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MODELING OF ROUGH RICE DRYING KINETICS USING ARTIFICIAL NEURAL NETWORK

M. TOHIDI[1], M. SADEGHI[2], S. R. MOUSAVI[3]

[1]Graduate Student, Department of Farm Machinery, College of Agriculture, Isfahan University of Technology, 84156-83111, Isfahan, Iran, mojtaba_thd@yahoo.com
[2]Assistant Professor, Department of Farm Machinery, College of Agriculture, Isfahan University of Technology, 84156-83111, Isfahan, Iran, sadeghimor@cc.iut.ac.ir
[3]Assistant Professor, Department of Electrical and Computer Engineering, Isfahan University of Technology, 84156-83111, Isfahan, Iran, srm@cc.iut.ac.ir

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ABSTRACT The artificial neural network (ANN) approach is a generic technique to establish non-linear mappings between inputs and outputs without knowing the details of such mappings. The objective of this study was to predict Isfahan (central Iran) rough rice drying kinetics during hot air drying using ANN in deep bed mode. The inlet air temperature at seven levels (40, 50, 55, 60, 65, 70 and 80 °C), inlet air velocity at three levels (0.5, 0.8 and 1.1 m/s), and inlet air relative humidity at four levels (40, 50, 60 and 70 %) were the inputs of the neural network. To create training and test patterns, drying experiments were conducted by a laboratory fixed bed dryer. The multi layer perceptron (MLP) and generalized feed forward (GFF) neural networks with momentum and Levenberg-Marquardt (LM) algorithms were used to predict the drying kinetics. It was observed that the MLP network with LM learning algorithm produced the most accurate model. It was also revealed that the 4-15-1 topology and the hyperbolic tangent activation function provided better performance in comparison with other examined topologies. This topology predicted the drying kinetics with normalized mean square error (*NMSE*) less than 0.00079 and mean absolute error (*MAE*) 0.05215 and linear correlation coefficient 0.996.

Keywords: Artificial neural network, drying kinetics, rough rice.

INTRODUCTION Rough rice (*Oryza sativa* L.) is one of the most consumed crops and main food for more than half of the world population. Depending on the harvesting method, the rice type and variety, the number of the cuttings, and the growth location, harvested rough rice may have average moisture content ranging from 16 to 28% (w.b.). Moisture content is one of the most important factors affecting the quality of rough rice during storage which is at a high level at the time of the harvest. As even short term storage of high moisture paddy rice can cause quality deterioration. High moisture promotes the development of insects and molds that are harmful to the rough rice. This also lowers the germination rate of product. Therefore, drying of rice is critical to prevent insect infestation and quality deterioration of rice grain by which the product moisture content is reduced to nearly 14% (w.b.) with an appropriate process.

Drying is, however, a complicated process involving simultaneous heat and mass transfer phenomena which depend on different factors such as air temperature, velocity and relative humidity, air flow rate and pressure, physical nature and initial moisture content of the drying material as well as the dryer exposed area (Akpinar et al., 2003). To design, simulation and optimization of the drying process, it is important to know the drying behavior (Senadeera et al., 2003). Many researchers have studied the drying process and drying behavior of grains and foods and have developed simulation models for drying processes (Akpinar et al., 2003, Senadeera et al., 2003, Doymaz, I., 2006, Wang et al., 2007, Scala and Crapiste, 2008).

Mathematical modeling is used for describing the drying kinetics of agricultural materials. The models fall into three categories namely, theoretical, semi-theoretical and empirical models. The semi-theoretical models are derived from the general solution of Flick's law by simplification. The empirical models are derived from statistical relations and they directly correlate moisture content with time, having no physical connection with the drying process itself. These types of models (empirical and semi-empirical) are valid in the specific ranges of temperature, air velocity and humidity for which they are developed and cannot be used as a general correlation for a vast range of drying parameters. Furthermore, they are often used for thin layer drying of products, mostly fruits slices, while commercial grain dryers commonly work in deep bed mode. For this mode the theoretical models are used which are generally solutions of simultaneous heat and mass transfer partial differential equations. So the result is often complicated and consequently requires some assumptions that do not meet the real drying systems.

