Determination of the controlling resistance to moisture transfer during drying

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Summary

In this study the correlation between lag factor *G* and Page´s mathematical model parameter *n* was developed. Using the newly developed correlation the presence of internal or external resistance to moisture transfer during thermal drying can be verified. As modeling tools Artificial neural networks (ANN) and Adaptive neuro-fuzzy inference system (ANFIS) were used. The best model for determination and modeling of drying curves was selected using coefficient of correlation, chi-square, mean bias error, root mean square error and relative percentage error. Multilayer perceptron (MLP) ANN model with two hidden layers, nine neurons in each hidden layer, trained in 2500 epochs with hyperbolic activation function was found to be the most suitable for prediction of lag factor *G* values. The optimal model was used to develop new *G-n* correlation in polynomial form. When the drying behavior of particular material is described by Page´s model and the parameter *n* values are in the range $0.6<n<1.9$ new correlation can be used to calculate the lag factor *G*.

Keywords Artificial neural networks, Drying kinetics, Fuzzy Inference System, Mathematical modeling, Page´s model

Introduction

When various types of materials and driers are taken into consideration, there is no simple and elegant way for description of the drying kinetics (Sander et al., 2010). If one material is dried in different dryer types under equal conditions it produces different drying curves (Prlić Kardum et al., 2001) or if several materials are dried in one dryer type under equal conditions different drying curves will be produced, as well (Jurendić, 2010). Using the same mathematical model for description of drying curves in the first or second case mentioned above (one material-different dryer type; different materials-one dryer type) several values of mathematical model parameter can be obtained. The study of drying behavior of different materials has been of great interest for many researchers for a long time. Many mathematical models have been used to describe the drying processes, but thin layer drying models are the most common models used nowadays (Mohammadi et al., 2008). Thin layer models are equations aimed to describe the drying phenomena in a combined way, despite of the controlling mechanism, and have been used to estimate drying times for several products and to access drying curves (Guiné et al., 2009). Several, more or less complicated, empirical mathematical models which can be used to describe drying kinetics are available in literature. Each of such models has one or more parameters that are represented as a function of drying conditions (Mohammadi et al., 2008). There are two models of a particular interest for this work, Henderson-Pabis and Page`s model. The aim of this study is to develop new lag factor *G* and Page´s model parameter *n* correlation *G-n* used in indication of the resistance (internal or external) to moisture transfer during drying. In order to estimate the best correlation between experimental data of lag factor *G* and parameter *n* Artificial neural network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) were used as modeling tools.

Theoretical background

Henderson-Pabis model

Henderson-Pabis model for describing of drying kinetics is defined as follows (Mrkić et al., 2007):

$$\frac{X(t)-X_e}{X_0-X_e}=Ge^{-kt} \tag{1}$$

G is the lag factor, indicating the internal resistance in the wet solid to moisture transfer during drying (Dincer and Hussain, 2004). Lag factor *G* can be also defined as the indicator of magnitude of both internal and external resistance of an object to the heat or moisture transfer in course of drying time (Dincer and Dost, 1995; Mrkić et al., 2007).

As shown by Dincer and Hussain (2004) using lag factor *G* the Biot number Bi_m can be calculated through Bi_m-*G* correlation. Bi_m-*G* correlation was successfully applied for microwave drying of lactose powder

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(McMinn, 2004) and for tunnel drying of baby food (Jurendić and Tripalo, 2011).
Biot number Bi_m is one of the most important dimensionless drying parameters, indicating whether internal or external resistance to mass transfer prevails (Mrkić et al., 2007). When the value for Bi_m number $Bi_m \leq 0.1$ negligible internal resistance to the mass diffusivity within the solid is present, when $0.1 < Bi_m < 100$ exists the finite internal and surface resistances and $Bi_m \geq 100$ negligible surface resistance at the solid object is present (Dincer and Dost, 1995).
If lag factor G takes values between 1 and 2.2732 for infinite slab object, between 1 and 1.6021 for infinite cylindrical object and between 1 and 2 for spherical object, the Biot number has the value in the range $0.1 < Bi_m < 100$ (Dincer and Dost, 1996). When the lag factor G takes values higher than the above mentioned, it corresponds to $Bi_m > 100$ (Dincer and Dost, 1996). It can be observed when the drying behavior of the dried material is described by Henderson-Pabis model the Biot number Bi_m can be easily calculated through Bi_m-G correlation presented by McMinn (2004).
However, when other mathematical model describes drying kinetics and the drying behavior of dried material, the presence of internal or external resistance to moisture transfer cannot be verified.

Page's model

One of the most frequently used equations during the past few decades has been the Page´s mathematical model, because of its very good correlation with the drying experimental data (Sander et al., 2010). This model can be found as adequate in describing drying behavior of many materials. For instance, conductive, convective and irradiative drying of cereal based baby foods (Jurendić, 2010), convective drying of lemon grass (Ibrahim et al., 2009) and many other examples can be found in literature.
Page`s model is given by the following relation (Sander et al., 2010):

$$\frac{X(t) - X_e}{X_0 - X_e} = e^{-kt^n} \qquad (2)$$

where k and n are model parameters.

Values of k and n vary for each material being considered (Yadollahinia et al., 2008). Parameter n is of particular interest for this work because it is used for development of a new correlation. In literature many examples where the parameter n was expressed as a function of drying conditions can be found.

