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PREDICTION OF PROCESS AND PRODUCT PARAMETRERS IN DEEP BED DRYING OF ROUGH RICE USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT The objective of this study was to predict the performance indices in deep bed drying of Isfahan rough rice (Sazandegi variety) using artificial neural networks (ANNs). In our experiments, the effects of air temperature, air velocity, and air relative humidity on product output rate (*POR*) as an indicator of work capacity dryer, evaporation rate (*ER*) as a quality index of drying kinetics, and kernel cracking (*KC*) percentage as a criterion of dried product quality were investigated. To create training and test patterns, drying experiments were conducted using a laboratory dryer in deep bed mode. The desired parameters for various input variables were calculated using physical and thermodynamics relations. To predict the dependent parameters, three well-known networks namely multi layer perceptron (MLP), generalized feed forward (GFF), and modular neural network (MNN) were examined. Four learning algorithms consisted of step, momentum, conjugate gradient, and Levenberg-Marquardt (LM) were also used for the training purpose of the networks. The GFF network provided superior results than those achieved by MLP and MNN networks. Among several examined topologies and activation functions for the GFF network, the 3-8-7-3 topology and the hyperbolic tangent function revealed the best results. A remarkably high degree of prediction accuracy was achieved by the resulting GFF neural network, with a normalized mean square error (*NMSE*) of only 0.00865, mean absolute error (*MAE*) of 0.97514 and Spearman correlation coefficients (*r*) of 0.9912. It was concluded that the ANN could be an effective method to model Isfahan rough rice drying process.

Keywords: Artificial neural network, performance indices, rough rice.

INTRODUCTION 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 between 16 to 28%. The researches results indicate that in general the head rice yield is maximized if the harvest moisture is high. However, higher energy is required for drying grain at such a harvest. Therefore, the objective of rice drying process is optimizing yield and energy consumption, without affecting the cooking characteristics of rice (Brooker et al., 1992). High moisture content promotes the development of insects and molds which are harmful to the grain. This also lowers the germination rate of the rice. Therefore, drying of rice is critical to prevent insect infestation and quality deterioration of rice grain as it reduces the moisture content of rough rice to a safe level for storage (Simal et al., 2000). With an appropriate drying process the moisture content of wet grains must be reduced to nearly 14% (w.b.).

To have the best dried product quality, it is important to properly design, simulate and control the drying process. Predictive models including the mathematical models are used for this goal. However, the empirical models derived from statistical relations have no physical connection with the drying process itself and are valid only in the specific ranges of temperature, air velocity and humidity for which they are developed.

The artificial neural network (ANN) as a data-processing system inspired by biological neural system is a generalized mathematical model for human perception and is a well-known tool for solving complex, non-linear problems (De Baerdemaeker and Hashimoto, 1994). ANN, in appropriate form can also give reasonable solutions in the event of technological faults (Lin and Lee, 1995). An ANN has the ability to re-learn to improve its performance if new data are available (Hertz et al., 1991). It is the advantage of ANN model that it can accommodate multiple input variables to predict multiple output variables even without prior knowledge of the process relationships (Ramesh et al., 1996). This means that no mathematical model is needed for ANN.

In recent years, ANNs have been used widely for drying processes. Huang and Mujumdar (1993) used ANNs to predict the performance of an industrial paper dryer. In another work an ANN model was used to control the grain drying process (Jay and Oliver, 1996). 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 in rough rice drying. Cubillos and Reyes, (2003) indicated that the ANN results can be used for primary design of a dryer and selecting the optimum operational conditions. An ANN was used to model a hazelnut fixed bed dryer assisted with heat pump (Ceylan and Aktas, 2008). Relative humidity, drying air temperature and drying time were considered as the ANN input parameters and bed moisture content and inlet air velocity as the output parameters.

