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SCIENTIFIC PAPER

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COMPARISON OF MATHEMATICAL MODELS AND ARTIFICIAL NEURAL NETWORKS FOR PREDICTION OF DRYING KINETICS OF MUSHROOM IN MICROWAVE-VACUUM DRIER

Drying characteristics of button mushroom slices were determined using microwave-vacuum drier at various powers (130, 260, 380 and 450 W) and absolute pressures (200, 400, 600 and 800 mbar). To select a suitable mathematical model, 6 thin-layer drying models were fitted to the experimental data. The fitting rates of models were assessed based on three parameters: highest R^2, lowest χ^2 and root mean square error (RMSE). In addition, using the experimental data, an ANN trained by standard back-propagation algorithm was developed in order to predict moisture ratio (MR) and drying rate (DR) values based on the three input variables (drying time, absolute pressure, microwave power). Different activation functions and several rules were used to assess percentage error between the desired and the predicted values. According to our findings, the Midilli et al. model showed a reasonable fitting with experimental data, while the ANN model showed its high capability to predict the MR and DR quite well with determination coefficients (R^2) of 0.9991, 0.9995 and 0.9996 for training, validation and testing, respectively. Furthermore, their predictions mean square error were 0.00086, 0.00042 and 0.00052, respectively.

Keywords: microwave-vacuum drier, mushroom, mathematical model, artificial neural networks.

Drying is a well known method to preserve fruits and vegetables since water removal during this process can prevent harmful chemical reactions as well as growth of microorganisms which all together lead to a longer storage time [1].

Amongst the available drying methods, fan-assisted convection driers are the most common ones used for drying, but they usually have some undesirable effects such as surface burning, shrinkage and discoloration on the dried product. In addition, long drying periods and high energy consumption are other disadvantages associated with these driers. Therefore, over the recent years the researchers have tried to modify the available methods as well as elucidate the capability of other types of driers in order to overcome the abovementioned issues. The most examined modifications were the use of vacuum as well as novel heating methods namely microwave in order to decrease the drying temperature as well as to improve the qualitative properties of the dried product [2,3].

Microwave drying is a relatively inexpensive method and has attracted many researchers in recent years. In a microwave drier, electromagnetic energy is directly converted to kinetic energy of water molecules and heat is produced within the product. Since the electromagnetic waves can penetrate into the material therefore the whole volume of the treated material can be heated and the occurrence of this phenolmenon can increase the drying rate [4]. Moreover, microwave driers can be combined with vacuum systems in order to achieve the benefits of both [5,6].

In this regard, the capability of microwave-vacuum driers for drying the button mushroom has been evaluated where 70-90% decrease in the drying time and better rehydration characteristics in comparison

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to convective air drying were reported [7]. In some other studies, the potential of mathematical modeling as a measure by which one can predict and improve the efficiency of the processes where the relationship between interfering factors and final outputs is of great value for researchers and technicians [8].

Apart from mathematical modeling, the efficacy of artificial neural networks (ANN), as a novel approach, has been successfully approved in resolving a wide variety of issues in science and engineering, particularly for some areas where the conventional modeling methods fail. A well-trained ANN can be used as a predictive model for a specific application, which is a data-processing system inspired by biological neural system [9]. Prediction of heat and mass transfer in the drying process of mango and cassava was achieved using neural networks [10]. Erenturka *et al.* [11] reported on the comparison of neural networks and the regression analysis for the estimation of drying behavior of *Echinacea anguishfolia*. Neural networks as an approximation approach has been also used for the prediction of microwave-assisted drying process [12], prediction of drying kinetics [13], solar drying performance [14], tomato drying [15], pomegranate arils drying with microwave pretreatment [16] and mushroom slice [17].

Therefore, the main objectives of this study were to investigate the drying kinetics as well as comparing the capabilities of artificial neural network and mathematical models for describing the prediction of thin-layer drying of mushroom slices in a microwave-vacuum drier under various microwave powers and absolute pressures.

EXPERIMENTAL

Materials. The fresh button mushroom was purchased from a local supermarket and kept in a refrigerator (5 °C) prior to the experiments. To measure the initial moisture content, the mushroom (15 g) was dried using an oven (105±2 °C for 7 h) until there was no change in weight between the weightings. This process was repeated five times. The initial moisture content of the mushroom was about 94.1±0.4% on wet basis.

Microwave-vacuum drier (Figure 1). A schematic description and the set up of the laboratory equipment utilized for button mushroom drying are shown in Figure 1. This system consisted of a domestic microwave oven (Micromat 725, 0.36×0.33×0.23 m, 2.45 GHz, AEG, Germany) with variable power output settings (130, 260, 380 and 450 W) where a glass desiccator (150 mm I.D.) was embedded inside the microwave cavity as vacuum chamber connected to evacuation pump. The rotation speed of the desiccator was 12 rpm and its absolute pressure was monitored and regulated using a vacuum tester (VT1 NP, Italy, 0.1 mbar). A water load (approximately 80 g in a Pyrex beaker) was used to protect the magnetron from overheating by standing waves when the product moisture was low, especially during the latter stages [18-19]. The weight (Sarturius, TE214S, AG Germany, 0.0001 g) and thickness (micrometer, 1 μm) of samples were 15±1 g and 4.2±0.6 mm, respectively. In addition, drying process performed without any pretreatment. The drying was carried out until reaching moisture content about 8% on wet basis. All treatments were replicated 3 times unless stated.