Artificial neural networks

ANN is a powerful data modeling tool (Ochoa-Martinez and Ayala-Aponte, 2007). It does not require parameters of physical models, has an ability to learn from experimental data, and is capable to handle complex systems with nonlinearities and interactions between decision variables (Lertworasirikul, 2008). ANNs permit an adequate and precise prediction of the drying process in industrial application (Nazghelichi et al., 2011) and have been used in food drying applications by many researchers (Assidjo et al., 2008; Khoshal et al., 2010; Kingsly and Singh, 2007; Menlik et al., 2010; Movagharnejad and Nikzad, 2007; Omid et al., 2009; Raisul Islam et al., 2003; Topuz, 2010).

Adaptive Neuro-Fuzzy Inference System

ANFIS is heuristic model which has gained momentum for process modeling and can be used as a good tool to improve the efficiency of food process control (Lertworasirikul, 2008). In ANFIS are connected fuzzy inference systems (FIS) and ANN. FIS are based on the concept of fuzzy logic and fuzzy set theory (Lertworasirikul, 2008). Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic, where the mapping then provides a basis from which decisions can be made (Ozcep et al., 2010). Fuzzy logic is a generalization of the binary logic where truth-values in the range (0; 1) are assigned to variables (Odejobi and Umoru, 2009).
Neuro-fuzzy models are able to take advantage of the fuzzy inference mechanism capabilities in fuzzy logic and the learning ability of neural networks. The ANN technique is usually used as the learning algorithm for the defuzzification process in fuzzy logic based models (Odejobi and Umoru, 2009). Using a given data set, ANFIS constructs a FIS whose membership functions parameters are adjusted using back propagation or hybrid algorithm. This way fuzzy inference system learns from the modeling data. Detailed description of ANFIS was given by Lertworasirikul (2008).

Materials and Methods

Data collection

To develop adequate mathematical model for new G-n correlation 189 experimental data from published literature sources (Table 1) were used. For calculations no selections according drying techniques, drying conditions or materials were made. To be suitable for the analysis in this work reported data should contain values for lag factor G and Page´s model parameter n obtained in the same drying process. It was observed that the most parameters *n* values presented in the literature used in this work are in the range $0.6<n<1.9$ and only these values were taken into consideration for newly developed correlation.

Table 1. Material characteristics and drying conditions of selected literature sources

Material		Drying conditions			Literature
Name	*Aggregate State*	*Dryer type*	*Temperature (°C)*	*Air velocity (m/s)*	
Nigerian popcorn	solid	rotary dryer	50, 60, 70, 80	0.83, 1.397, 2.79	Ademiluyi et al., 2008
Cocoa beans	solid	solar drying	29-30	0.76-1.21	Akmel et al., 2009
Durian chips	solid	microwave vacuum	-	-	Bai-Ngew et al., 2011
Wastewater sludge	semiliquid	convective belt dryer	120, 122, 140, 147, 158	1.58, 1.68, 1.73, 1.79, 1.82	Bennamoun et al., 2010
Grapes	solid	hot air + microwave	60	-	Bingol et al., 2008
Olive oil sludge	semiliquid	air dryer	20, 40, 80	1	Celma et al., 2007
Carrots	solid	microwave vacuum	-	-	Changrue and Orsat, 2009
Rice	solid	convective	40	1.5	Cihan et al., 2007
Grapes	solid	sun drying	-	-	Doymaz, 2011
Leek	solid	cabinet dryer	50	-	Doymaz, 2008
Canola	solid	betch fluidised dryer	30-100	1	Gazor and Mohsenimanesh, 2010
Pear	solid	solar drying	-	-	Guiné et al., 2009
Pears	solid	solar dryer, tunnel dryer	41	1.1	Guiné, 2010
Tomato	solid	solar dryer	-	-	Gürlek et al., 2009
Cocoa beans	solid	air oven + solar	60		Hii et al., 2008
Cocoa beans	solid	oven drying	60, 70, 80	0.01	Hii et al., 2009
Thai red curry	paste	microwave, hot air	60, 70, 80	9.02	Inchuen et al., 2008
Lemon Grass	solid	convective	35, 45, 55	1	Ibrahim et al., 2009
Baby foods (wheat, soya and corn)	semiliquid	tunnel dryer, infrared dryer, drum dryer	60, 80, 100 60, 80, 100 -	0.5, 1, 1,5	Jurendić, 2010
Sesame seeds	solid	natural and forced convective	25-35	0-15	Khazaei and Daneshmandi, 2007
Carrot pomace	paste	hot air	60, 65, 70, 75	0.7	Kumar et al., 2011
Onion	solid	hot air	50, 60, 70	0.66	Lee and Kim, 2008
Zizyphus jujuba Miller	solid	vacuum	50, 60, 70	-	Lee and Zuo, 2011
Pine forest residues	solid	hot air	40, 50, 60, 70, 80	0.3 - 0.35	Phanphanich and Mani, 2009
Drumstick leaves	solid	hot air	50, 60, 70, 80	0.5	Premi et al., 2010
Pandanus amaryllifolius leaves	solid	heat pump dryer; hot air	35, 45	-	Rayaguru and Routray, 2010
Pepper	solid	bed dryer	45, 55, 65	1	Reis et al., 2011
Grape seeds	solid	convective	40, 50, 60	1.5	Roberts et al., 2008
Hull-less seed pumpkin	solid	hot air and solar tunnel dryer	40, 50, 60	0.8	Sacilik, 2007a
Tomato	solid	air dryer	50, 60, 70	0.8	Sacilik, 2007b
Grapes	solid	convective	50, 60, 70, 80	0.25, 0.5, 0.75, 1	Sawhney et al., 2009
Banana	solid	fixed bed dryer	50, 60, 70	1.5	Sant'Ana Silva, 2009
Perlette grapes	solid	circulated tray dryer	60	-	Thakur et al., 2010
Cassava chips	solid	hot air	60	1.5	Tunde-Akintunde and Afon, 2010
Red bell paper	solid	convective dryer	50, 60, 70, 80	2.5	Vega et al., 2007
Gracilaria algae	solid	convective	30, 40, 50, 60, 70	2	Vega-Galvez et al., 2007
Aloe vera leaves	solid	hot air	70	2	Vega-Galvez, 2011
Apple pomace	semiliquid	microwave	-	-	Wange et al., 2007
Sultana Grape	solid	cabinet dryer	37-53	4.7-9.3	Zomorodian and Dadashzadeh, 2009
Cuminum cyminum	solid	cabinet solar dryer	10-23	1.15, 1.75, 2.05	Zomorodian and Moradi, 2010

