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Artificial neural network modeling of process and product indices in deep bed drying of rough rice

Mojtaba TOHIDI[1], Morteza SADEGHI[1,*], Seyed Rasoul MOUSAVI[2], Seyed Ahmad MIREEI[1]

[1]Department of Farm Machinery, College of Agriculture, Isfahan University of Technology, Isfahan 84156-83111 – IRAN

[2]Department of Electrical and Computer Engineering, Isfahan University of Technology, Isfahan 84156-83111 – IRAN

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Abstract: This study aimed to model the performance indices of deep bed drying of rough rice using artificial neural networks (ANNs), compare the ANN approach to the multivariate regression method, and determine the sensitivity of the ANN model to the input variables. The effects of air temperature, air velocity, and air relative humidity on drying kinetics, product output rate (POR), evaporation rate (ER), and percentage of kernel cracking (KC) were investigated. To predict the dependent parameters, 3 well-known networks, namely the multilayer perceptron, generalized feed forward (GFF), and modular neural network, were examined. The GFF networks with the Levenberg–Marquardt learning algorithm, hyperbolic tangent activation function, and 4-15-1, 3-4-4-1, 3-7-1, and 3-11-1 topologies provided superior results, respectively, for predicting moisture content, POR, ER, and CK. The values of all of the drying indices predicted by the ANN were closer to the experimental data than linear and logarithmic regression models. The output variables were significantly affected by the dependent variables. However, air temperature and air relative humidity showed the maximum and the minimum influence on the network outputs, respectively.

Key words: Artificial neural network, drying kinetics, performance indices, regression, rice, sensitivity analysis

Introduction

Rice (*Oryza sativa* L.) is one of the most consumed crops and the main staple food for more than half of the world's population. Depending on the harvesting method, the variety, the number of cuttings, and the growth location, harvested rough rice may have an average moisture content ranging from 16% to 28% (wb) (Brooker et al. 1992). It has been proven that harvesting rough rice at high levels of moisture content will maximize its head yield (Brooker et al. 1992). Therefore, an appropriate drying process is essential in order to prevent insect infestation and spoilage of rice grain (Cihan et al. 2002).

Drying is a complicated process involving simultaneous heat and mass transfer phenomena, which depend on various factors such as temperature, velocity, relative humidity and pressure of the air, physical nature and initial moisture content of the drying material, and the dryer's exposed area (Akpinar et al. 2003; Movagharnejad and Nikzad 2007). In order to design, simulate, control, and optimize the drying process for achieving the best product quality, it is important to know the drying behavior (Senadeera et al. 2003).

Many researchers have studied the drying process of grains and foods and have developed

* E-mail: sadeghimor@cc.iut.ac.ir

several models to simulate this important unit operation (Akpinar et al. 2003; Senadeera et al. 2003; Doymaz 2006; Wang et al. 2007; Scala and Crapiste 2008). These models fall into 3 categories, namely theoretical, semitheoretical, and empirical models. Both empirical and semitheoretical models are only valid for the certain ranges of temperature, air velocity, and humidity for which they are developed. Therefore, they 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 fruit slices, while commercial grain dryers commonly work in deep bed mode. For this mode, the theoretical models are used, which are generally solutions of partial differential equations obtained from the heat and mass balance. However, the results are usually complicated and, consequently, require some assumptions that do not match the real drying systems.

The artificial neural network (ANN), as a data-processing system inspired by biological neural systems, is a generalized mathematical model for human perception and is a well-known tool for solving complex and nonlinear problems (De Baerdemaeker and Hashimoto 1994; Liu et al. 2007; Bayat et al. 2008). ANNs, in an appropriate form, can also provide reasonable solutions in the event of technological faults (Lin and Lee 1995). An ANN has the ability of relearning to improve its performance if new data are available (Hertz et al. 1991). One advantage of ANN modeling is that it can accommodate multiple input variables to predict multiple output variables even without prior knowledge of the process relationships (Ramesh et al. 1996).