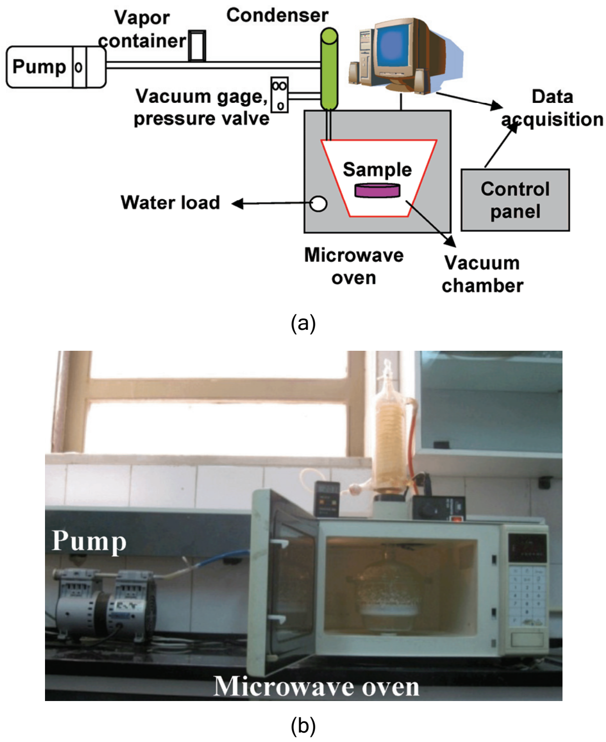


Figure 1. Microwave-vacuum drying system; a) schematic and b) practical set-up.

Modeling based on moisture ratio. For mathematical modeling purposes, the following equation was used for calculating the moisture ratio (MR) of mushroom during the drying process:

$$MR = \frac{M_t - M_e}{M_0 - M_e} \tag{1}$$

where MR stands for moisture ratio (dimensionless); M_t, the mean moisture content of mushroom at any time (kg water/kg dry matter); M_0, the initial moisture content of mushroom (kg water/kg dry matter); and M_e, the equilibrium moisture content of mushroom (kg water/kg dry matter).

As the value of M_e is negligible compared to that of M_0 and M_t, the error of omitting M_e is often insignificant, so the equation simplified as follows [20]:

$$MR = \frac{M_t}{M_0} \tag{2}$$

Selected mathematical models (Table 1) were fitted to experimental data (moisture ratio versus drying time) using MATLAB 2007 software. To determine the best model to represent the drying behavior of mushroom slices, the following equations were used for calculation of determination coefficient (R^2), chi square (χ^2) and root mean square error ($RMSE$) parameters:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(MR_{\mathrm{pred},i} - MR_{\mathrm{exp},i})^2}{\sum_{i=1}^{N}(\overline{MR}_{\mathrm{pred}} - MR_{\mathrm{exp},i})^2} \tag{3}$$

$$\chi^2 = \frac{\sum_{i=1}^{N}(MR_{\mathrm{exp},i} - MR_{\mathrm{pre},i})^2}{N-m}$$

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

where $MR_{\mathrm{exp,i}}$ and $MR_{\mathrm{pre,i}}$ are experimental and predicted dimensionless moisture ratios, respectively; N is the number of observations; and m is the number of drying constants. The most suitable mathematical model for describing drying characteristics of mushroom slice would be a model with the highest R^2 and the lowest χ^2 and $RMSE$ values.

Modeling based on drying rate. The following equation has already been reported for the calculation of the drying rate of mushroom [21]:

$$DR = \frac{MC_{t+\mathrm{d}t} - MC_t}{\mathrm{d}t} \tag{6}$$

where DR is the drying rate, MC_{t+dt} is moisture content at time of t+dt, MC_t is moisture content at time of t and dt is the time interval between two weightings.

Since at the very early stages of drying process, the drying rate rapidly increases and continuously decreases therefore, it was suggested to employ the following equation to describe the drying rate [22]:

$$DR = DR_{\max}\left(\frac{t}{l}\right)\exp\left(1-\frac{t}{l}\right) \tag{7}$$

where l represents the time when the highest drying rate is occurred, DR is the drying rate in a given time, DR_{max} is maximum drying rate and t is the drying time.

It is noteworthy that in many cases the values of k and $DR_{\max}$ can be directly obtained from the measured data of drying rate.

The three aforementioned criteria (R^2, χ^2 and $RMSE$) were used to verify the fitting rate of the models.

Artificial neural network design. To obtain the best prediction by the network, several architectures were evaluated and trained using the experimental data. The back-propagation algorithm was utilized in training of all ANN models. This algorithm uses the supervised training technique where the network weights and biases are initialized randomly at the beginning of the training phase. The error minimization process is achieved using the gradient descent rule. There were three inputs: time (t, min), microwave power (P, W), absolute pressure (abs P, mbar) and two outputs: moisture ratio (MR) and drying rate (DR) in the developed ANN model (Figure 2).