Artificial neural networks

ANNs were used as a modeling tool because of their feature to generate better predictions than the classical linear regression (Odejobi and Umoru, 2009). For this purpose *Statistica 7* software was applied. Beside many different ANN architectures (Odejobi and Umoru, 2009) in this paper Multilayer Perceptron (MLP) was used. The input layer has one node (parameter n) and the output layer has also one node (lag factor G). MLP with different number of hidden layers (1, 2 and 3) and neurons (3, 6, 9, 12 and 15) in the hidden layers were tested. MLP model that consists of one input layer, one or more hidden layers and one output layer, is the most common flexible and general purpose kind of ANN (Rai et al., 2005). Hyperbolic functions in hidden layers and linear regression output function as activation functions were used. In order to find the optimal ANN structure the experimental data are randomly divided into training, validation and test set. There is no single method that works best in order to determine the data number in each set (Çakmak and Yildiz, 2011). A general opinion is that the data number of training set is selected more than that of the other two sets so as to increase the learning capability of the network (Çakmak and Yildiz, 2011). In this work 94 data were used for training, 47 for validation and 47 for testing. Two-phase training procedure was applied for training of MLP. In the phase one back propagation algorithm and in the phase two Levenberg-Marquardt algorithm were applied. The learning rate for the phase one was equal to 0.1 and the momentum term to 0.3. For optimizing the network 500-2500 epochs were tested. The number of hidden layers and neurons in each layer was sought by trial and error methods, whereas evaluation criteria statistical parameters (see *Statistical analysis*) were used. Using this approach the optimal ANN structure was selected.

As proposed by Ochoa-Martinez and Ayala-Aponte (2007), the training process should be repeated several times in order to get the best performance of the ANN, because there is a high degree of variability due to the fact that first estimates of weights and biases are always different. After the repeated training process the best ANN model was further tested using different combination of activation functions (Table 3) in hidden layer in order to find better correlation between experimental and predicted data. Other conditions as learning rate, momentum term, linear output layer function and training algorithm were the same as earlier.

Adaptive Neuro-Fuzzy Inference Systems

Using Fuzzy Logic Toolbox in MATLAB 7.0 the Sugeno type FIS was used to estimate new G-n correlation. Sugeno´s FIS uses the following rule (Lertworasirikul, 2008):

IF parameter n is x
THEN lag factor G is $ax+b$

For the MLP model 189 data were divided into three sets: training, validating and testing. Input was Page´s model parameter n with the fuzzy set with triangular-shaped built-in membership function. Output was lag factor G with output linear function. Input function was generated by a grid partition. As the FIS optimization method the hybrid algorithm was used. The number of membership functions was 2, 3 and 4. Learning was stopped when the error tolerance was 0. After the learning process the parameters of models were estimated. The best model was selected using statistical analysis.

Statistical analysis

The goodness of fit between experimental and predicted data was determined by various statistical parameters such as coefficient of correlation R, reduced chi-square χ^2, mean bias error MBE, root square error $RMSE$ and the relative percentage error PE. For quality fit R value should be higher and χ^2, MBE, $RMSE$ and PE values should be lower (Roberts et al. 2008; Sacilik 2007). Statistical parameters were calculated as follows (Ibrahim et al., 2009; Roberts et al., 2008):

Chi-square χ^2:

$$\chi^2 = \frac{1}{N-n}\sum_{i=1}^{N}(G_{\exp} - G_{pred})^2 \tag{3}$$

Mean bias error MBE:

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(G_{\exp} - G_{pred})^2 \tag{4}$$

Root mean square error $RMSE$:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(G_{\exp} - G_{pred})^2} \tag{5}$$

Relative percentage error *PE*:

$$PE = \frac{100}{n}\sum_{i=1}^{N}\frac{\left|G_{\exp} - G_{pred}\right|}{G_{\exp}} \qquad (6)$$

G_{exp} value is lag factor *G* taken from experimental literature data and G_{pred} is the lag factor *G* calculated through ANN or ANFIS model. To indicate good fit the relative percentage error should be lower than 10 % (Roberts et al., 2008).

Results and Discussion

Using experimental drying data where for mathematical modeling drying kinetics of the same drying process both Page´s and Henderson-Pabis model were applied and the parameter *n* and lag factor *G* were calculated, very similar behavior of both parameters *n* and *G* follow can be observed. It can be seen, when the value of *n* is $n<1$ then the value of *G* is $G<1$, and when the value of *n* is $n>1$, the value of *G* is $G>1$.

Among all 189 experimental data only some data (4.7 %) do not follow above described rule. These exceptions are observed when the material was dried on the temperatures 65 °C or lower. It might be due to the fact that at higher drying temperatures drying curves become steeper (Lee and Kim, 2008) and at lower drying temperatures smoother. Because of different mathematical models (Eq. 1 and 2) and different position of parameters *G* and *n* in models the difference in their values can be observed. At lower drying temperatures (smooth drying curve) the differences between *G* and *n* values are more expressed and they have resulted in their higher discrepancy.

