaya et al. 2008):

Table 1 Performance of the final selected (a) static and (b) recurrent ANN models to predict each of the two output parameters

Parameter	Number of neurons	Number of epochs	MSE	MAE	R^2
(a)					
Moisture ratio	30	2,500	0.000415	0.01408495	0.992769
Drying rate	5	2,500	0.000407	0.009897	0.94929883
(b)					
Moisture ratio	30	2,500	7.61346E-05	0.00506221	0.998769
Drying rate	30	2,500	9.5658 E-04	0.00034516	0.968264

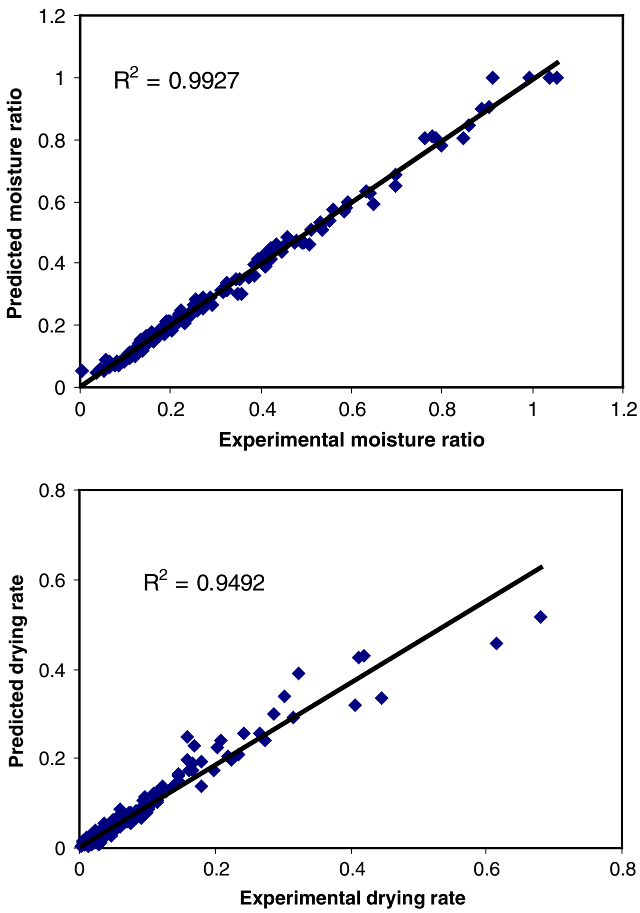

Fig. 5 Comparison of predicted and desired output values for the moisture ratio and drying rate using static MLFF

$$DR = \frac{M_t - M_{t+dt}}{dt} \quad (2)$$

Where M_{t+dt} is the sample moisture content at time ($t+dt$); M_t is the sample moisture content at time (t); dt is the time between two sample weighings.

Artificial neural network development

Static neural network

The schematic structure of static ANNs used in present study for predicting the moisture ratio and drying rate are shown in Fig. 2. The data patterns, obtained from different conditions of experiments, were randomly divided into 60%, 20%, and 20% data for good representation of the situation diversity, which were used for training, cross-validation (CV), and testing the neural networks, respectively. The input variables for the model were drying time, drying air temperature, cubes size and bed depth and the network output variables including moisture ratio or drying rate.

To achieve the optimum network, various numbers of multilayer feed-forward (MLFF) neural network were made and tested with different number of hidden layers (1, 2 and 3) and neurons. Among the trained networks, the one hidden layer MLFF neural networks was chosen as optimum because of best result presentation. Commonly, error minimization algorithms for the feed-forward networks were the gradient descent (GD), Levenberg-Marquardt (LM), and conjugate gradient (CG) algorithms. The results showed that the GD is the best selection for error minimization in this research. The number of 5 to 30 neurons in the hidden layer and number of 500 to 2,500 epochs were investigated to optimization of the network with trial and error method. The learning rate was set to 0.1 and the momentum term to 0.7.

The hyperbolic tangent sigmoid (TANH) was used for activating function in hidden layer to get the network the ability of non-linear learning, and a linear transfer function was used in the output layer.