In recent years, ANNs have been widely used for modeling the drying process. Jay and Oliver (1996) used ANNs to control the grain drying process. Farkas et al. (2000a) examined a physical model and an ANN to predict moisture distribution in fixed bed grain dryers. Using randomly varying time series for training the ANN, they showed that a feedback model for input parameters could predict the moisture content of the grain layers more accurately than the physical model (Farkas et al. 2000b). After testing and training several algorithms, Zhang et al. (2002) found a 4-layer network with 8 and 5 neurons in its hidden layers to be 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 could be used for the primary design of a dryer and selection of the optimum operational conditions. An ANN was used to model a hazelnut fixed bed dryer assisted with a heat pump (Ceylan and Aktaş 2008). Relative humidity, drying air temperature, and drying time were used as the ANN input parameters, and bed moisture content and inlet air velocity were the output parameters. Topuz (2010) used ANNs to predict the moisture content of agricultural products (hazelnut, bean, and chickpea) in fluidized bed drying.

Although many researchers have modeled the drying process using ANNs, few of them have considered the effect of air relative humidity. Furthermore, a limited number of studies have investigated the performance and process indices of grain drying. The main objectives of this study were to: 1) develop an appropriate ANN for modeling the drying kinetics and predicting the process and product parameters of rough rice drying, including product output rate, evaporation rate, and kernel cracking at various combinations of drying air temperature, velocity, and relative humidity; 2) determine the sensitivity of the desired ANN model to the input variables; and 3) compare the ANN approach with the multivariate regression method for modeling rough rice drying in a deep bed mode.

Materials and methods

Rough rice, experimental setup, and drying experiments

Rough rice of the Sazandegi (medium-grain) variety was acquired from the Isfahan Center for Agricultural and Natural Resources Research. The samples were stored at 4 ± 0.5 °C until the experiments were performed. Before the experiments, the samples were stored at room temperature for 12 h in order to thermally equilibrate them with the environment. To determine the initial moisture content, the samples were placed in an oven set at 130 °C for 24 h (ASAE 2001). The initial moisture content of the rough rice was determined to be 20.4% (wb).

Since the commercial rough rice dryers are usually deep bed dryers, the drying experiments were performed in deep bed mode (grain column height of 20 cm). Figure 1 shows the schematic view of the dryer used in the experiments (Tohidi 2010). It consists of a power supply system, a fan with air pressure of 3.5 kPa and air flow rate of 0.4 $m^3\ s^{-1}$, an electrical heater constructed of 8 elements with a total heat capacity of 5.6 kW, an air supply channel, a drying chamber, and the required instruments to measure and control the air parameters (temperature, relative humidity, and velocity). The specifications of the measurement and control instruments are given in Table 1.

An ultrasonic humidifying instrument was designed and used to change and control the relative humidity of the air. The specific purpose of the instrument was to create a cold humid area. The control of the median temperature during the test was possible with an accuracy of ±2% and a linearity of ±2% for an operating span of 20%–95% relative humidity (RH).

To achieve the desired conditions, the dryer was run without the sample for about 20 min before each drying experiment. Rough rice samples were then placed in the drying chamber of the dryer. The weight reduction of the sample was recorded at 2–5 min intervals of the drying duration. The final moisture