Among all experimental data used in this work in 129 data the lag factor *G* takes value $G>1$, indicating finite internal and surface resistances (Dincer and Dost, 1996). In other 60 data *G* value were $G<1$, implying a negligible internal resistance to moisture transfer within a material. Generally, it can be observed that the values of $G>1$ in literature data used in this work dominate.

Fig. 1 shows plot of experimental data used in this work and confirms the above mentioned behavior of lag factor *G* and parameter *n*. Non-linear relations between lag factor *G* and parameter *n* can be observed.

In order to find the optimal MLP structure different combination of hidden layers (1, 2 and 3), neurons (3, 6, 9, 12 and 15) and epochs (500, 1000, 1500, 2000 and 2500) were tested.

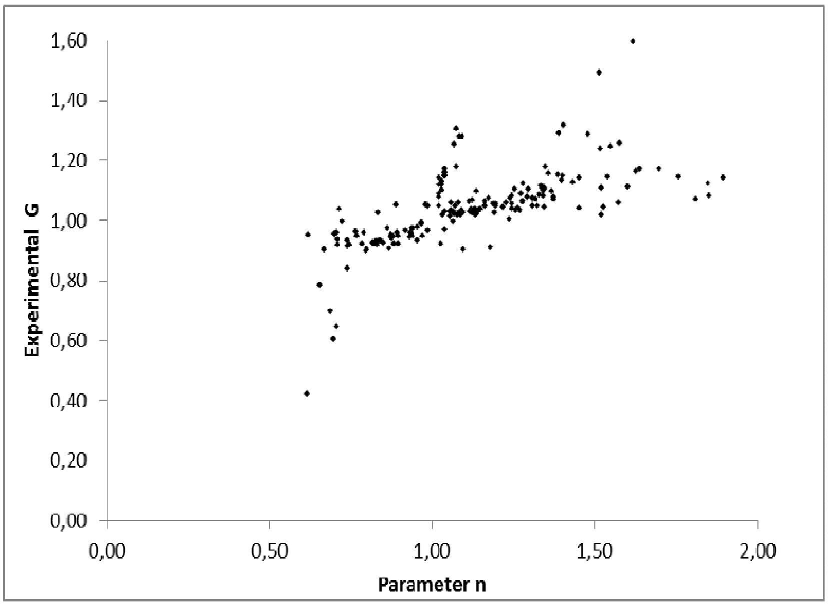

Fig. 1. Correlation between experimental lag factor G and parameter n

Fig. 2-4 show the behavior of coefficient correlation *R* values when MLP was trained with different hidden layers, epochs and number of neurons. The irregular dependency between R values and chosen hidden layers, epochs and number of neurons can be explained by using of the ANN as a soft modeling tool. Increasing number of neurons and epochs within the same hidden layer did not lead to higher *R* values. Higher *R* values were observed by increasing of hidden layer number. Using only one hidden layer the

R values were *R=0.73*, wherever by using two or three hidden layers the obtained maximum *R* values were *R>0.76*. The results have shown that using only one hidden layer in MLP structure without testing two or more hidden layers can be inadequate to obtain a good model.

Among all 75 tested combinations the highest *R* value (*R>0.79*) was obtained by MLP structure with 2 hidden layers and 9 neurons in each layer when trained in 2500 epochs. For the given neural network the calculated statistical parameters had the following values: $\chi^2=0.00733$, $MBE=0.0073$, $RMSE=0.08543$ and $PE=5.16$ %. Obtained *PE* value for this neural network structure is lower than 10 % what indicates a good fit (Roberts et al., 2008).

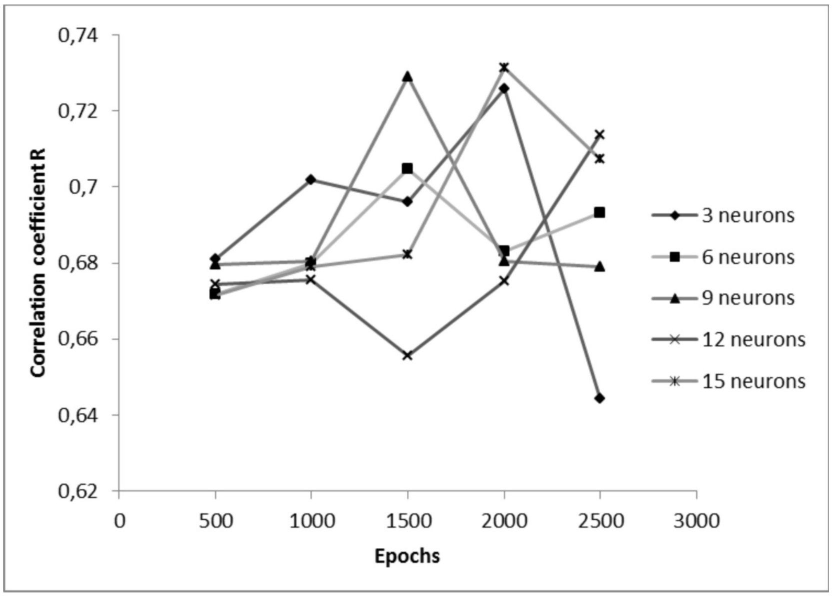

Fig. 2. Variation of correlation coefficients R versus epochs after MLP training in one hidden layer with different neuron numbers