The artificial neural network (ANN) is a well-known tool for solving complex problems and it can give reasonable solutions even in extreme cases or in the event of technological faults (Lin and Lee, 1995). The literature cited clearly encourages further study of the application of artificial ANNs to model the drying process. The ANN model developed by Jay and Oliver (1996) was used for predictive control of drying process of grain. Trelea et al, (1997) used explicit time and recurrent ANNs for modeling the moisture content of thin-layer (5 cm) of corn during the drying process and for its wet-milling quality at constant air flow rate and absolute humidity and variable temperature. Kaminski et al., (1998) used an ANN for data smoothing and for modeling material moisture content and temperature. Farkas et al., (2000a) set up an ANN to predict moisture distribution in agricultural fixed bed grain dryers. Using randomly varying time series for training the ANN, they showed that a feedback model for input parameters can predict layers moisture with 1% precision higher than that of physical model (Farkas et al., 2000b). After testing and training several algorithms, Zhang et al., (2002) found a four layer network with eight and five neuron in its hidden layers as the optimum algorithm to predict several drying characteristics including evaporation rate, product output rate, kernel cracking percentage and energy consumption. An ANN was used to model a hazelnut fixed bed dryer assisted with the heat pump (Ceylan and Aktas, 2008). Relative humidity, dryer temperature and drying time were considered as the ANN input parameters and bed moisture content and inlet air velocity as the output parameters. The ANN with four neurons in its hidden layer and back propagation algorithm was the best model.

Although many researches have been conducted in drying process, but a few of them considered the effect of air relative humidity. The objective of this study was to investigate the ability of ANN models to predict the drying behaviour of rough rice at different experimental conditions including various combinations of drying air temperature, velocity and relative humidity.

MARERIALS AND METHODS

Rough rice Rough rice of Sazandegi (medium-grain) variety was acquired from Isfahan Center for Agricultural and Natural Resources Research. The whole samples were stored at 4 ± 0.5°C. Before performing the experiments, the samples were imposed at room temperature for 12 hours in order to thermally equilibrate with the environment. To determine the initial moisture content, the samples were placed in an oven at 130°C for 24 h (ASAE, 1982). In this way the initial moisture content of rough rice was 20.4% (w.b).

The laboratory dryer and instrumentations Commercial rough rice dryers are commonly deep bed dryers. So in the present study drying experiments were performed in deep bed mode (20 cm). Figure 1 shows the schematic view of the dryer used for experimental work. The dryer consisted of a power supply system, fan, electrical heater, air supply channel, a drying chamber, and instrumentation for measuring and controlling the air temperature and velocity. The dryer chamber was built of plexiglas with dimensions of 0.40 m in height and 0.0154 m^2 in bed area. The chamber was mounted on the top of a balance in order to record the weight of samples during the test. The temperature of drying air was adjusted to the desired value with a control unit with accuracy of ± 0.1 °C. Table 1 illustrates the specifications of measurement instruments.