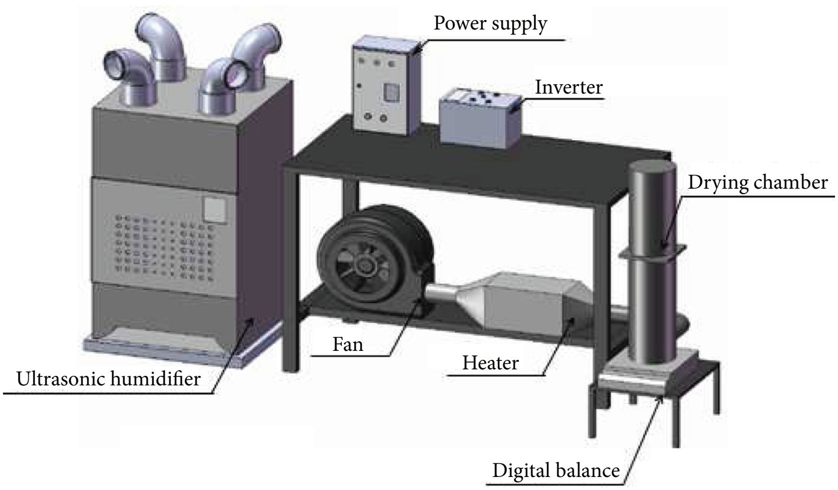

Figure 1. Schematic view of the dryer used for conducting the experiments.

Table 1. Characteristics of the measurement and control equipment.

Instrument	Trademark	Properties	Uncertainty (%)
Temperature sensor	Elimko	Input Pt-100R/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 H8302	Accuracy 0.01	-------
Hot wire anemometer	Lutron AM4204	Velocity 0.2–20 $m\ s^{-1}$ Accuracy 0.1 $m\ s^{-1}$	0.00195
Inverter	Teco 7300 cv	Input AC 1-phase 50–60 Hz Output AC 3-phase 0–650 Hz Amps 7.5 A	-------

content of the rough rice was set to be 12% (wb), which is usually recommended for proper hulling and milling of rice (Brooker et al. 1992).

The drying experiments were carried out at different combinations of drying air temperature (7 levels of 40, 50, 55, 60, 65, 70, and 80 °C), inlet air velocity (3 levels of 0.5, 0.8, and 1.1 m s^{-1}), and air relative humidity (4 levels of 40%, 50%, 60%, and 70%). Totally, 72 sets of drying experiments were conducted in August and September 2010.

After the experiments were conducted, 3 important drying parameters, including kernel cracking (KC) percentage as an indicator of the dried product quality, product output rate (POR) as an indicator of the dryer working capacity, and evaporation rate (ER) as a quality index of the drying kinetics, were calculated and measured. To determine KC percentage, 48 h after each drying test, 100 kernels of each sample were manually husked and the fissured kernels were determined using a binocular microscope. The POR and ER values were calculated using Eqs. (1) and (2), respectively.

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

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

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

Artificial neural network modeling approach

In the present study, 3 networks were used: 1) multilayer perceptron (MLP), 2) generalized feed forward (GFF), and 3) modular neural network (MNN). The MLP network is one of the most useful and common neural network architectures, and it is appropriate for a variety of applications such as prediction and process modeling. An MLP network comprises a number of identical units organized in layers. The units in each layer are connected to the units in the subsequent layer, so that the outputs of one layer are regarded as inputs to the next layer. The GFF network is a generalization of MLP in which connections can jump over one or more layers. Finally, the MNN is a combination of several independent neural networks (Happel and Murre 1994). More specifically, this network consists of n individual networks, A_1, A_2, …, A_n, n > 1, each of which receives input and generates its own output independently. There is also an intermediary module that receives as input the outputs of the individual networks A_1, A_2, ..., A_n, n > 1, from which it determines the final output of the MNN.

Among the various kinds of activation functions, the well-known hyperbolic tangent and sigmoid functions, given in Eqs. (3) and (4), respectively, were used to achieve the best results for predicting the dependent variables. A total of 4 learning algorithms, namely step, momentum, conjugate gradient, and Levenberg–Marquardt (LM), were also used for training the networks.

$$Y_j = \tanh(X_j) = \frac{e^{X_j} - e^{-X_j}}{e^{X_j} + e^{-X_j}} \tag{3}$$

$$Y_j = \frac{1}{1 + \exp(-X_j)} \tag{4}$$

$$X_j = \sum_{i=1}^{m} W_{ij} \times Y_i + b_j \tag{5}$$

Here, m is the number of the neurons in the output layer, W_{ij} is the weight of the connections between layer i and layer j, Y_i is the output of the neurons in layer i, and b_j is the bias of the neurons in layer j.