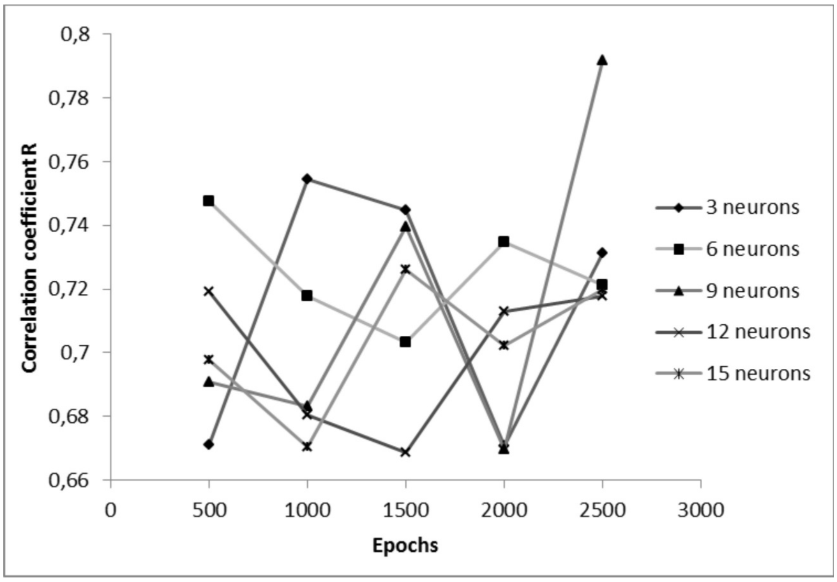

Fig. 3. Variation of correlation coefficients R versus epochs after MLP training in two hidden layers with different neuron numbers

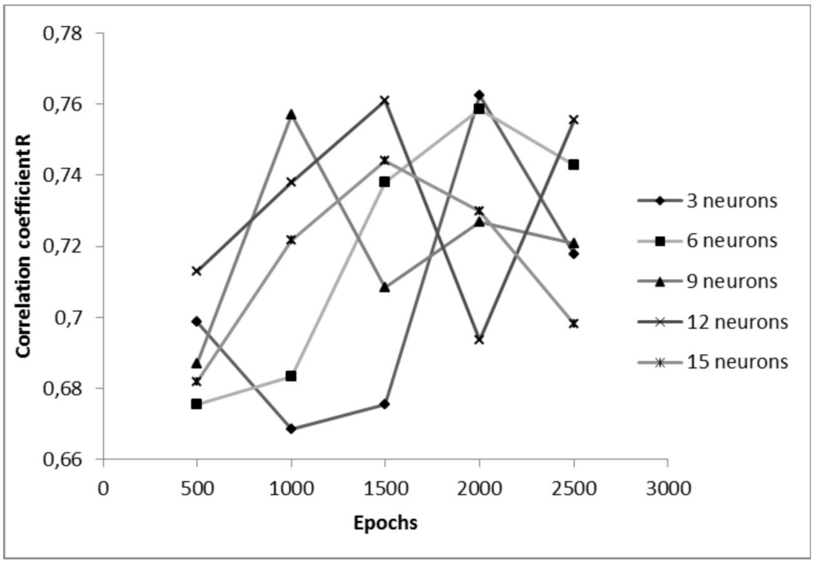

Fig. 4. Variation of correlation coefficients R versus epochs after MLP training in three hidden layers with different neuron numbers

The training process was repeated 10 times and the results are presented in Table 2. It can be seen that the best performance was achieved in the first training and further repeating did not improve the performance of ANN.

Using the optimal ANN model the performance analysis for different types of activation functions (Table 3) in hidden layers 1 and 2 was evaluated. Table 4 shows statistical analysis of all combinations of chosen hidden layer activation functions. All tested combinations did not improve the performance of developed ANN. Good results were obtained using the combination of logistic and hyperbolic activation functions but the best performance was obtained by using hyperbolic function in both hidden layers.

Table 2. Statistics parameters obtained by repeated ANN training process

Number of Repeating	*R*	χ^2	*MBE*	*RMSE*	*PE*
1	**0.79171**	**0.00733**	**0.0073**	**0.08543**	**5.16383**
2	0.75238	0.01863	0.01854	0.13615	10.04587
3	0.75324	0.01019	0.01014	0.10068	8.37901
4	0.75963	0.01385	0.01378	0.11737	9.65142
5	0.76149	0.01732	0.01723	0.13128	11.26829
6	0.74513	0.02248	0.02237	0.14955	10.2392
7	0.76115	0.0141	0.01403	0.11843	9.48905
8	0.75777	0.01949	0.0194	0.13927	10.31133
9	0.75977	0.01598	0.0159	0.12609	9.78778
10	0.75751	0.01849	0.0184	0.13564	9.0319

Table 3. Activation functions

Name	Function	Definition	Range
A	Logistic	$1/(1-e^{x})$	(0,1)
B	Hyperbolic	$(e^{x}-e^{-x})/(e^{x}+e^{-x})$	(-1,1)
C	Unit sum	$x/\sum_i x_i$	(0,1)
D	Sin	Sin (x)	[0,1]

Table 4. Statistical parameters of the selected neural network structure using different combinations of transfer functions

