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SCIENTIFIC PAPER

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PREDICTION OF PADDY DRYING KINETICS: A COMPARATIVE STUDY BETWEEN MATHEMATICAL AND ARTIFICIAL NEURAL NETWORK MODELING

Article Highlights

- Drying curves of paddy were modeled using mathematical and ANN modeling techniques
- Among the applied models, the Midilli model was determined as the best one describing drying curves
- ANN with 4-10-14-1 topology, tansig transfer function and LM algorithm provided the best results
- ANN modelling had better performance in prediction of drying curves

Abstract

The present study aimed at investigation of deep bed drying of rough rice kernels at various thin layers at different drying air temperatures and flow rates. A comparative study was performed between mathematical thin layer models and artificial neural networks to estimate the drying curves of rough rice. The suitability of nine mathematical models in simulating the drying kinetics was examined and the Midilli model was determined as the best approach for describing drying curves. Different feed forward-back propagation artificial neural networks were examined to predict the moisture content variations of the grains. The ANN with 4-18-18-1 topology, transfer function of hyperbolic tangent sigmoid and a Levenberg-Marquardt back propagation training algorithm provided the best results with the maximum correlation coefficient and the minimum mean square error values. Furthermore, it was revealed that ANN modeling had better performance in prediction of drying curves with lower root mean square error values.

Keywords: mathematical modeling, artificial neural networks, feed forward-back propagation, Paddy.

Rice, as a cereal grain, is the most important grain providing more than one-fifth of the calories consumed worldwide by humans. Depending on some factors such as harvesting method, variety, number of cuttings and growth location, harvested rough rice may have an average moisture content ranging from 18 to 26 mass% ($g_{water}/g_{wet\ matter}$) [1]. Generally, these high levels of moisture content are not suitable for safe processing, usage and/or storage and it is recommended they should be kept at 13 mass% for storage and in the range of 10-13 mass% for milling [2]. Therefore, immediate and proper drying of the freshly harvested grains is essential for high quality grains.

Open sun drying is the traditional method still used for dehydrating agricultural products due to some advantages, *e.g.*, simplicity and low costs. However, it poses some serious problems, *e.g.*, long drying time, dust and microbial contamination as well as fluctuation in the quality of the dried materials. To overcome these problems, industrial drying equipment has been employed. Over recent decades, to dehydrate different agricultural and food products, various artificial methods such as convective hot air drying, microwave drying, vacuum drying, infrared drying, etc., have gained popularity as alternative

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drying techniques. Recently, some new methods such as continuous fluidized bed microwave drying [3], super-heated steam fluidized bed drying [4] and spouted bed drying [5] are reported as energy and quality efficient drying methods for paddy. However, their usage in industrial setting is still limited and fixed deep bed hot air dryers are the most common method used for paddy drying [6].

Mathematical modelling is widely used to predict drying behaviour of materials being dried, design new dryers, and control of the process. Theoretical, semi-theoretical and empirical models are the key proposed mathematical models used to describe the drying behaviour of agricultural materials. Theoretical models are built based on the understanding of the fundamental phenomena and mechanisms involved during drying process, whereas the two other models are built by fitting model parameters to experimental data. Although theoretical simulations could give an explanation for phenomena occurring during the process, they are more difficult to execute and require a substantial amount of computing time. The empirical models are derived from a direct correlation between moisture content and drying time and neglect fundamentals of drying process. The semi-theoretical models offer a compromise between theory and ease of application and generally are derived from direct solution of Fick's second law by assuming some simplifications [7]. To date, several researchers have investigated regression modelling of various agricultural and food products drying curves, *e.g.*, sweet cherry [8], rapeseed [9], pomegranate arils [10], onion [11], mushroom [12], potato [13], tomato [14] and red seaweed [15].