Experimental data from drying experiments were used to train and test the 3 aforementioned artificial neural networks (MLP, GFF, and MNN) for predicting rough rice moisture content during the drying process and the 3 drying parameters (POR, ER, and KC). The data collected from 72 experiments were divided into 3 subsets. The first subset was used to compute the gradient and learn the network weights and biases (the training set). The second subset was used to prevent overfitting (the validation set), and the last subset was the test set. In other words, the third subset was only used for comparing the results of the adopted models, and not for training the networks or avoiding overfitting. The dataset was initially shuffled and 70%, 15%, and 15% of the total dataset was used for training, validating, and testing purposes, respectively.

The numbers of neurons in the input and output layers depend on the input and output variables, respectively. As the moisture content was a time-dependent variable, 1 and 4 neurons were devoted to the output and the input layers, respectively (Figure 2a). To predict parameters POR, ER, and KC, we used inlet air temperature, inlet air velocity, and inlet air relative humidity as the interdependent variables. Hence, 1 and 3 neurons were devoted to the output and the input layers, respectively (Figure 2b). The number of neurons in the hidden layers was determined by calibration through several runs.

The performance of the models was evaluated using 4 criteria, namely mean square error (MSE), normalized mean square error (NMSE), mean absolute error (MAE), and correlation coefficient (r), which are defined by Eqs. (6) through (9), respectively (Obe and Shangodoyin 2010).

$$\mathrm{MSE} = \frac{\sum_{j=0}^{P}\sum_{i=0}^{P}(\mathrm{d}_{ij}-\mathrm{y}_{ij})^2}{\mathrm{P.N.}} \tag{6}$$