The mathematical definition of TANH transfer function was expressed in Eq. 3.

$$\tan sigm = \frac{2}{1 + \exp(-2n)} - 1 \quad (3)$$

The final static network was selected on the basis of the lowest error on the cross-validation data set. The goodness of fit of the selected static ANN to the experimental data were based on coefficient of determination, R^2, mean square error (MSE) and mean absolute error (MAE) for the tested models. These statistical parameters are as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (x_{pi} - x_{di})^2}{\sum_{i=1}^{N} (x_{pi} - \bar{x})^2} \quad (4)$$

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (x_{pi} - x_{di})^2 \quad (5)$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |x_{pi} - x_{di}| \quad (6)$$

where x_{pi} is the network (predicted) output from observation i, x_{di} is the experimental output from observation i, x is the average value of experimental output, and N is the total number of data observation.

Recurrent neural network

The structure of recurrent ANNs used in this study for predicting the moisture ratio and drying rate at following time in advance are shown in Fig. 3.

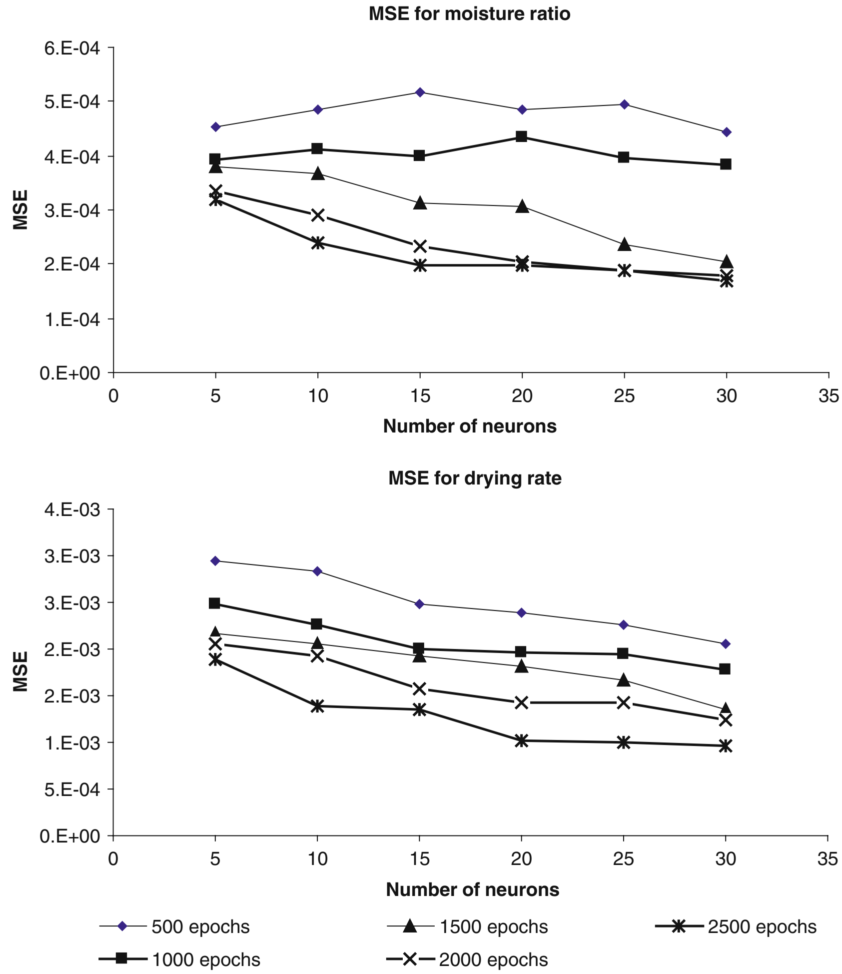

Fig. 6 MSE of various MLFF ANN versus the number of hidden layer for different number of neurons and training epochs using recurrent network

The model inputs consisted of the drying time, the drying air temperature, cube size, bed depth, and the current moisture ratio or drying rate and the desired output were the moisture ratio or drying rate at following time in advance. The data of moisture ratio had been pre-sampled such that the first 259 exemplars contain the data for times 0, 10, 20, 30 … (min) and the last 259 exemplars contain the data for times 5, 15, 25, 35 ... (min) for each experiment. The first 259 exemplars were used for training and the last 259 exemplars were used for evaluating the trained networks performance.