Artificial neural network (ANN) is a mathematical model for human perception and inspired by biological neural systems. Generally, artificial neural network is a famous tool to simulate complex and non--linear problems. It has brilliant capability to accommodate several input variables to estimate several output variables, even without prior information of the process relations [16]. These networks are important tool being increasingly applied for process control and for a variety of other areas including dynamic modelling, prediction and fault analysis of processes [17]. Lately, several researchers have used the ANNs modelling methods to simulate drying process [17-21].

Although many researchers have simulated the drying process using mathematical models and ANNs, no study considered different thin layers of drying bed, as a critical parameter, in the deep-bed grain dryers. The main objectives of the presented study were to determine the suitable mathematical model and ANN topology for prediction of variations in the grains moisture ratio of different thin layers in the deep bed column of rough rice during hot air drying, and compare the performance of the applied modelling techniques in prediction of drying curves.

EXPERIMENTAL

The common rough rice variety in Isfahan province (central Iran), namely Sazandegi, was selected for the study. Fresh rough rice samples were sealed in polyethylene bags to avoid moisture variation due to evaporation, and stored at 4-6 °C until the experiments were conducted. Prior to each drying experiment, the samples were placed in the laboratory for 4 h to warm up at room temperature. The initial moisture content of the samples was determined using ASAE standard (2001) [22], and applying Eq. (1):

$$M_0 = 100\frac{W_0 - W_d}{W_d} \tag{1}$$

where W_d and W_0 are the mass (g) of dried and fresh samples, respectively.

The average value for paddy moisture content was obtained approx. 29.9 mass%. Drying conditions were selected for different combinations of drying air temperature (40, 50, 60 and 70 °C), and drying air velocity at two levels of 0.4 and 0.9 m s^{-1}. Drying time of 100 min was selected for each experiment.

A novel drying column (made of a Plexiglas cylinder with 20 cm in height, 14 cm internal diameter and 5 mm thickness) was fabricated in order to separate the drying bed into four easily removable individual thin layers (each of 5 cm height). The layers of drying column; marked by numbers 1 to 4 from bottom to the top, were filled with wet rough rice and weighed on a digital laboratory balance (Sartorius 18100P with accuracy of 0.01 g, Sartorius Co., Germany). Then, the layers were attached together according to their numbers, as if they were a drying column with a height of 20 cm. The drying chamber was removed in 5 min intervals, the layers were separately weighed, and the instantaneous moisture content for each layer was computed using Eq. (2) [23]:

$$M = \frac{W(M_0 + 100)}{W_0} - 100 \tag{2}$$

where M and M_0 are the moisture content at any given time and the initial moisture content, respectively. Also, W and W_0 are the weight of the samples at any given time (g) and the initial weight of the fresh samples (g), respectively.

Using Eq. (3), the moisture content data were converted to dimensionless moisture ratio (MR) [24]:

$$MR = \frac{M - M_e}{M_0 - M_e} \tag{3}$$

where M_e is the equilibrium moisture content obtained by drying the paddy at the applied air temperatures and velocities until constant weight.

Mathematical modeling

To describe the drying curves of the samples, nine most widely used mathematical models (listed in Table 1) were selected. Curve fitting tool of MATLAB 7.10 (MathWorks, Inc., Natick, MA) and nonlinear regression technique were applied to fit the models to the experimental moisture ratio data. The fit goodness of the mathematical models was evaluated and compared in terms of two famous statistical factors including root mean square error (*RMSE*) and chi-square (χ^2). These parameters are defined as stated in literature [24]:

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}\left(MR_{\mathrm{pre},i} - MR_{\mathrm{exp},i}\right)^2\right]^{\frac{1}{2}} \tag{4}$$

$$\chi^2 = \frac{\sum_{i=1}^{N}\left(MR_{\mathrm{exp},i} - MR_{\mathrm{pre},i}\right)^2}{N - Z} \tag{5}$$

where $MR_{\mathrm{exp},i}$ is the i-th experimental moisture ratio, $MR_{\mathrm{pre},i}$ is the i-th predicted moisture ratio, N is the observation number and Z is the number of constants.

Amongst models, the model having minimum *RMSE* and χ^2 was selected as the best one to describe the drying curves.