Several transfer functions including sigmoid, logarithmic and linear functions together with supervised training algorithms and feed forward back-propagation approach were evaluated. To ensure that each input variable provides an equal contribution to the ANN, the inputs of the model were preprocessed and normalized, after which, 65 and 25% of 165 input patterns were devoted to training and validation data sets, respectively. The remaining 10% of the data was utilized for the tests. The learning rate of 0.2 and momentum of 0.1 were adjusted to all the tested networks. Optimum topologies were defined based on the highest R^2 and lowest mean square error (MSE) values. The complexity and size of the network was

Table 1. Selected mathematical models for describing the drying kinetics of button mushroom

Mathematical Expression	Model
$MR = \exp(-kt)$	Lewis [31]
$MR = a\exp(-kt)$	Henderson and Pabis [32-33]
$MR = \exp(-kt^n)$	Page [34]
$MR = a\exp(-kt) + (1-a)\exp(-kbt)$	Logarithmic [35]
$MR = a\exp(-kt) + (1-a)\exp(-gt)$	Verma *et al.* [36-37]
$MR = a\exp(-kt^n) + bt$	Midilli *et al.* [38]

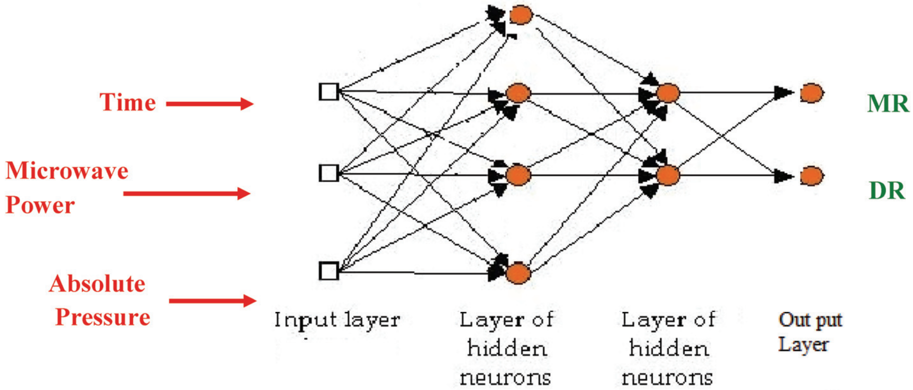


Figure 2. Configuration of multilayer (t, P, abs P) neural network for predicting MR and DR.

important, therefore the smaller ANNs had the priority to be selected [16,23]. The required codes were developed using MATLAB 2007.

RESULTS AND DISCUSSION

At the beginning of the drying process, due to the high initial moisture content of the mushroom, the drying rate was also high. Over time, the drying rate decreased owing to the reduction of moisture content (Figure 3). It can clearly be seen that mushroom lost the majority of its moisture within the first few minutes of drying while a long time is required to remove the remaining moisture. It is noteworthy that high microwave power and low absolute pressure led to lower moisture ratio at a reasonably shorter time (Figure 3). The highest drying rate is obtained at a reasonably high microwave power level (450 W). Rotation of dipole molecules (*e.g.*, water) is the main mechanism which explains the heat production in an object placed inside a microwave field. These molecules generally have a random direction but when inside a microwave field, they adapt themselves to the polarity of the field. It needs to be noted that with increasing the microwave power level, although the frequency is the same, but the energy density increases therefore produces more heat which leads to faster drying. Also, applying vacuum during drying results in the expansion of air

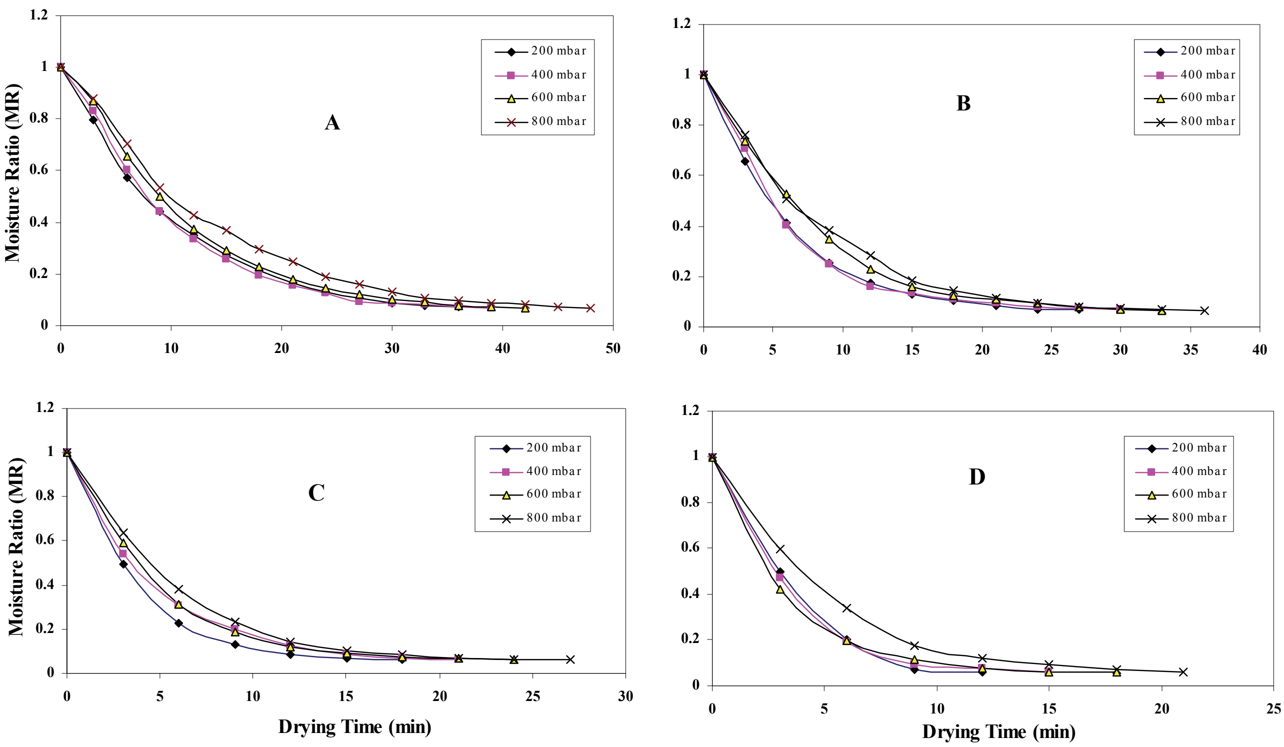


Figure 3. Influence of absolute pressure (200 ♦, 400 ■, 600 ▲ and 800 × mbar) on moisture ratio of mushroom slices dried at various microwave powers, A) 130, B) 260, C) 380 and D) 450 W.