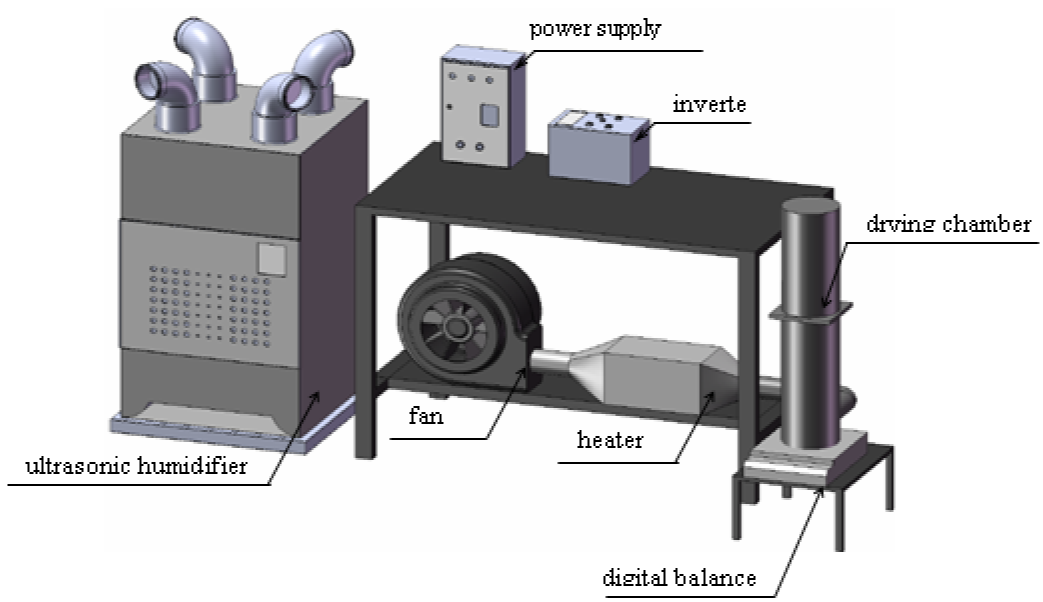

Figure 1. Schematic view of the dryer used for the experiments.

An ultrasonic humidifier instrument was designed and used to change and control the air relative humidity. The specific ability of the instrument was to produce the cold humidity instead of hot humidity; therefore, the control of medium temperature during the test was very precise.

Table 1. Description of the measurement and control equipments.

Instrument	Trade mark	Properties	Uncertainty (%)
Temperature sensor	Elimko	Input Pt-100 R/T Tip Scale 0–90 °C Feed 24 V-DC Output 4–20 mA	0.0238
Digital balance	Kern 572-57	Accuracy 0.01 g	1.495
RH-sensor	PHILIPS	Accuracy 0.01	-
Hot wire anemometer	Lutron AM 4204	velocity 0.2–20 m s^{-1} Accuracy ±5%+1d m s^{-1}	0.00195
Inverter	Teco 7300 cv	Input Ac 1phase 50/60 Hz Output Ac 3phase 0-650 Hz Amps 7.5 A	-

Drying experiments and data collection To achieve the desired conditions, the dryer was run without the sample for about 20 min before each drying experiment. Then rough rice samples were placed in drying chamber of the dryer. Sample weight loss was recorded at 5 min intervals of drying duration. The final moisture content of rough rice was 12% (w.b.) which is usually recommended for proper hulling and milling.

Drying experiments were carried out at different combinations of drying air temperatures at seven levels of 40, 50, 55, 60, 65, 70, and 80° C, inlet air velocity at three levels of 0.5, 0.8 and 1.1 m s^{-1} and inlet air relative humidity at four levels of 40, 50, 60 and 70%. Totally, 72 sets of drying experiments were conducted in August and September 2009. The independent variables along with their levels have been shown in table 2.

Table 2. Specifications of experimental drying runs.

	Air Temperature (°C)	Relative humidity (%)	Air velocity (m s^{-1})
Minimum	40	40	0.5
Maximum	80	70	1.1
levels	7	4	3

ANN MODELIND APPROACH In the present study, two networks of multi-layer perceptron (MLP) and the generalized feed forward (GFF) were used. Multi-layer perceptron network was selected as it is one of the most useful and common neural network architecture, which is appropriate for a vast range of applications such as prediction and process modeling. An MLP network comprises a number of identical units organized in layers, with those on one layer connected to those on the next layer, so that the outputs of one layer are regarded as inputs to the next layer. GFF networks are a generalization of the MLP network, such that connections can jump over one or more layers. In theory, an MLP can solve any problem that a GFF can solve. However, the speed and accuracy of learning by a GFF is higher. MLP and GFF neural networks are normally trained using a supervised training algorithm. Figures 2 and 3 illustrate the topology of a three-layerd MLP network and four-layered GFF network, respectively.