Artificial neural networks (ANNs) modelling procedure

In this study, multilayer feed-forward back propagation neural networks (MFBPNNs) were used. Although multilayer feed-forward neural networks (MFNNs) are popular structures among artificial neural networks widely used to predict and control food processing operations and solve complex problems by modelling complex input-output relations, these networks often end up being over trained and adopt trials-and-errors to seek for possible values of parameters for convergence of the global optimum [25]. The back-propagation learning algorithm (BPLA) is a widely used method for MFNN learning in many applications with the great advantage of simple implementation [26]. Using the gradient-descent search method to adjust the connection weights, in the learning process, it increases the ANNs accuracy. The back-propagation ANNs have been successfully used by some researchers in diverse applications, *e.g.*, pattern recognition, location selection and performance evaluations [27-29].

To predict the variations in paddy moisture ratio changes versus drying time, the input layer consisted of four datasets of inlet air temperature, inlet air velocity, drying bed depth and drying time. To select for the best network architecture, several network configurations and various model parameters, including the number of hidden layers, the number of neurons in the hidden layers, different transfer functions, and the training algorithms, might be evaluated [30]. In this study, three and four layer network configurations of ANNs and the hyperbolic tangent sigmoid (Tansig) and log sigmoid (logsig) transfer functions were used. The tansig and logsig functions are defined in Eqs. (6) and (7), respectively [20]:

$$Y_j = \tanh(X_j) = \frac{\exp(X_j) - \exp(-X_j)}{\exp(X_j) + \exp(-X_j)} \tag{6}$$

$$Y_j = \frac{1}{1 + \exp(-X_j)} \tag{7}$$

where X_j is defined as:

$$X_j = \sum_{i=1}^{m} W_{ij} Y_i + b_i \tag{8}$$

Table 1. Mathematical models applied to the drying curves

Model number	Model name	Model expression
1	Newton	$MR = \exp(-kt)$
2	Page	$MR = \exp(-kt^n)$
3	Modified Page	$MR = a\exp(-(kt)^n)$
4	Henderson and Pabis	$MR = a\exp(-kt)$
5	Logarithmic	$MR = a\exp(-kt) + b$
6	Two term exponential	$MR = a\exp(-kt) + (1-a)\exp(-kat)$
7	Wang and Singh	$MR = 1 + at + bt^2$
8	Diffusion Approach	$MR = a\exp(-kt) + (1-a)\exp(-kbt)$
9	Midilli	$MR = a\exp(-kt^n) + bt$

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

In addition, several back-propagation training algorithms, *e.g.*, scaled conjugate gradient (SCG), Polak-Ribiere conjugate gradient (PCG), BFG quasi--Newton (BFG), and Levenberg-Marquardt (LM) were applied to train the network [31].

The number of neurons in the input and output layers depend on the input and output variables, respectively. Therefore, for each combination, 4 and 1 neurons were applied to the input and the output layers, respectively. Furthermore, the number of neurons in the hidden layer(s) was determined by calibration through several runs.

In order to improve the generalization of ANN models, in this study, early stopping method was used. The obtained experimental data were divided into three subsets. The first subset was used for computation of the gradient and updating weights and biases of the network (the training subset), the second one was used for prevention over fitting (the validation subset), and the last part was allocated to compare the predicted results (the test subset) [18,20]. A total of 70% of the data sets obtained from the experiments were applied for the training, 15% for validations, and the remaining 15% to test the model [18,20,31].

The performance of the developed ANNs models was determined based on the least mean square error (MSE) [20]:

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{P}(d_{ij}-y_{ij})^2}{PN} \tag{9}$$

where 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.

RESULTS AND DISCUSSION

Mathematical modelling of drying curves

Statistical analysis results obtained through fitting experimental moisture ratio data with the mathematical models are shown in Table 2. As the results show, the Midilli model with sum values of $RMSE$ = = 0.112233 and χ^2 = 0.000559, was found to be the best model for describing drying kinetics of the paddy. In contrast, among the applied models, the Newton model was found to be the worst fit with sum values of $RMSE$ = 1.69229 and χ^2 = 0.096669. In a similar manner, Midilli model has been introduced as the best mathematical model to describe drying curves of some other agricultural crops such as lemon slices [24], potato pulp waste [32], apple slices [33] and white mulberry [34].