and steam inside the foodstuff which forms a puffy structure. This structure of foodstuff leads to easier escape of moisture.

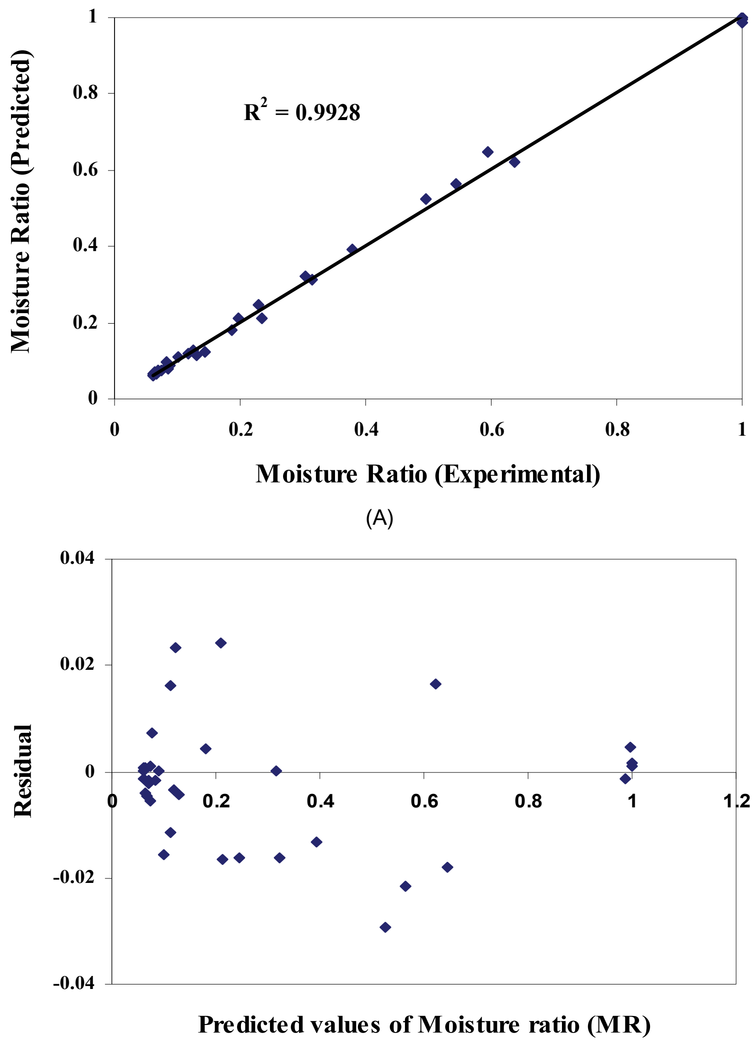
In the next step, the experimental data (the moisture ratios obtained at different absolute pressures and microwave powers) were fitted with various mathematical models (Table 1) and goodness of fit was evaluated based on R^2, χ^2 and *RMSE* values. The results showed that the model developed by Midilli *et al.* could predict mushroom thin layer drying kinetics more accurately than the others (Table 2).

Validation of the determined model was established by comparing the experimental data, for drying curve (in 380 W microwave power), with the values predicted by the Midilli *et al.* model and the results are plotted in (Figure 4a). The closeness of experimental data with regression line demonstrates the suitability of the model in describing the thin-layer drying behavior of the mushroom slice. In order to confirm the suitability of the selected model, the residual *versus* predicted values of moisture ratio were plotted (Figure 4b). As it can be seen, the proximity of residuals around zero line shows the sufficiency of the derived model. In this regard, it has been reported [24,25] that the fall of data points in a horizontal band centered on zero line displays no systematic tendencies toward a clear pattern. Therefore, there was no systematic pattern.

Figure 5 also shows the effects of absolute pressure and microwave power on the drying rate of mush-

Table 2. Fitting rate of mushroom drying kinetics (moisture ratio) with Midilli et al. model at various microwave power and absolute pressures