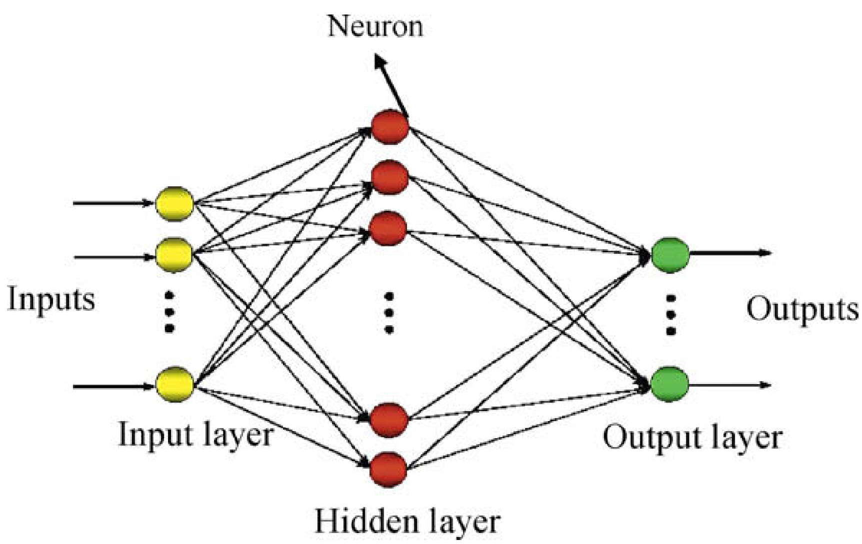

Figure 2. Topology of a three-layered perceptron neural network.

Among various kinds of activation functions, the well-known hyperbolic tangent function (equation 1) was used to achieve the best network in order to predict drying kinetics. Also momentum and Levenberg-Marquardt learning algorithms were used for training the networks.

$$f(x) = \tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \quad (1)$$

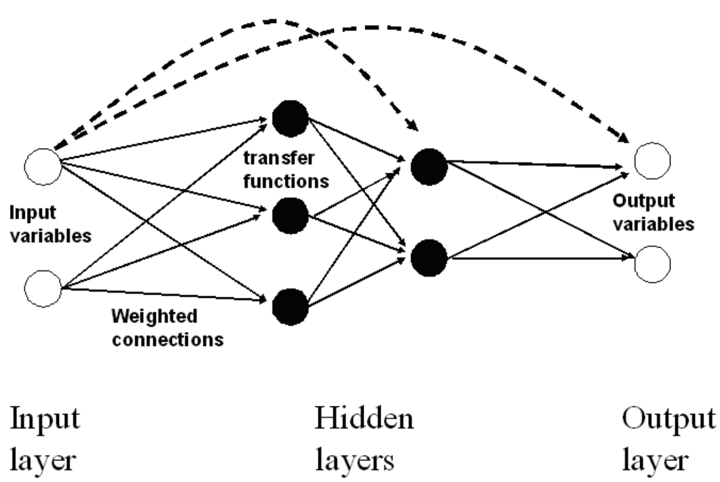

Figure 3. Topology of a four-layered generalized feed forward network.

Training the neural networks Experimental data from drying experiments were used to train and test two artificial neural networks (MLP and GFF) for prediction of rough rice moisture content during the drying process. All data collected from 72 experiments were divided into three subsets. The first subset was for the training set which is used to compute the gradient and updating the network weights and biases. The second subset was used for the validation set, used to prevent over fitting and the last subset was applied for the testing set. The latter subset is not used during the training, but used to compare different models. In this study, the data set was initially shuffled, and then 70, 15 and 15% of the total data set were used for training, validating, and testing, respectively.