Table 2. Sum of RMSE and χ^2 values of the models

Model	Sum of χ^2	Sum of RMSE
Newton	0.096669	1.69229
Page	0.002720	0.24478
Modified Page	0.002679	0.24643
Henderson and Pabis	0.041328	1.09044
Logarithmic	0.006547	0.36337
Two-term exponential	0.000881	0.13766
Wang and Singh	0.038598	0.98070
Midilli	0.000559	0.11233
Diffusion approach	0.000793	0.13364

In order to evaluate the Midilli model, the predicted moisture ratio at any particular drying condition by using the model was compared with experimental data and the results for some randomly selected drying curves are shown in Figure 1. The results indicate the suitability of the Midilli model in describing the drying kinetics of the paddy. For the other drying conditions, similar results were also obtained.

ANNs prediction of rough rice drying curves

Table 3 presents the results of ANNs modelling of the paddy moisture ratio variations during drying process. The effects of hidden layer number and neuron number in each hidden layer on precision of the moisture ratio variation predictions are presented in Table 3. As shown, among the applied networks, the network with a topology of 4-18-18-1, transfer function of tansig and a LM training algorithm had better estimation with the minimum mean square error. The obtained results are comparable with previously reported in the literature by different researchers. Jafari *et al.* (2015) [11] examined different topologies of ANNs to predict the drying curves of onion slices and introduced the feed forward-back propagation network with Levenberg-Marquardt training algorithm, hyperbolic tangent sigmoid transfer function and 2-5-1 topology as the best neural network system. Zare *et al.* (2015) conducted a study to investigate combined hot air/infrared drying process and reported that feed forward-back propagation neural network with topology of 4-8-14-1, training algorithm of Levenberg-Marquardt and a transfer function of hyperbolic tangent sigmoid had the best prediction of drying curves [18]. Momenzadeh *et al.*

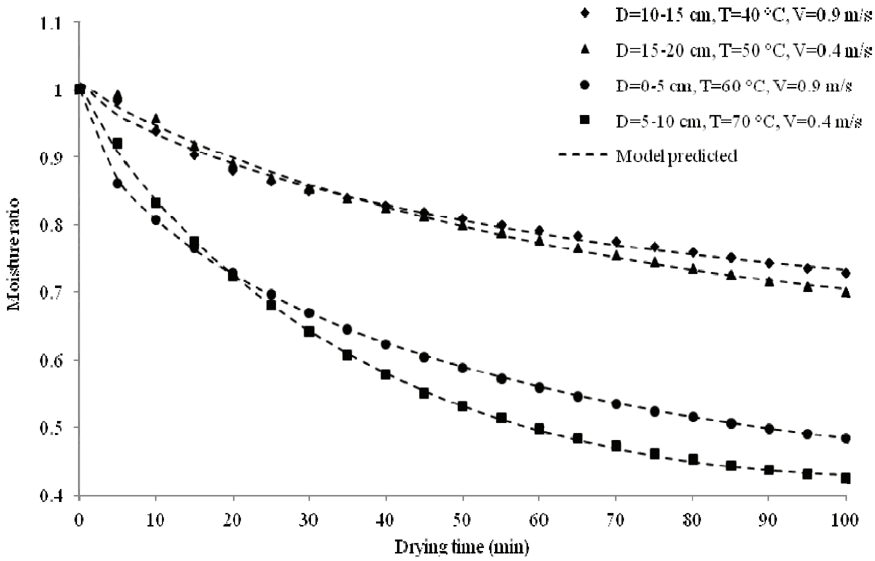

Figure 1. Comparison between moisture ratio data predicted by the Midilli model and the experimental ones for the rough rice during hot air drying.