Absolute pressure mbar	Power, W											
	130			260			380			450		
	R^2	*RMSE*	χ^2	R^2	*RMSE*	χ^2	R^2	*RMSE*	χ^2	R^2	*RMSE*	χ^2
Midilli *et al.*												
200	0.9943	0.0335	0.00041	0.9943	0.0232	0.00919	0.9949	0.01478	0.00065	0.9988	0.01183	0.00021
400	0.9958	0.0324	0.00022	0.9943	0.2022	0.07494	0.9993	0.00870	0.00012	0.9993	0.01078	0.00020
600	0.9977	0.0341	0.00038	0.9998	0.1035	0.05362	0.9871	0.01018	0.01731	0.9999	0.01078	0.00032
800	0.9961	0.0260	0.00055	0.9911	0.01223	0.01869	0.9973	0.00632	0.00048	0.9911	0.00149	0.00078
Lewis												
200	0.9962	0.023	0.00055	0.9949	0.1983	0.00747	0.9981	0.01016	0.000175	0.9801	0.03532	0.03368
400	0.9934	0.021	0.00040	0.9973	0.1472	0.00389	0.9923	0.07709	0.001009	0.9879	0.02758	0.02054
600	0.9947	0.015	0.00022	0.9987	0.1013	0.00018	0.9914	0.03325	0.000176	0.9982	0.00112	0.003301
800	0.9965	0.022	0.00385	0.9973	0.1472	0.00389	0.9786	0.03593	0.009615	0.9986	0.00113	0.003337
Henderson and Pabis												
200	0.9521	0.0113	0.03337	0.9483	0.04113	0.05925	0.9674	0.04994	0.002993	0.9756	0.02014	0.004055
400	0.9605	0.0055	0.00976	0.9784	0.09261	0.00291	0.9688	0.05098	0.002859	0.9656	0.02014	0.004055
600	0.9092	0.0685	0.01693	0.9576	0.11545	0.00452	0.9409	0.03989	0.001752	0.9905	0.01591	0.002278
800	0.9267	0.0624	0.01366	0.9668	0.01304	0.00595	0.9855	0.02033	0.004134	0.9665	0.02012	0.004055
Page												
200	0.9855	0.0335	0.002472	0.9811	0.0276	0.00152	0.9951	0.00518	0.000725	0.9939	0.00207	0.00059
400	0.9671	0.0324	0.002211	0.9901	0.0276	0.00152	0.9898	0.00523	0.007129	0.9904	0.00317	0.00278
600	0.9857	0.0341	0.002447	0.9685	0.0624	0.00741	0.9802	0.00451	0.005294	0.9925	0.00785	0.00149
800	0.9914	0.0260	0.001360	0.9913	0.0276	0.00152	0.9933	0.00217	0.001183	0.9892	0.00533	0.00907
Logarithmic												
200	0.9861	0.0303	0.00712	0.9926	0.00528	0.00525	0.8774	0.19192	0.02325	0.9922	0.02055	0.00470
400	0.9599	0.0307	0.00811	0.9916	0.00669	0.00127	0.8932	0.17494	0.02022	0.9901	0.02279	0.00871
600	0.9882	0.0281	0.02618	0.9906	0.00508	0.00080	0.9453	0.05362	0.00722	0.9946	0.01731	0.00601
800	0.9899	0.0154	0.00996	0.9599	0.01282	0.00525	0.9915	0.01869	0.00810	0.8774	0.07919	0.02320
Verma *et al.*												
200	0.8932	0.0499	0.02020	0.9453	0.05531	0.00652	0.9925	0.02091	0.002274	0.9956	0.01586	0.00459
400	0.8553	0.1536	0.10350	0.9669	0.05510	0.00503	0.9881	0.0261	0.003611	0.9914	0.05477	0.00299
600	0.9435	0.0186	0.01223	0.9724	0.04631	0.00436	0.9783	0.01079	0.005935	0.9918	0.02251	0.00599
800	0.9622	0.0205	0.01478	0.9935	0.01941	0.00395	0.9421	0.05652	0.019172	0.9984	0.009603	0.00525



(B)

Figure 4. A) Comparison of experimental moisture ratio with predicted moisture ratio from the Midilli el al.'s model B) Residuals versus predicted values of moisture ratio for drying mushroom slice (microwave power 380 W, absolute pressure 400 mbar).

room during thin layer drying. As can be seen (Figure 5), at the early stages of drying (up to 5 min) the drying rate sharply increased followed by a steady decrease over time (falling rate period). Similar results have been reported for drying of other crops [26-29].

The fitting of drying rates at various levels of microwave power and absolute pressure with the presented model (Table 3) confirmed its suitability. Even though, the occurrence of some irregular variations, shallow depth of mushroom slice, was unable to keep moist the top layer during the whole drying time.

Artificial neural network modeling. Our findings (Figure 6) showed that the back propagation training algorithm was well suited for prediction of moisture ratio and drying rate based on different drying time, absolute pressure and microwave power levels. The prediction mean square error (*MSE*) values for training, validation and testing were 0.00086, 0.00042 and 0.0052, respectively.

ANN predictions for the *MR* and *DR* yielded determination coefficients (R^2) of 0.9991, 0.9995 and 0.9996 for training, validation and testing, respectively (Table 4). Furthermore, their predictions for *MSE* were 0.00086, 0.00042 and 0.00052, respectively.

Figure 7 shows the correlation between the experimental and prediction data in the test (for *MR* and *DR*) by the developed ANN model (test data) for mushroom slices dried at various microwave powers and absolute pressures. It can be seen that the determination coefficient is quite high for both *MR* and *DR*, which implies the desirability of ANN for prediction of drying kinetics of mushroom slices dried in a microwave drier. Similar results have been reported for other agriculture products [11,15-16,23].