This literature survey shows that ANNs truly model drying process. However, to predict the drying process by ANNs, the selection of an appropriate topology is important in terms of model accuracy and model simplicity. The performance of an ANN is greatly affected by its structure. To this aim, many algorithms are derived based on data in a specific area of application (Blanco et al. 2000, Boozarjomehry and Svrcek, 2001).

Although many researches have been conducted in modeling drying process by ANNs, a few of them considered the effect of air relative humidity. The objective of this study was to develop an ANN for predicting the process and product parameters of rough rice drying including product output rate, evaporation rate and kernel cracking percentage at different experimental conditions including various levels 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. 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).

Equipments and drying experiments Drying experiments were performed in a laboratory deep bed dryer. Figure 1 shows a schematic view of the dryer. As it is shown, the dryer consisted of a power supply system, fan, an electrical heater, an air supply channel, a drying chamber, and instrumentation for measuring and controlling air temperature and velocity. The dryer chamber built of plexiglas had dimensions of 0.40 m in height and 0.0154 m^2 in bed area. The chamber was mounted on top of a digital balance. The temperature of drying air was adjusted to the desired value using a control unit with accuracy of ± 0.1 °C. 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 illustrates the specifications of measurement instruments.

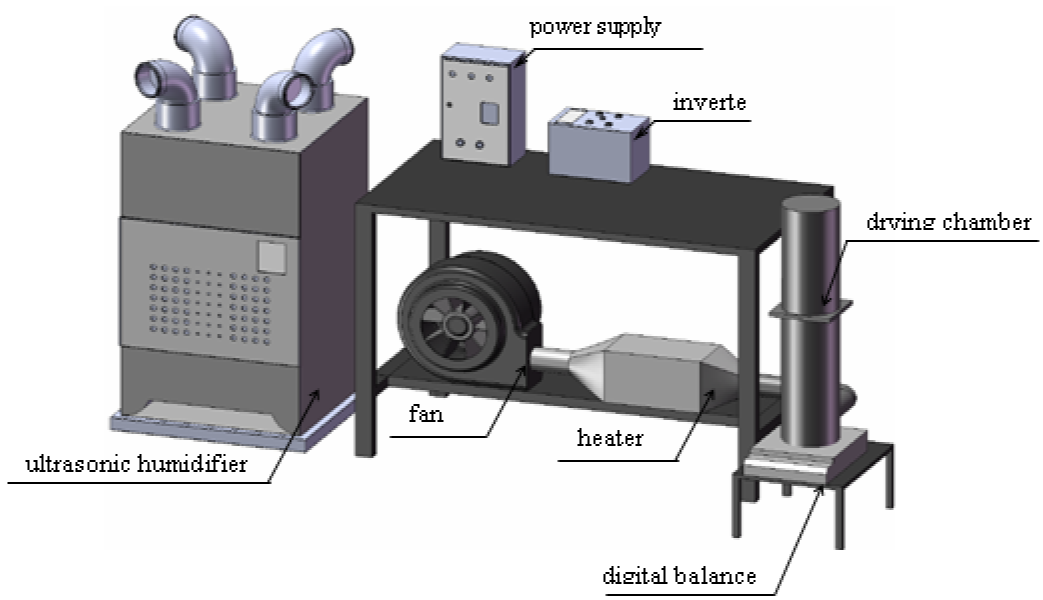

Figure 1. Schematic view of the dryer used for the experiments.

The 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. Before performing the experiments, the samples were imposed at room temperature for 12 hours in order to thermally equilibrate with the environment. To achieve the desired conditions, the dryer was run without the sample for about 20 min. Then rough rice samples were placed in drying chamber of the dryer for performing the main experiment. The final moisture content of rough rice was 12% (w.b.) which is usually recommended for proper hulling and milling. The independent variables along with their levels have been shown in table 2.