Table 3. The results of artificial neural networks modeling in prediction of moisture ratio of the rough rice

Network topology	Transfer function	Training algorithm	Number of training cycles	*MSE*
4-6-1	Logsig	SCG	93	0.712
4-6-1	Logsig	CGP	132	0.7591
4-6-1	Logsig	BFG	33	0.728
4-6-1	Logsig	LM	31	0.807
4-6-1	Tansig	SCG	48	0.535
4-6-1	Tansig	CGP	168	0.236
4-6-1	Tansig	BFG	103	0.0422
4-6-1	Tansig	LM	400	0.0323
4-6-10-1	Logsig	SCG	106	0.791
4-6-10-1	Logsig	CGP	48	0.757
4-6-10-1	Logsig	BFG	87	0.837
4-6-10-1	Logsig	LM	42	0.746
4-6-10-1	Tansig	SCG	246	0.107
4-6-10-1	Tansig	CGP	108	0.141
4-6-10-1	Tansig	BFG	107	0.017
4-6-10-1	Tansig	LM	163	0.0051
4-18-18-1	Logsig	SCG	101	0.773
4-18-18-1	Logsig	CGP	100	0.681
4-18-18-1	Logsig	BFG	69	0.757
4-18-18-1	Logsig	LM	17	0.829
4-18-18-1	Tansig	SCG	196	0.051
4-18-18-1	Tansig	CGP	350	0.0198
4-18-18-1	Tansig	BFG	88	0.0096
4-18-18-1	Tansig	LM	37	0.00055
4-30-30-1	Logsig	SCG	113	0.734
4-30-30-1	Logsig	CGP	41	0.827
4-30-30-1	Logsig	BFG	78	0.803
4-30-30-1	Logsig	LM	37	0.723
4-30-30-1	Tansig	SCG	321	0.0216
4-30-30-1	Tansig	CGP	292	0.0354
4-30-30-1	Tansig	BFG	67	0.0182
4-30-30-1	Tansig	LM	34	0.0007

(2012) applied artificial neural network to predict drying time of green pea in a microwave-assisted fluidized bed dryer and found that a network with logsig transfer function and back propagation algorithm made the most accurate predictions [35]. Yousefi *et al.* (2012) [36] estimated the moisture content of papaya fruit during drying in a cabinet dryer by using artificial neural networks and reported the multi-layer perceptron network with 3-9-1 topology, LM training algorithm and the logsig transfer function as the best network to predict the drying curves.

To assess the performance of the preferred artificial network in modelling rough rice drying curves, the predicted moisture content values were plotted (Figure 2). As presented, the ANN could be successfully used to predict paddy moisture ratio variations during the drying process. Moreover, the variation in the experimental and predicted moisture ratio of the grains is illustrated by randomly selected drying condition, Figure 3. These figures show very good agreement between experimental data and those obtained from ANN. Similar results were calculated for other drying conditions indicating a suitable prediction.

Comparison between mathematical and ANNs modeling techniques

Based on the obtained results, the applied mathematical models and ANNs could predict variation of moisture ratio values of the rough rice kernels during drying process with high accuracy. However, the Midilli model and the best ANN were compared by using *RMSE* indicator. For the drying layers at different drying conditions, *RMSE* values were calculated by using Eq. (4) and the results are listed in Table 4. As shown, for all the conditions, the ANN performed better in prediction of moisture ratio variation in comparison with the Midilli model. The obtained results indicate the capability of ANNs in predicting the drying curves, especially when we consider the simple arithmetic operations and low computing time of the artificial neural networks. Similar results have been reported in the literature about advantageous application of ANNs and a high accuracy obtained for final selected topologies in predicting drying curves of different products such as Elaeagnus angustifolias [37], mushroom [38], papaya fruit [36] and onion [11].