The number of neurons in input and output layers depends on input and output variables, respectively. Moisture content was considered as dependent variable and inlet air temperature, inlet air velocity, inlet air relative humidity and time were selected as independent variables. Therefore, one and four neurons were devoted to output and input layers, respectively (figure 4). The number of neurons in the hidden layers was determined by calibration through several run tests.

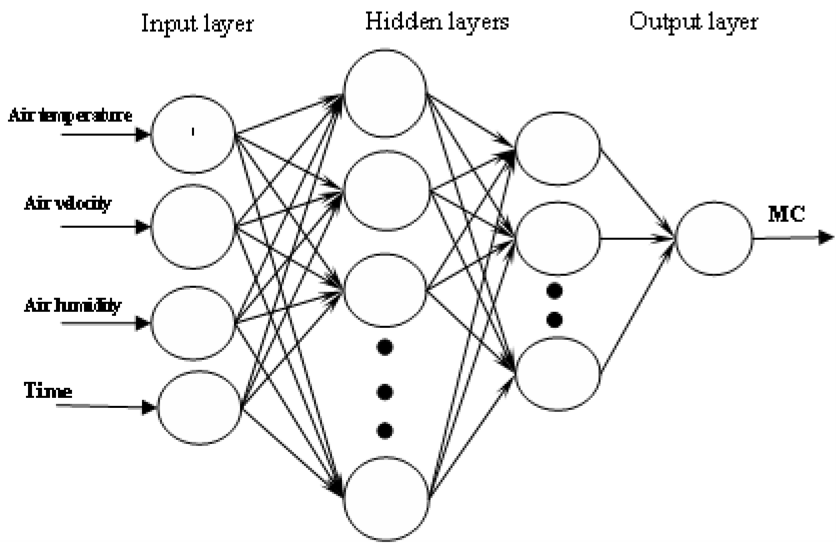

Figure 4. Schematic topology of the neural network used for predicting moisture content.

Spearman correlation coefficient (*r*), normalized mean square error (*NMSE*) and mean absolute error (*MAE*), were used to evaluate the efficiency of different models using the following equations:

$$NMSE = \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y_i})^2}{s^2} \tag{2}$$

$$MAE = \tfrac{1}{n}\sum_{i=1}^{n}\left|(y_i - \hat{y}_i)\right| = \tfrac{1}{n}\sum_{i=1}^{n}\left|e_i\right| \tag{3}$$

where y_i is measured values, $\hat{y}_i$ predicted values, $\overline{y}_i$ mean of measured values and *n* the number of data. The higher value of *r* and the lower values of *NMSE* and *MAE*, the more accurate is the developed network.

Creating and verification of ANN models were used by NeuroSolution (ver 5.2) software.

RESULT AND DISCUSSION The results showed that the GFF network with Levenberg-Marquardt learning algorithm and topology of 4-15-1 was the most accurate among all designed networks. So, the highest value of *r* (0.996) and the lowest values of *NMSE* (0.00079) and *MAE* (0.05215) were belonged to this network specified in bold form in table 3.

Figure 5 illustrates the comparison between the experimental and predicted data obtained by the best aforementioned network at air temperature of 70 °C, air velocity of 0.5 m s^{-1} and air relative humidity of 50%. As it is shown, the predictions were very close to the experimental data (figures 5). Figure 6 indicates the moisture content values predicted by the best GFF network compared to the experimental values for randomly selected data from the whole data set. As it is obvious there is a very good closeness between the predicted and measured data. Therefore, it can be concluded that the artificial neural network model can be used as a suitable tool to estimate the moisture content of rice during drying time in a deep bed dryer mode.

Table 3.The results of different networks with various learning algorithms and topologies for predicting drying kinetics.