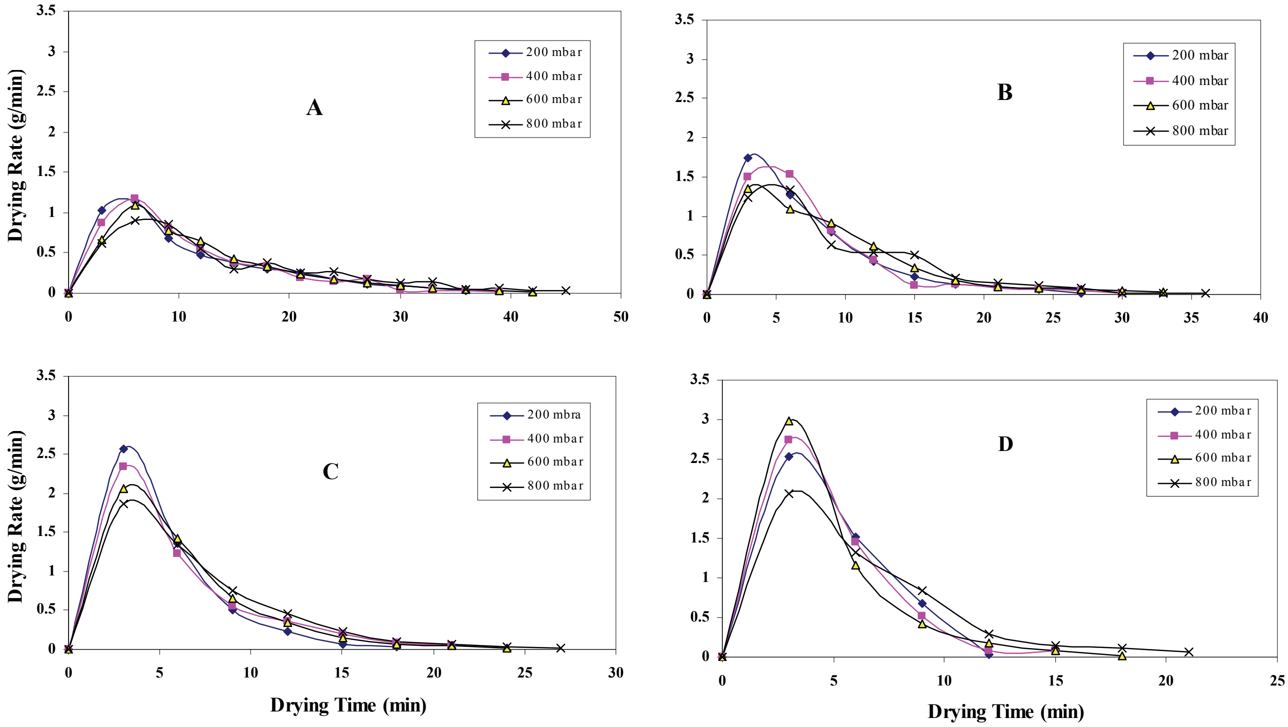


Figure 5. Influence of absolute pressure (200 ♦, 400 ■, 600 ▲ and 800 × mbar) on drying rate of mushroom slices during drying process at various microwave powers, A) 130, B) 260, C) 380 and D) 450 W/

Table 3. Fitting rate of mushroom drying kinetics (drying rate) with Eq. (7) at various microwave power and absolute pressure

Pressure, mbar	Power, W											
	130			260			380			450		
	R^2	*RMSE*	χ^2	R^2	*RMSE*	χ^2	R^2	*RMSE*	χ^2	R^2	*RMSE*	χ^2
200	0.8324	0.0263	0.0133	0.9076	0.01426	0.00913	0.9862	0.01871	0.00875	0.9771	0.03531	0.02493
400	0.8052	0.0422	0.02055	0.8832	0.01933	0.01046	0.9345	0.02282	0.01252	0.9363	0.03787	0.02581
600	0.7809	0.04732	0.02145	0.8631	0.02324	0.01561	0.9091	0.02892	0.01839	0.9496	0.03228	0.01979
800	0.7688	0.05601	0.02693	0.8956	0.01131	0.00345	0.9549	0.02159	0.01026	0.9548	0.01024	0.02915

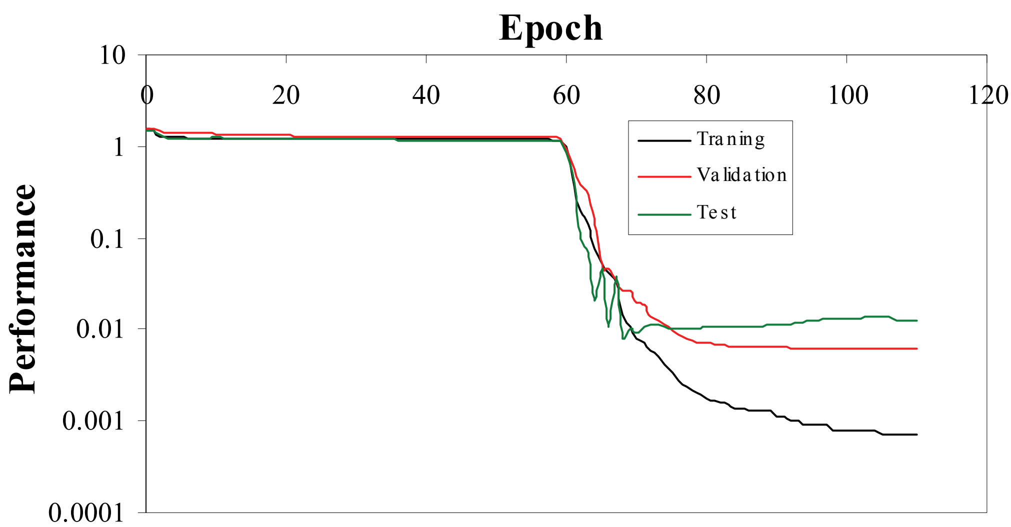


Figure. 6. Training error.