The data of drying rate had been pre-sampled such that the first 246 exemplars contain the data for times 5, 15, 25 … (min) and the last 246 exemplars contain the data for times 10, 20, 30 ... (min) for each experiment. The first 246 exemplars were used for training and the last 246 exemplars were used for evaluating the trained networks performance.

After design and test of different configuration of networks, a MLFF network with one hidden layer trained by back propagation (BP) was selected to develop the prediction models.

The GD with a momentum (GDM) algorithm was selected for avoiding local minima, speeding up learning and stabilizing convergence (Omid et al. 2009). The learning rate and momentum term were set to 0.1 and 0.7, respectively. The TANH Eq. 3 was used as the transfer function in hidden layer, and a linear transfer function was used in the output layer. The number of hidden layer neurons varied from 5 to 30 and the number of epochs varied from 500 to 2,500. The final recurrent network was selected on the basis of the lowest error on the training data set. The values of R^2, MSE and MAE were compared to evaluate the performances of optimal recurrent ANN models. The design and testing of ANN models were done by NeuroSolutions 5.0 software (NeuroSolutions for Excel 2005).

To develop a statistically sound model, all static and recurrent ANNs were trained three times and the best values were recorded for each parameter (Omid et al. 2009).

Result and discussion

Static ANN models

The static ANN with different configuration of the learning epochs and number of neurons were applied for kinetics analysis of fluidized bed drying of carrot cubes by using four inputs and output. Since the dependent variable (the moisture ratio or drying rate) was depended on four exogenous inputs (the drying time, drying air temperature, cubes size and bed depth), therefore one and four neurons were chosen for output and input layer. The static ANNs were utilized for kinetics analysis of fluidized bed drying of carrot cubes by using four inputs, one output, six different nodes in hidden layer that were 5, 10, 15, 20, 25, and 30 and five training epochs that were 500, 1,000, 1,500, 2,000, and 2,500 epochs. To select the number of neurons in the hidden layer, thirty trial configurations based on neural network performance, were designed and tested. The variation of training MSE for different configuration of the developed static MLFF ANNs is shown in Fig. 4.

The networks with 30 and 5 nodes in the hidden layer and 2,500 training epochs appeared to be the best selection due to the results of training errors for moisture ratio and drying rate using static ANNs, respectively. Performance of the selected static ANNs with GD learning algorithms and hyperbolic transfer function to predict drying kinetics of carrot cubes is shown in Table 1(a).

From Table 1(a), it is clear that the ability of selected static ANN to predict moisture ratio was better than that for predicting drying rate, due to high value of R^2 for moisture ratio.

Figure 5 compares the predicted values with the desired output values on a plot of moisture ratio and drying rate for kinetics analysis of fluidized bed drying of carrot cubes using the optimal static ANN.

The data points are banded around a 45° straight line, demonstrating the suitability of the selected static MLFF ANNs in predicting the kinetics analysis of fluidized bed drying of carrot cubes. Process control and its simulation in the field of drying technology has always been a quite challenging task for the engineers due to the time-varying properties and non-linearity of drying phenomena. Therefore, the ANN approach is an attractive alternative to classical methods, which can give a higher estimation power and make it possible to work in a wider range.

Recurrent ANN models

The recurrent ANNs with different configuration of the learning epochs and number of neurons were utilized for kinetics analysis of fluidized bed drying of carrot cubes by using five inputs and output. Because one dependent variable (the following time moisture ratio or drying rate of fluidized bed drying of carrot cubes) depends on five variables (the drying time, drying air temperature, cubes size, bed depth, and the current moisture ratio or drying rate of fluidized bed drying of carrot cubes), therefore one and five neurons were chosen for output and input layers, respectively. The performance of training MSE for different configuration of the developed recurrent MLFF ANNs is shown in Fig. 6.

From Fig. 6, it is clear that the networks with 30 nodes in the hidden layer and 2,500 training epochs appeared to be the best selection due to the results of training errors for moisture ratio and drying rate using recurrent ANNs.

Performance of the selected recurrent ANNs to predict drying kinetics is shown in Table 1(b). The ability of selected recurrent ANN to predict moisture ratio was better than that for predicting drying rate, due to high value of R^2 for moisture ratio in Table 1(b). Figure 7 compares the predicted values with the desired output values on a plot of drying kinetics at following time in advance for fluidized bed drying of carrot cubes using the optimal recurrent ANNs.