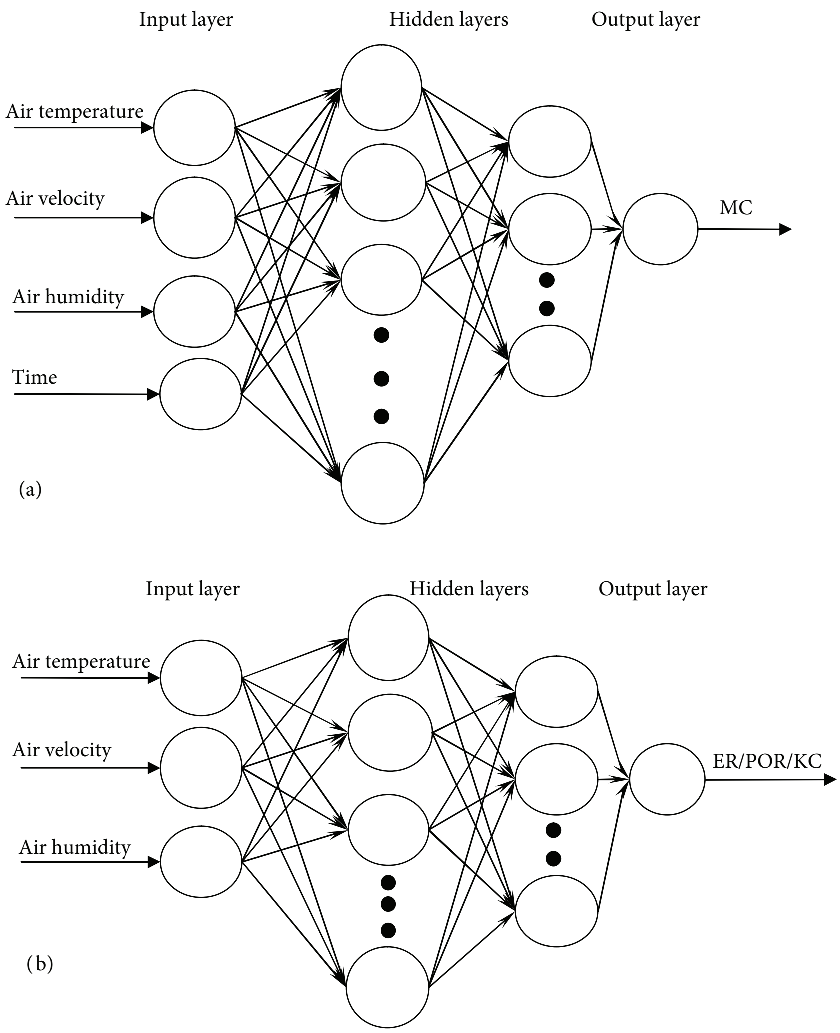

Figure 2. Schematic topology of the neural networks used for predicting a) rough rice moisture content (MC) and b) evaporation rate (ER), product output rate (POR), and kernel cracking (KC).

Here, P is the number of output neurons, N is the number of exemplars in the dataset, y_{ij} is the network output for exemplar i at processing element j, and d_{ij} is the desired output for exemplar i at processing element j.

$$\mathrm{NMSE} = \frac{\mathrm{P.N.MSE}}{\sum_{j=0}^{P} \frac{\mathrm{N}\sum_{i=0}^{N} \mathrm{d}_{ij}^{2} - (\sum_{i=0}^{N} \mathrm{d}_{ij})^{2}}{\mathrm{N}}} \tag{7}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{N}}\sum_{i=0}^{N} |\, \mathrm{d}_i - \mathrm{X}_i \,| \tag{8}$$

Here, x_i is the network output and d_i is the desired output.

Although the MSE values indicate the difference between the predicted and experimental values, this criterion does not determine their direction. Therefore, the correlation coefficient (r) was also calculated.

$$r = \frac{\frac{\sum_i (\mathrm{X}_i - \overline{\mathrm{X}})(\mathrm{d}_i - \overline{\mathrm{d}})}{\mathrm{N}}}{\sqrt{\frac{\sum_i (\mathrm{d}_i - \overline{\mathrm{d}})^2}{\mathrm{N}}}\sqrt{\frac{\sum_i (\mathrm{X}_i - \overline{\mathrm{X}})^2}{\mathrm{N}}}} \tag{9}$$

Here, x is the network output, $\overline{X}$ is the mean of the network outputs, d is the desired output, $\overline{d}$ is the mean of the desired outputs, and N is the number of exemplars in the dataset. The higher the value of r and the lower the values of MSE, NMSE, and MAE, the more accurate the developed network is. NeuroSolution software was used to model the experiments.

Multivariate regression analysis

Regression analysis is a statistical method that is used to study and model the relationship between unknown parameters and independent variables in a study. In this research, to correlate the dependent variables to the independent ones, linear and logarithmic regression models were used. The stepwise training method was used in SPSS to create multivariate regression models. Air temperature, velocity, and relative humidity were the independent variables and POR, ER, and KC were the dependent variables. The validation of the regression models was assessed using the coefficient of determination (R^2) and MSE values.

Sensitivity analysis

The sensitivity analysis process provides valuable information about the sensitivity of a developed ANN model to the input variables. By identifying the effects of input variables on the prediction accuracy of the model, less important variables can be removed and a simpler network can be obtained. A sensitivity coefficient of less than 0.1 for a variable indicates that the variable does not have a significant effect on the model prediction accuracy and consequently can be removed from the input variable set (Hill 1998).

Results

The result showed that among the 3 networks, the GFF network with a LM learning algorithm and the hyperbolic tangent activation function was the most accurate network for predicting rice drying kinetics, as well as process and product indices. Moreover, the speed of the prediction process was higher for this network than for the combination of other networks. Table 2 presents the topologies and the performance criteria values related to the best artificial neural network for predicting moisture content, product output rate, evaporation rate, and kernel cracking. It is observed that the 4-15-1, 3-4-4-1, 3-7-1, and 3-11-1 topologies provided the best results, respectively, for predicting moisture content, POR, ER, and CK.