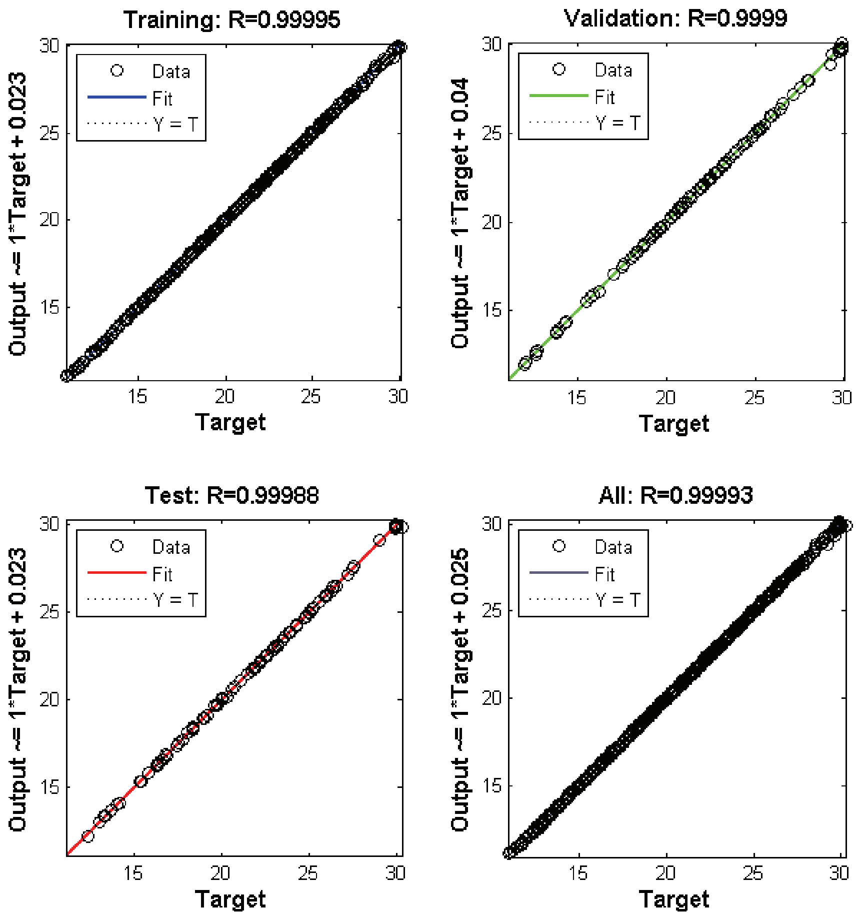

Figure 2. Comparison between experimental and predicted values of moisture ratio of the rough rice during training, validation and testing of the best ANN model, provided in MATLAB.

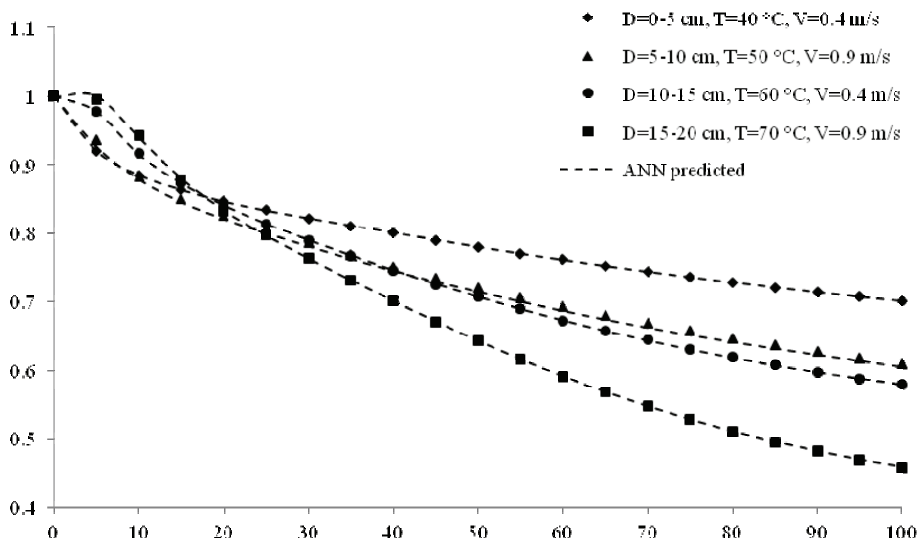

Figure 3. Comparison between moisture ratio data predicted by the best ANNs and the experimental ones for the rough rice during hot air drying.