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	-

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
level	7	4	3

After conducting the experiments, three drying parameters were calculated and measured. The parameters were kernel cracking (*KC*) percentage as a criterion of dried product quality, product output rate (*POR*) as an indicator of dryer working capacity and evaporation rate (*ER*) as a quality index of drying kinetics. To determine kernel cracking percentage, 48 h after drying operation, 100 kernels of each sample were manually husked and then the fissured kernels were determined by a binocular. Product output rate and evaporation rate were computed with the following equations:

$$POR = \frac{m_d}{A_b \times t} \tag{1}$$

$$ER = \frac{m_v}{A_b \times t} \tag{2}$$

where, *POR* is product output rate (kg m^{-2} s^{-1}), m_d mass of dried product (kg), A_b the area of dryer chamber (m^{-2}), *t* drying time (s), *ER* evaporation rate (g m^{-2} s^{-1}) and m_v mass of vaporized moisture (g).

Artificial neural network In this work, three networks were used: 1) the multi-layer perceptron network (MLP), 2) generalized feed forward (GFF) and 3) modular neural network (MNN). 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, such that connections can jump over one or more layers. MNN networks are a special class of MLP and process their input using several parallel MLPs, and then recombine the results. This tends to create some structure within the topology, which will foster specialization of function in each sub-module. In theory, a MLP can solve any problem that GFF and MNN networks can solve. Figures 2, 3 and 4 illustrate the topology of a three-layered MLP network, a four-layered GFF network and a MNN network, respectively.

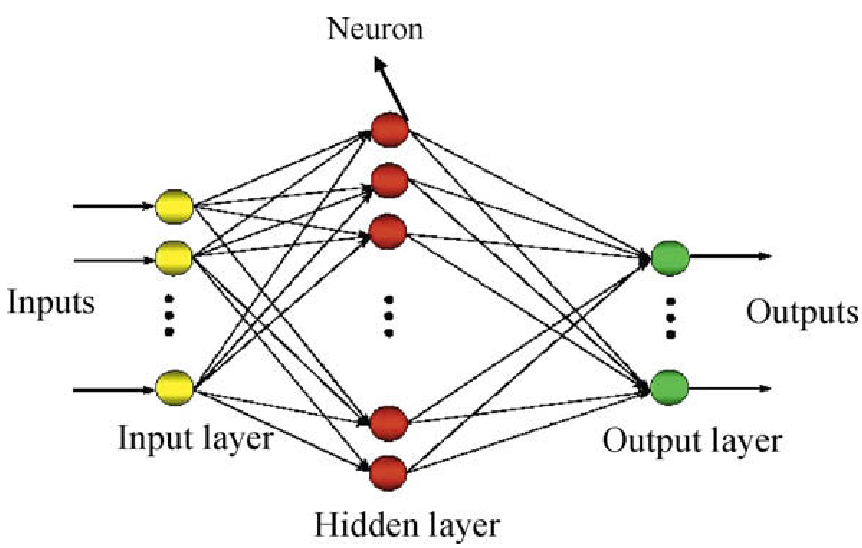

Figure 2. Topology of a three-layered perceptron neural network.

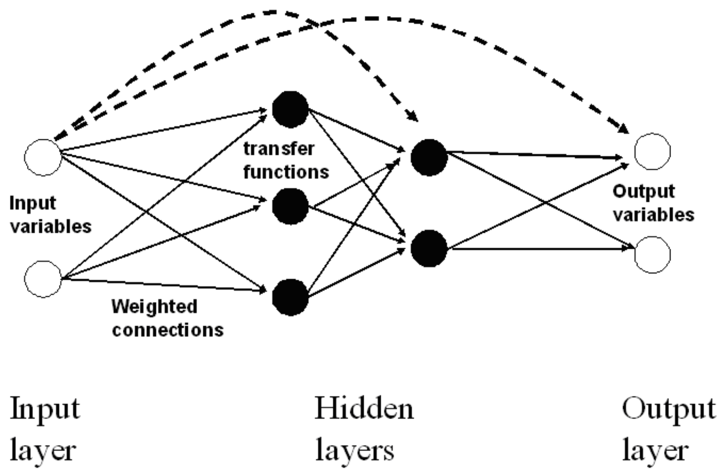

Figure 3. Topology of a four-layered generalized feed forward network.