Network	Learning algorithm	Topology	*NMSE*	*MAE*	*r*
MLP	Levenberg Marquardt	4-14-1	0.00104	0.06315	0.994
MLP	Momentum	4-6-5-1	0.00642	0.15074	0.969
GFF	Levenberg Marquardt	**4-15-1**	**0.00079**	**0.05215**	**0.996**
GFF	Momentum	4-14-1	0.00980	0.29801	0.956

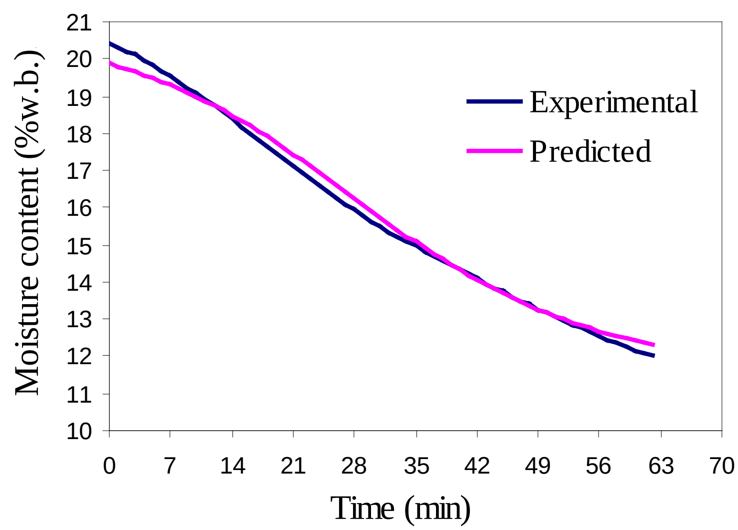

Figure 5. Comparison between the experimental and predicted data using GFF network at air temperature of 70 °C, air velocity of 0.5 m s^{-1} and air relative humidity of 50%.

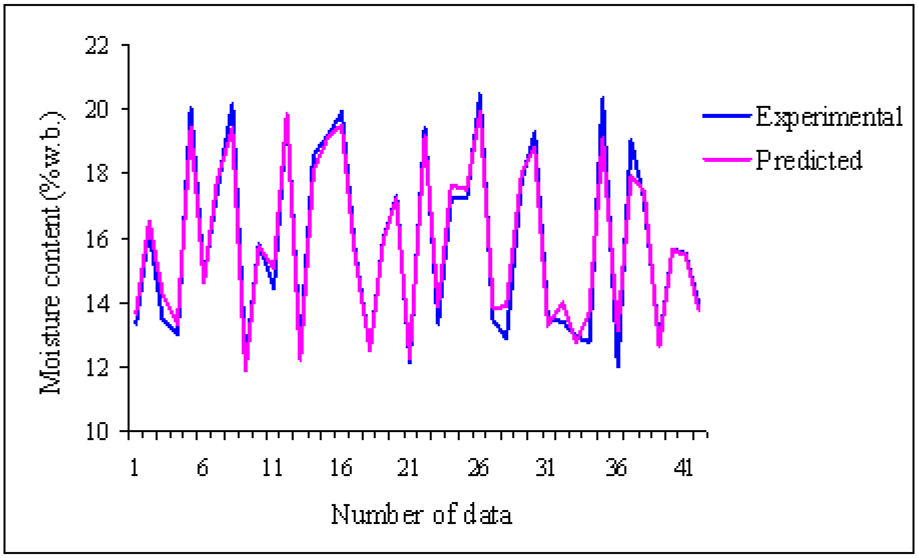

Figure 6. Random comparison of the predicted moisture content using GFF network with the experimental values.

CONCLUSION The drying behavior of rough rice Sazandegi was investigated in a laboratory dryer at different levels of drying air temperature, velocity and humidity. On the basis of the obtained results, it can be concluded that the artificial neural network model can be used for estimation of the moisture content of rice during drying time in a deep bed dryer.

The best model to describe the drying kinetics of rice was found to be the GFF neural network with Levenberg-Marquardt learning algorithm, topology of 4-15-1 and hyperbolic tangent activation function

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