Table 4. RMSE values for the Midilli model and the best ANN at different drying conditions

Temperature °C	Velocity m s^{-1}	Layer 1 (0-5 cm)		Layer 2 (5-10 cm)		Layer 3 (10-15 cm)		Layer 1 (15-20 cm)	
		Midilli model	Best ANN	Midilli model	Best ANN	Midilli model	Best ANN	Midilli model	Best ANN
40	0.4	0.002432	0.000471	0.004238	0.000561	0.005444	0.000483	0.005616	0.000619
	0.9	0.002841	0.000539	0.008346	0.00127	0.003964	0.000397	0.009431	0.002164
50	0.4	0.003237	0.000374	0.002974	0.000548	0.003983	0.000607	0.005924	0.001151
	0.9	0.003125	0.000518	0.006109	0.001125	0.004167	0.000591	0.006281	0.002781
60	0.4	0.004106	0.000603	0.004813	0.001089	0.003146	0.000485	0.003562	0.000672
	0.9	0.002941	0.001092	0.001466	0.001132	0.003328	0.000836	0.004916	0.00159
70	0.4	0.004686	0.000507	0.003642	0.000736	0.004645	0.000629	0.005394	0.000696
	0.9	0.007139	0.001104	0.004518	0.000821	0.005108	0.000752	0.004170	0.000864

CONCLUSIONS

Deep bed column (20 cm) of rough rice kernels was dried using a hot air dryer at different air conditions including four temperature levels (40, 50, 60 and 70 °C) and two flow rate levels (0.4 and 0.9 m s^{-1}). The drying bed was divided into 4 thin layers (each 5 cm in height) and the kinetics of the thin layers of the grains was investigated. Among the nine famous mathematical models used for prediction of the drying curves, the Midilli model was found to be the best for describing drying curves according to the minimum *RMSE* and chi-square values. The different artificial neural networks were examined to predict the variation in moisture ratio of the rough rice during the drying process. The ANN with 4-18-18-1 topology, transfer function of hyperbolic tangent sigmoid and a Levenberg-Marquardt back propagation training algorithm was found to be the best model for prediction of variations in the rough rice moisture content during hot air drying. The comparison between the Midilli model and the best ANN showed that ANN modeling could be effectively used for prediction of grain drying curves.

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PREDVIĐANJE KINETIKE SUŠENJA PIRINČA: KOMPARATIVNO PROUČAVANJE MATEMATIČKOG MODELOVANJA I VEŠTAČKE NEURONSKE MREŽE

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NAUČNI RAD

Ovaj rad je imao za cilj istraživanje sušenje grubih pirinčanih zrna u sloju različite debljine pri različitim temperaturama i protocima vazduha. Izvršeno je poređenje matematičkog modela sušenja u tankom sloju i veštačke neuronske mreže. Devet matematičkih modela je korišćeno za simulaciju kinetike sušenja, a kao najbolji pokazao se model Midillija. Istražene su i mogućnosti predviđanja promene vlaćnosti zrna različitim veštačkim neuronskim mrežama (VNM). VNM sa topologijom 4-18-18-1, prenosnom hiperboličko tangento sigmoidnom funkcijom i Levenberg-Marquardt algoritmom sa pozitivnim i negativnim povratnim prostiranjem za treniranje je dala najbolje rezultate sa maksimalnim koeficijentom korelacije i minimalnom srednjom kvadratnom greškom. Osim toga, otkriveno je da je VNM imala bolje performanse u predviđanju krive sušenje sa manjom srednja srednjom kvadratnom greškom.

Ključne reči: matematičko modelovanje, veštačke neuronske mreže, pozitivno--negativno povratno prostiranje, Paddy.