Hidden layer 1	Hidden layer 2	*R*	χ^2	*MBE*	*RMSE*	*PE*
A	A	0.75443	0.01866	0.01856	0.13624	10.63626
B	B	**0.79171**	**0.00733**	**0.0073**	**0.08543**	**5.16383**
C	C	0.22768	0.01987	0.01977	0.14061	8.97784
D	D	0.41473	0.05745	0.05716	0.23907	13.82188
A	B	0.68607	0.02183	0.02172	0.14738	11.84951
A	C	0.72949	0.01511	0.01503	0.12261	10.21516
A	D	0.13837	0.0281	0.02795	0.16719	11.13324
B	A	0.75808	0.00833	0.00828	0.09101	5.31057
B	C	0.71522	0.00969	0.00964	0.09819	5.98457
B	D	0.07677	0.0252	0.02507	0.15834	11.27678
C	A	0.04996	0.02075	0.02064	0.14368	9.26195
C	B	0.32193	0.01794	0.01784	0.13358	8.37662
C	D	0.04996	0.01945	0.01935	0.13911	8.39942
D	A	0.74217	0.0092	0.00915	0.09568	5.75402
D	B	0.74493	0.00883	0.00878	0.09372	5.70106
D	C	0.66862	0.01208	0.01202	0.10965	7.0864

The results from the learning process of the ANFIS model were shown in Table 5. The correlation coefficients *R* have the same values despite of various number of membership functions. The second ANFIS model with 3 membership function was chosen to be the best because of the lowest PE (*PE=8.68 %*).

Table 5. Statistical parameters from the learning process of ANFIS model

ANFIS	*R*	χ^2	*MBE*	*RMSE*	*PE*
2-1	0.63574	0.02787	0.02773	0.16653	15.5787
2-2	0.63574	0.03613	0.03595	0.18959	13.6854
3-1	0.63574	0.03134	0.03119	0.17659	17.20536
3-2	0.63574	0.01586	0.01578	0.1256	8.67729
3-3	0.63574	0.04153	0.04132	0.20328	14.64598
4-1	0.63574	0.03277	0.03261	0.18057	17.84915
4-2	0.63574	0.01669	0.01661	0.12888	9.23388
4-3	0.63574	0.02036	0.02025	0.14232	10.21801
4-4	0.63574	0.04376	0.04354	0.20867	15.01043

The predicted values derived from ANFIS model were compared with the selected ANN model, and the comparison indicates that the ANN performed much better than the ANFIS. The ANN selected model was the best model for the prediction of lag factor *G* in this work.

Using predicted lag factor *G* values obtained by ANN model further analysis was conducted. Nonlinear regression analysis (NLR) in *Microsoft Office Excel 2007* software was used to develop new correlation between experimental and predicted lag factor *G*. Different mathematical functions (linear, exponential, polynomial, power and logarithmic) were tested. The best results ($R>0.83$, $\chi^2=0.00726$, $MBE=0.00722$, $RMSE=0.08497$ and $PE=5.11$ %) were obtained using power model in the following form:

$$G = 1.0009 G_{pred}^{0.9387} \tag{7}$$

Fig. 6 shows correlation between predicted lag factor *G* and experimental parameter *n* values. The adequate model was sought using NLR. The best prediction of *G* values in dependence on *n* values to experimental data was observed by polynomial model ($R>0.89$) in the following form:

$$G = -3.8494n^4 + 18.793n^3 - 33.464n^2 + 26.084n - 6.5405 \tag{8}$$

To verify the developed correlation 10 randomly chosen literature data (Lahsasni et al., 2004; Martinazzo et al., 2007; Premi et al., 2010; Saeed, 2010; Sharma et al., 2005), where the lag factor *G* and parameter *n* values were present, were tested. New *G-n* correlation was used for calculating the lag factor *G*. The statistical analysis ($R>0.83$, $\chi^2=0.00097$, $MBE=0.00088$, $RMSE=0.0296$ and $PE=2.62$ %) shows a very good approximation of experimental lag factor *G* using new *G-n* correlation. *PE* value is much lower than 10 % indicating a very good fit.

The developed *G-n* correlation between lag factor *G* and parameter *n* can be used to calculate the lag factor *G* and to determine whether *G* value is higher or lower than 1, when the drying behavior of dried material is described by Page´s model. As shown by McMinn (2004) and Dincer and Dost (1995) knowing the value of lag factor *G* is very important because of indicating whether internal or external resistance to moisture transfer during drying dominates. The estimated *G* values can be used to calculate Biot number Bi_m and moisture transfer parameters through Bi_m-*G* correlation (McMinn, 2004).

This way the importance of Page´s mathematical model and included parameter *n* was further enhanced.

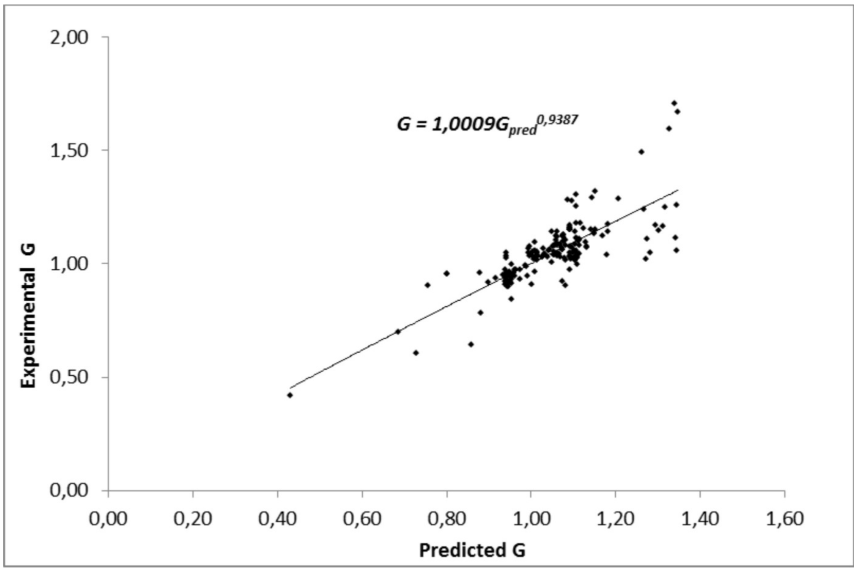

Fig. 5. Correlation between experimental and predicted lag factor G values obtained by ANN model