The data points all occur around a 45° straight line for the drying kinetics and it is evident that selected recurrent ANN models have acceptable estimation power over static ANN,

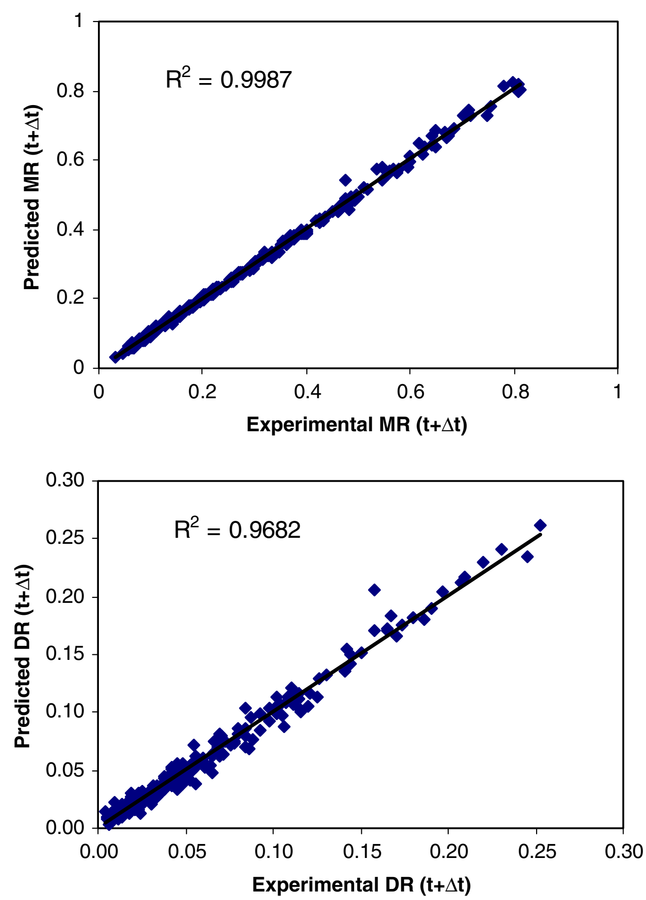

Fig. 7 Comparison of predicted and desired output values for the moisture ratio and drying rate using recurrent MLFF ANNs

especially for dying rate. The statistical results showed that R^2, MSE and MAE of the selected ANNs are highly acceptable to predict the drying kinetics at following time in advance, whereas these value variations do not show a regular trend during drying because the fluidized bed drying was unable to supply stable temperature and humidity at a constant rate over a period of time. It could be related to non-linear increase in the resistance for heat and mass transfer in samples during drying. The recurrent ANNs were superior to the static ANNs in predicting the drying kinetics as indicated by high value of R^2 for recurrent ANNs in Figs. 5 and 7. This is extra evident to the applicability of the recurrent ANNs to simulation of complex and non-linear dynamic systems such as drying equipment. As recurrent ANNs capture the non-linear nature of the drying process it has the potential advantages over the mathematical models widely used in the drying technology. If the dryer system is applied for known values of air temperature, cube size and bed depth, the drying process can precisely be predicted, controlled and optimized by recurrent MLFF ANNs at any time of drying process. The recurrent ANNs help the researchers to carry out the kinetics analysis of drying systems to increase the efficiency of drying systems with acceptable accuracy. Nevertheless, ANNs offer an attractive possibility for control design that results in a controller with a higher level of robustness due to information contained in the model.

Conclusions

This work used static and recurrent ANNs to kinetics simulation of fluidized bed drying of carrot cubes. Various learning epochs and number of neurons were investigated. Experimentally obtained data were used as a basis for training two ANN schemes to capture the relationships of drying kinetics. The trained recurrent ANN models were validated with experimental data and found to attain high prediction quality than the static ANN models. The developed models could be used for determining the appropriate drying conditions to reach the optimal energy efficiency and product quality in fluidized bed drying. The methodology in this paper could be applied for other products as well. In addition, the developed recurrent ANN models are useful tool for implementing fluidized bed dryer unit to an automatic control system.

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