Figure 3 shows a typical drying kinetics curve (moisture content versus time) at an air temperature of 70 °C, air velocity of 0.5 m s^{-1}, and air relative humidity of 50%. A comparison between the experimental data and the predicted data by the developed GFF network indicates that the prediction values were very close to the experimental values. Figure 4 compares the moisture content values obtained by the selected ANN with the experimental values randomly selected from the whole dataset.

Table 3 presents the experimental data for POR, ER, and KC variables used in training the ANN and the predicted values obtained by the ANN. It was observed that the predicted values were very close to the experimental data.

Table 2. Topologies and performance criteria values for the selected GFF network to predict moisture content, product output rate, evaporation rate, and kernel cracking.

	Output variable of the GFF network			
	Moisture content	Product output rate	Evaporation rate	Kernel cracking
Topology	4-15-1	3-4-4-1	3-7-1	3-11-1
MSE	0.0028	0.0047	0.0047	0.0089
NMSE	0.0291	0.0834	0.0997	0.1181
MAE	0.0118	0.0160	0.0317	0.0306
r	0.991	0.983	0.970	0.963

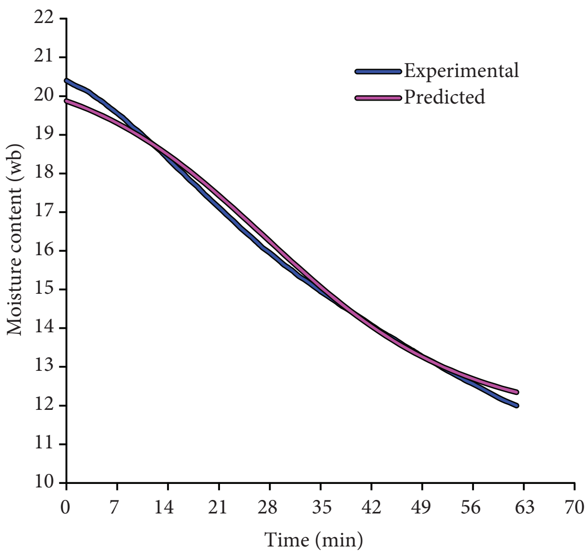

Figure 3. Comparison between the experimental moisture contents and the predicted values using the GFF network at an air temperature of 70 °C, air velocity of 0.5 m s^{-1}, and air relative humidity of 50%.

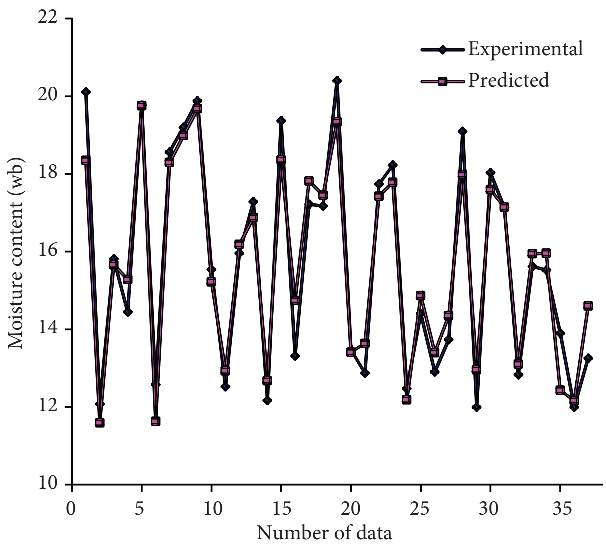

Figure 4. Random comparison between the experimental moisture contents and the predicted values using the selected GFF network.

The regression models for predicting drying indices are given in Table 4. As shown, the logarithmic regression equations were more accurate than the linear regression equation for predicting ER and KC, whereas the linear regression equation provided better results for predicting POR. Figures 5–7 illustrate the comparison between the experimental data and the predicted values obtained by the ANN and regression models for prediction of POR, ER, and KC, respectively.