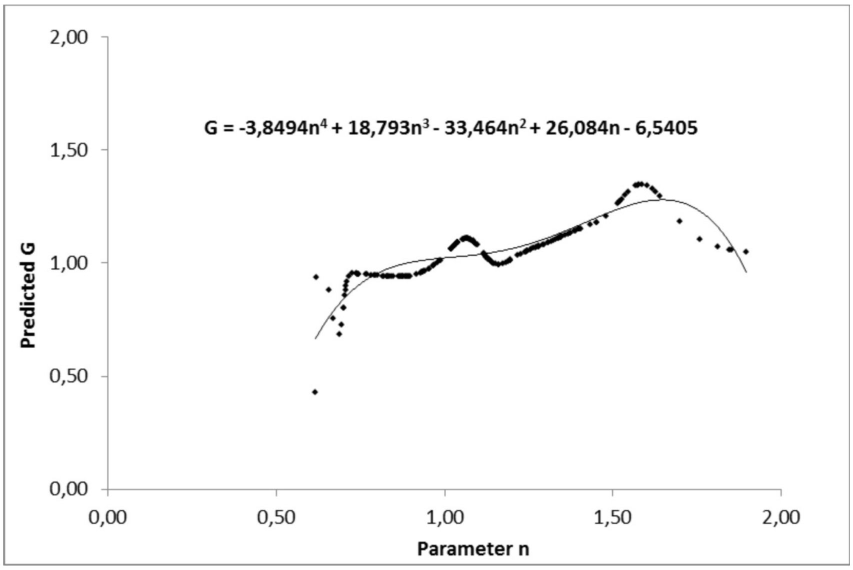

Fig. 6. Correlation between predicted lag factor G obtained by ANN model and parameter n

Conclusions

Artificial neural networks have shown very good applicability as a modeling tool in order to obtain new correlation *G-n* between lag factor *G* and Page´s model parameter *n*. Compared to ANFIS model, ANN model performed better to experimental data. Developed polynomial correlation *G-n* between lag factor *G* and parameter *n* can be applied in order to calculate the lag factor *G* using parameter *n* and to indicate whether internal or external resistance to moisture transfer within the dried material dominates. The applicability of Page´s model for indicating of moisture transfer resistance during drying was confirmed.

Nomenclature

$X(t)$ – moisture content (kg water/kg dry basis)
X_0 – initial moisture content (kg water/kg dry basis)
X_e – equilibrium moisture content (kg water/kg dry basis)
G – lag factor
k, n – model parameters
Bi_m – Biot number

References

Ademiluyi, T., Oboho, E.O., Owudogu, M. (2008): Investigation into the Thin Layer Drying Model of Nigerian Popcorn Varieties, *Leonardo El J Pract Technol* 13, 47-62.

Akmel, D.C., Assidjo, N.E., Kouamé, P., Yao, K.B. (2009): Mathematical Modelling of Sun Drying Kinetics of Thin Layer Cocoa (Theobroma Cacao) Beans, *J Appl Sci Res* 5(9), 1110-1116.

Assidjo, E., Yao, B., Kisselmina, K., Amané, D. (2008): Modeling of an industrial drying process by artificial neural networks, *Braz J Chem Eng* 25(3), 515-522.

Bai-Ngew, S., Therdthai, N., Dhamvithee, P. (2011) Characterization of microwave vacuum dried durian chips, *J Food Eng* 104, 114-122.

Bennamoun, L., Belhamri, A., Léonard, A. (2010): Contribution to the modelling of wastewater sludge drying kinetics: study of the operating conditions effect. In: Proceedings of 17th International Drying Symposium (IDS 2010), Magdeburg, Germany, pp. 828-833.

Bingol, G., Pan, Z., Roberts, J.S., Devres, Y.O., Balaban, M.O. (2008) Mathematical modeling of microwave-assisted convective heating and drying of grapes, *Int J Agric & Biol Eng* 1(2), 46-54.

Çakmak, G., Yildiz, C. (2011): The prediction of seedy grape drying rate using a neural network method, *Comput Electron Agr* 75, 132-138.

Celma, A.R., Rojas, S., López, F., Montero, I., Miranda, T. (2007): Thin-layer drying behaviour of sludge of olive oil extraction, *J Food Eng* 80, 1261-1271.

Cihan, A., Kahveci, K., Hacihafizoğlu, O. (2007): Modelling of intermittent drying of thin layer rough rice, *J Food Eng* 79, 293-298.

Changrue, V., Orsat, V. (2009): Osmotically dehydrated microwave vacuum drying of carrots, *Can Biosyst Eng* 51, 3.11-3.19.

Dincer, I., Dost, S. (1995): An analytical model for moisture diffusion in solid objects during drying, *Drying Technol* 13(1&2), 425-435.

Dincer, I., Dost, S. (1996): A modeling study for moisture diffusivities and moisture transfer coefficients in drying of solid objects, *Int J Energy Res* 20, 531-539.

Dincer, I., Hussain, M.M. (2004): Development of a new Biot number and lag factor correlation for drying applications, *Int J Heat Mass Transfer* 47, 653-658.

Doymaz, I. (2011): Sun drying of seedless and seeded grapes, *J Food Sci Technol* doi:10.1007/s13197-011-0272-9.