Table 4. Summary of the various ANN networks evaluated to yield the best determination coefficient (R^2) and mean square error

Activation function	Neurons in hidden layer 1	Neurons in hidden layer 2	Training error	R^2 (training)	R^2 (validation)	R^2 (test)	*MSE* (training)	*MSE* (validation)	*MSE* (test)	Epoch
Log/Tan	5	0	0.00025	0.9016	0.8775	0.8968	0.00028	0.00060	0.00373	51
Log/Tan	10	0	0.00064	0.9535	0.9041	0.9393	0.00059	0.00891	0.00239	62
Log/Tan	15	0	0.00013	0.9478	0.9404	0.9595	0.00059	0.00010	0.01264	69
Log/Tan	25	0	0.00085	0.9218	0.9662	0.9386	0.00071	0.00377	0.00735	59
Log/Tan	40	0	0.00096	0.9008	0.9341	0.9886	0.00081	0.00775	0.05605	77
Log/Tan/Tan	5	10	0.00014	0.8621	0.8571	0.8997	0.00011	0.00249	0.00308	89
Log/Tan/Tan	10	15	0.00053	0.9147	0.9486	0.9291	0.00044	0.00141	0.00220	96
Log/Tan/Tan	20	30	0.00034	0.9364	0.9529	0.9533	0.00021	0.00111	0.00307	134
Log/Tan/Tan	25	25	0.00070	0.9831	0.9943	0.9792	0.00054	0.00107	0.00056	149
Log/Tan/Tan	30	40	0.00070	0.9031	0.9287	0.8935	0.00011	0.00811	0.00388	174
Log/Tan/Tan	15	15	0.00086	0.9991	0.9995	0.9996	0.00037	0.00042	0.00052	112
Log/Tan/Tan	20	10	0.00015	0.9923	0.9983	0.9906	0.00069	0.00338	0.00811	124
Log/Tan/Tan	25	15	0.00044	0.9424	0.9083	0.9829	0.00072	0.00060	0.00373	129
Log/Tan/Tan	10	5	0.00082	0.9954	0.9971	0.9964	0.00012	0.00891	0.00239	89

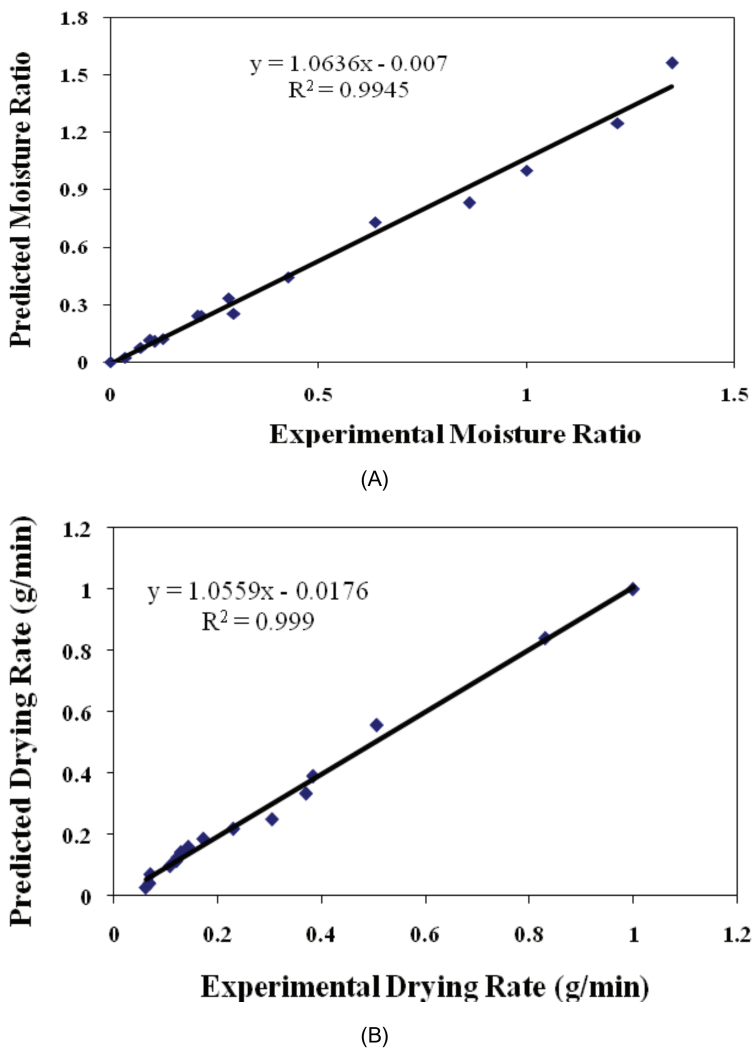
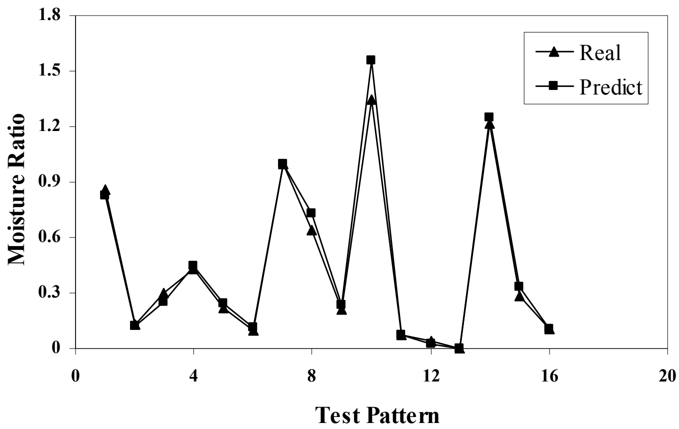


Figure 7. Correlation between the experimental data and ANN model for prediction of A) moisture ratio and B) drying rate (based on test data).