The sensitivity analysis results showed that all of the sensitivity coefficients related to the air temperature, air velocity, and air relative humidity were higher than 0.1 (Table 5). Therefore, none of them could be removed from the input variable set.

Considering the equal importance for the 3 drying indices (POR, ER, and KC), the best conditions of rough rice drying (maximum system efficiency) in terms of air velocity, air relative humidity, and air temperature were determined to be 0.5 m s^{-1},

Table 3. The experimental data of product output rate, evaporation rate, and kernel cracking used for training the ANN, and the predicted values by the best ANN.

Product output rate		Evaporation rate		Kernel cracking	
Experimental	Predicted	Experimental	Predicted	Experimental	Predicted
4.97	2.42	4.28	4.23	10	13.29
46.00	48.64	0.47	0.47	51	52.04
38.33	40.83	4.39	4.21	46	47.13
40.89	41.05	3.66	4.50	47	45.15
5.07	2.14	3.90	5.45	12	9.08
34.71	31.48	0.48	0.47	44	39.23
11.72	11.52	3.32	3.24	16	18.31
27.05	24.83	1.12	1.16	36	35.11
39.18	40.85	2.54	2.46	44	47.92
52.57	52.45	3.73	3.89	55	52.45
12.26	11.40	5.02	5.32	19	17.74
4.87	2.14	1.17	1.17	9	12.63
30.16	30.23	0.46	0.43	40	39.71
25.20	24.42	2.88	2.92	37	38.41
10.82	9.69	2.4	3.12	14	17.10
17.35	18.60	1.03	1.06	29	26.92
4.97	2.42	1.66	1.76	10	13.29

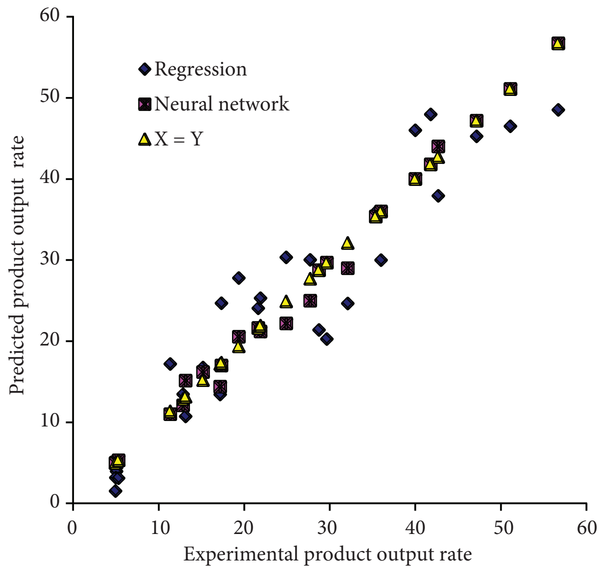

Figure 5. Comparison between the experimental and predicted product output rate (POR) values using ANN and regression methods.

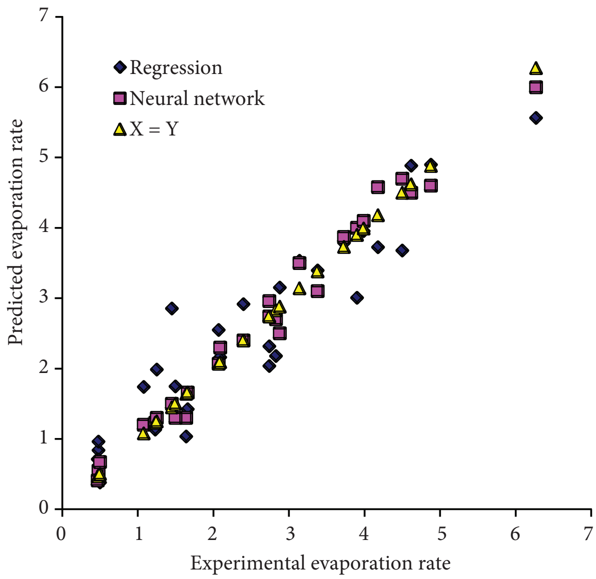

Figure 6. Comparison between the experimental and predicted evaporation rate (ER) values using ANN and regression methods.