Hyperbolic tangent and sigmoid functions were used to determine the best network to predict performance indices in deep bed drying. Four learning algorithms consisted of step, momentum, conjugate gradient, and Levenberg-Marquardt (LM) were also used for the training purpose of the networks.

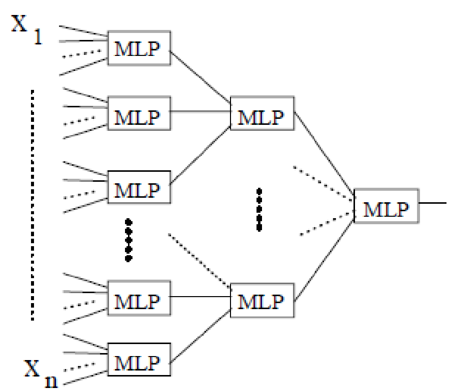

Figure. 4. Topology of Modular feed forward network.

Training the neural networks Experimental Figure 5 shows the structure of the applied ANN. The inputs of the structure were inlet air temperature, inlet air velocity and inlet air relative humidity. The outputs of the system were *POR*, *ER* and *KC* percentage. Experimental data were used to train and test three aforementioned artificial neural networks (MLP, GFF and MNN). 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 independent and dependent variables, respectively. Therefore, three neurons were devoted to both output and input layers (figure 5). The number of neurons in the hidden layers was determined by calibration through several run tests.

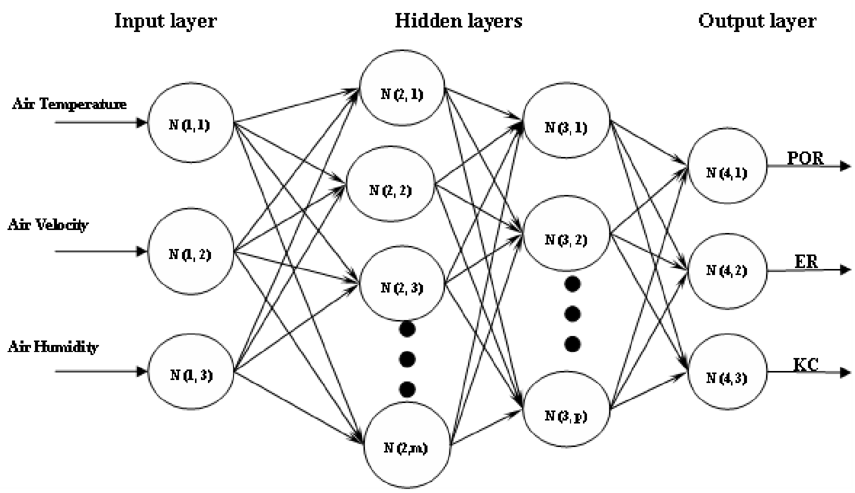

Figure 5. Schematic view of the artificial neural network used.

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:

$$NMSE = \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y_i})^2}{s^2} \tag{3}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|(y_i - \hat{y}_i)\right| = \frac{1}{n}\sum_{i=1}^{n}\left|e_i\right| \tag{4}$$

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.

Sensitivity Analysis Sensitivity analysis process gives valuable information about the model sensitivity to the input variables. Identifying effects of input variables on model prediction accuracy can remove lower important variables of the network and develop a simpler network. If the value of a variable sensitivity coefficient was less than 0.1, this variable has not a significant effect on the model prediction accuracy and consequently can be removed from input variables set. In this research, Hill's method was used for doing sensitivity analysis (Hill, 1998). The sensitivity analysis calculations were done by MatLab (ver. 7.6) software.