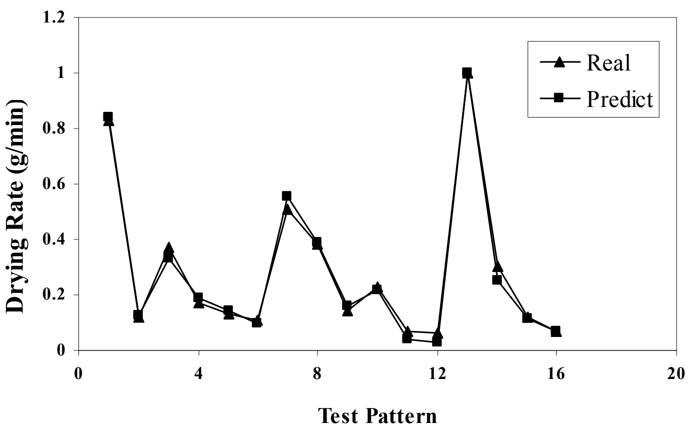
Figure 8 shows that the accuracy of predicted value is excellent for the moisture ratio and drying rate. The accuracy of ANN model is tested through the comparison of predicted and experimental mushroom slice moisture ratio and drying rate with test pattern during microwave-vacuum drying process. This figure shows the results of analysis for moisture ratio and drying rate, respectively. As can be seen, all the investigated prediction models simulate the experiments satisfactorily for both moisture ratio and drying rate. The developed network had a good generalization in predicting the drying quality (*MR* and *DR*) of the mushroom slice for test data during drying process. Thus, this network model could be used to determine the moisture ratio and drying rate of the agriculture product under the dynamic drying system. Similar results have been reported [14,30]. Moreover, our results have shown that the indicators for goodness of fit of the proposed ANN model are better than the values obtained by the mathematical model (comparison of Figures 4 and 7 and Tables 2 and 4). Therefore, the proposed ANN model was selected to represent the thin-layer drying behavior of mushroom.

CONCLUSION

Non-linear regression analysis was used to evaluate the capability of six thin-layer drying models to simulate microwave-vacuum drying of mushroom. Experimental data were obtained over wide range of microwave powers (130, 260, 380 and 450 W) and absolute pressures (200, 400, 600 and 800 mbar) in a laboratory microwave-vacuum drier. The mathematical model developed by Midilli *et al.* showed the best fit with the experimental data. Regarding the ANN algorithm, the selected model, 3-15-15-2 (3 neurons in input layer, 15 neurons in the hidden layer 1, 15 neurons in the hidden layer 2 and 2 neurons in the output layer) successfully learned the relationship between input and output parameters. The ANN results were quite satisfactory; R^2 values in this model were close to one, while mean square errors (*MSE*) were found to be very low. Analysis of the experimental data by the ANN revealed a good correlation between the ANN-predictions and the experimental data. Generally speaking, artificial neural networks performed better than mathematical models in predicting mois-



(A)



(B)

Figure 8. Comparison of experimental data and the ANN predictions for A) moisture ratio and B) drying rate (based on test data).

ture ratio and drying rate of mushroom slice during the drying process.

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NAUČNI RAD

POREĐENJE MATEMATIČKIH MODELA I VEŠTAČKIH NEURONSKIH MREŽA ZA PREDIKCIJU KINETIKE SUŠENJA GLJIVA U MIKROTALASNOJ VAKUUM SUŠNICI

Određene su karakteristike sušenja kolutova šampinjona u mikrotalasnoj vakuum sušnici pri različitim snagama (130, 260, 380 i 450 W) i apsolutnim pritiscima (200, 400, 600 i 800 mbar). Da bi se izabrao odgovarajući matematički model, 6 modela sušenja u tankom sloju su poređena sa eksperimentalnim podacima. Prihvatljivost modela je procenjena na osnovu tri parametra: najviši R^2, najniži Hi-kvadrat (χ^2) i korena srednje kvadratne greške (RMSE). Takođe, korišćenjem eksperimentalnih podataka, ANN, obučena po standardnom algoritmu povratne propagacije, razvijena je u cilju predikcije vrednosti odnosa vlage (MR) i brzine sušenja (DR)na osnovu tri ulazne promenljive veličine (vreme sušenja, apsolutni pritisak, snaga mikrotalasa). Različite aktivacione funkcije i nekoliko pravila su korišćeni za procenu procentualne greške između željenih i predviđenih vrednosti. Prema dobijenim rezultatima, model Midilli-ja i saradnika solidno fituje eksperimentalne podatke. Sa druge strane, ANN model ima veliku mogućnost vrlo dobre predikcije MR i DR vrednosti sa odlučujućim koeficijentima (R2) treniranja, validacije i testiranja od 0,9991, 0,9995 i 0,9996, respektivno. Osim toga, njegove prognoze srednje kvadratne greške su 0,00086, 0,00042 i 0,00052, respektivno.

Ključne reči: mikrotalasna-vakuum sušnica, gljive, matematički model, veštačke neuronske mreže.