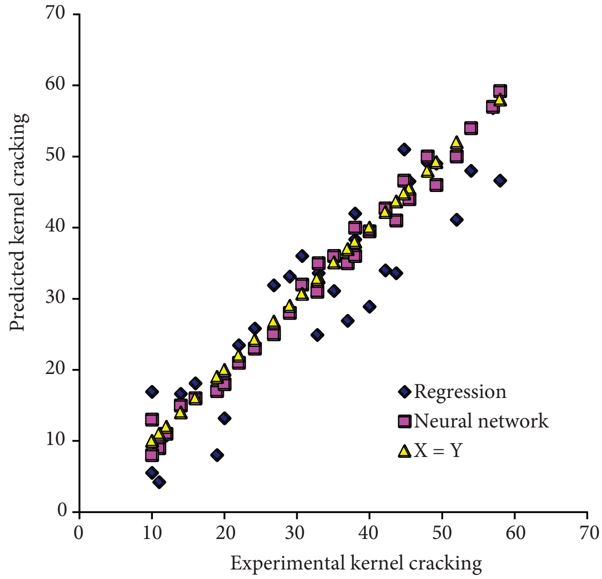

Figure 7. Comparison between the experimental and predicted kernel cracking (KC) values using ANN and regression methods.

Table 4. Regression models to estimate product output rate (POR), evaporation rate (ER), and kernel cracking (KC) as a function of input variables.

Regression equation	MSE	R^2
POR = –0.048 + 0.817 T + 0.100 V – 0.039 RH	0.0136	0.88
log ER = –0.190 + log T + 0.076 log V – 0.031 log RH	0.0133	0.88
log KC = –0.071 + 0.826 log T + 0.084 log V – 0.090 log RH	0.0197	0.84

Table 5. Sensitivity coefficient values for product output rate, evaporation rate, and kernel cracking related to various input variables.

	Sensitivity coefficient		
Input variables	Product output rate	Evaporation rate	Kernel cracking
Air temperature	1.00	1.00	1.00
Air velocity	0.87	0.70	0.82
Air relative humidity	0.14	0.27	0.74

60%, and 46 °C, respectively. Zhang et al. (2002) used multiple-objective programming to show that the optimal values for rough rice drying were layer thickness of 66 cm, hot airflow rate of 0.3 m s^{-1}, hot air temperature of 93.8 °C, and drying time of 23 min.

Discussion

According to the topology of the network for predicting moisture content (Table 2), the error values increased and the correlation coefficient value decreased when increasing the number of hidden layers from 15. To predict the product output rate, the best topology had 2 hidden layers, but similar to the moisture content for kernel cracking and evaporation rate, 1 hidden layer resulted in the best network. The results also indicated that increasing the number of hidden layers and the number of neurons in the hidden layer decreased the prediction accuracy.

As shown in Figure 3, the predicted values were very close to the measured values. Therefore, it is concluded that the GFF network model can be used as an appropriate tool to estimate the moisture content of rice during the drying process in a deep bed mode for drying rough rice.

Figures 5–7 show that compared to the regression method, the ANN approach provided more accurate predicted values in relation to the experimental data for all drying indices. This could be due to the existence of nonlinear relationships between the variables, which is considered in ANN modeling. Erenturk et al. (2004) also concluded that a neural network represented the drying characteristics of *Echinacea angustifolia* better than regression models. Therefore, the ANN models can estimate the parameters with an acceptable accuracy, and consequently can be an appropriate substitute for regression methods in modeling rough rice drying.

According to Hill's rule, air temperature, air velocity, and air relative humidity had a significant influence on the output variables. However, among the input parameters, air temperature and air relative humidity showed the greatest and the least effect on the network outputs, respectively. The lowest sensitivity coefficient (0.14) belonged to the effect of air relative humidity on POR.

Acknowledgments

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