RESULT AND DISCUSSION Table 3 indicates the results of different networks with various learning algorithms, activation functions and topologies for simultaneous predicting of POR, ER and KC. As shown, the GFF network with Levenberg-Marquardt learning algorithm, hyperbolic tangent active function, and 8 neurons in the first hidden layer and 7 neurons in the second hidden layer (topology of 3-8-7-3) was the most accurate among all designed networks. So, the highest value of *r* (0.912) and the lowest values of *NMSE* (0.00865) and *MAE* (0.97514) were belonged to this network specified in bold form in table 3.

Table 3. The results of different networks with various learning algorithms, activation functions and topologies for predicting *POR*, *ER* and *KC*.

Network	Learning algorithm	Activation function	Topology	NMSE	MAE	r
MLP	L.M.*	H.T.	3-13-3	0.009354	0.98661	0.905
	L.M.	Sigmoid	3-14-3	0.009841	1.00843	0.896
	Momentum	H.T.	3-7-6-3	0.013546	1.02055	0.887
	Momentum	Sigmoid	3-11-3	0.015829	1.03182	0.879
	Step	H.T.	3-14-3	0.018467	1.04663	0.871
	Step	Sigmoid	3-6-6-3	0.020564	1.05574	0.866
	C.G.	H.T.	3-12-3	0.012873	1.02915	0.891
	C.G.	Sigmoid	3-15-3	0.014003	1.03045	0.884
GFF	L.M.	H.T.	3-8-7-3	**0.008653**	**0.97514**	**0.912**
	L.M.	Sigmoid	3-14-3	0.008830	0.99736	0.901
	Momentum	H.T.	3-16-3	0.011773	1.01008	0.895
	Momentum	Sigmoid	3-8-7-3	0.012956	1.02035	0.890
	Step	H.T.	3-8-6-3	0.014707	1.07459	0.882
	Step	Sigmoid	3-5-5-3	0.015006	1.01004	0.873
	C.G.	H.T.	3-12-3	0.011594	1.01338	0.904
	C.G.	Sigmoid	3-10-3	0.012298	1.01526	0.891
MNN	L.M.	H.T.	3-16-3	0.010052	0.99486	0.895
	L.M.	Sigmoid	3-8-7-3	0.014202	1.01208	0.886
	Momentum	H.T.	3-17-3	0.016584	1.03692	0.875
	Momentum	Sigmoid	3-15-3	0.018993	1.04836	0.869
	Step	H.T.	3-8-7-3	0.024662	1.07014	0.856
	Step	Sigmoid	3-13-3	0.025828	1.07506	0.852
	C.G.	H.T.	3-9-7-3	0.014180	1.03641	0.887
	C.G.	Sigmoid	3-15-3	0.016071	1.04115	0.879

* L.M., C.G. and H.T. stand for Levenberg-Marquardt, conjugate gradient and hyperbolic tangent, respectively.

Sensitivity analysis results showed that all sensitivity coefficients related to three independent variables were higher than 0.1 (table 4). Therefore, according to Hill's rule three parameters had a significant effect on three output variables. However, among three input parameters, air temperature and air relative humidity had the maximum and minimum effect on the network outputs, respectively. Also the least sensitivity coefficient (0.14) belonged to the effect of air relative humidity on *POR*.

Table 4. Input variables sensitivity coefficients for *KC*, *ER* and *POR*.

	Sensitivity coefficient		
Input variables	Kernel cracking	Evaporation Rate	Product Output Rate
Air temperature	1	1	1
Air velocity	0.82	0.70	0.87
Air relative humidity	0.74	0.27	0.14

CONCLUSION Three important process and product parameters of a deep bed mode laboratory rough rice dryer including product output rate, evaporation rate and kernel cracking were predicted using ANN modeling at different levels of drying air temperature, drying air velocity and drying air humidity as network inputs. The best model to describe the output parameters was found to be the GFF neural network with Levenberg-Marquardt learning algorithm, hyperbolic tangent activation function and topology of 3-8-7-3.

Reasonable results were obtained from well trained ANN as an alternative tool for prediction of the drying parameters. The predictions were very close to the experimental data. Therefore, it was concluded that ANN is a simple and fast method for prediction of the outputs using a few experiments.

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