Doymaz, I. (2008): Influence of blanching and slice thickness on drying characteristics of leek slices, *Chem Eng Process* 47(1), 41-47.

Gazor, H.R., Mohsenimanesh, A. (2010): Modelling the Drying Kinetics of Canola in Fluidised Bed Dryer, *Czech J Food Sci* 28, 531-537.

Guiné, R.P.F. (2010): Analysis of the drying kinetics of S. bartolomeu pears for different drying systems, *Electron. J Environ Agric Food Chem* 9(11), 1772-1783.

Guiné, R., Lopes, P., Joao Barroca, M., Ferreira, D.M.S. (2009): Effect of ripening stage on the solar drying kinetics and properties of S. bartolomeu pears (Pyrus communis L.), *Int J Acad Res* 1(1), 46-52.

Gürlek, G., Özbalta, N., Güngör, A. (2009): Solar tunnel drying characteristics and mathematical modelling of tomato, *J Therm Sci Technol* 29(1), 15-23.

Hii, C.L., Law, C.L., Cloke, M. (2008): Modelling of thin layer drying kinetics of cocoa beans during artificial and natural drying, *J Eng Sci Technol* 3(1), 1-10.

Hii, C.L., Law, C.L., Cloke, M. (2009): Modeling using a new thin layer drying model and product quality of cocoa, *J Food Eng* 90, 191-198.

Ibrahim, M., Sopian, K., Daud, W.R.W. (2009): Study of the drying kinetics of Lemon Grass, *Am J Appl Sci* 6(6), 1070-1075.

Inchuen, S., Narkrugsa, W., Pornchaloempong, P., Chanasinchana, P., Swing, T. (2008): Microwave and hot-air drying of Thai red curry paste, *Maejo Int J Sci Technol* 1, 38-49.

Jurendić, T. (2010) Numerical model of baby food drying on drum dryer, *Ph.D. Thesis*, University of Zagreb, Croatia.

Jurendić, T., Tripalo, B. (2011): Biot-number – lag factor (Bi-G) correlation for tunnel drying of baby food, *Afr J Biotechnol* 10(59), 12706-12713.

Khazaei, J., Daneshmandi, S. (2007): Modeling of thin-layer drying kinetics of sesame seeds: mathematical and neural networks modeling, *Int Agrophys* 21, 335-348.

Khoshhal, A., Dakhel, A.A., Etemadi, A., Zereshki, S. (2010): Artifical neural network modeling of apple drying process, *J Food Process Eng* 33, 298-313.

Kingsly, A.R.P., Singh, D.B. (2007): Drying kinetics of pomegranate arils, *J Food Eng* 79, 741-744.

Kumar, N., Sarkar, B.C., Sharma, H.K. (2011): Mathematical modelling of thin layer hot air drying of carrot pomace, *J Food Sci Technol* doi: 10.1007/s13197-011-0266-7.

Lahsasni, S., Kouhila, M., Mahrouz, M., Mohamed, L.A., Agorram, B. (2004): Characteristic drying curve and mathematical modeling of thin-layer solar drying of prickly pear cladode (Opuntia ficus indica), *J Food Process Eng* 27, 103-117.

Lee, J.H., Kim, H.J. (2008): Drying kinetics of Onion Slices in a Hot-air Dryer, *J Food Sci Nutr* 13, 225-230.

Lee, J.H., Zuo, L. (2011): Mathematical modeling on vacuum drying of *Zizyphus jujuba* Miller slices, *J Food Sci Technol* doi:10.1007/s13197-011-0312-5.

Lertworasirikul, S. (2008) Drying kinetics of semi-finished cassava crackers: A comparative study, *LWT – Food Sci Technol* 41, 1360-1371.

Martinazzo, A.P., Corrêa, P.C., Resende, O., Melo, E.C. (2007): Analysis and mathematical description of drying kinetic of lemon grass leaves. *Rev Bras Eng Agric Ambient* 11(3), 301-306.

McMinn, W.A.M. (2004): Prediction of moisture transfer parameters for microwave drying of lactose powder using Bi-G drying correlation, *Food Res Int* 37(10), 1041-1047.

Menlik, T., Özdemir, M.B., Kirmaci, V. (2010): Determination of freeze-drying behaviours of apples by artifical neural network, *Expert Syst Appl* 37(12), 7669-7677.

Mohammadi, A., Rafiee, S., Keyhani, A., Emam-Djomeh, Z. (2008): Estimation of thin-layer drying characteristics of Kiwifruit (cv. Hayward) with use of Page´s model, *Am Eurasian J Agr Environ Sci* 3(5), 802-805.

Movagharnejad, K., Nikzad, M. (2007): Modeling of tomato drying using artificial neural network, *Comput Electron Agr* 59(1-2), 78-85.

Mrkić, V., Ukrainczyk, M., Tripalo, B. (2007): Applicability of moisture transfer Bi-Di correlation for convective frying of broccoli, *J Food Eng* 79, 640-646.

Nazghelichi, T., Kianmehr, M.H., Aghbashlo, M. (2011): Prediction of carrot cubes drying kinetics during fluidized bed drying by artificial neural network, *J Food Sci Technol* doi:10.1007/s13197-010-0166-2.

Ochoa-Martinez, C.I., Ayala-Aponte, A.A. (2007): Prediction of mass transfer kinetics during osmotic dehydration of apples using neural networks, *LWT – Food Sci Technol* 40, 638-645.

Odejobi, O.A., Umoru, L.E. (2009): Applications of soft computing techniques in material engineering: A review, *Afr J Math Comput Sci Res* 2(7), 104-131.

Omid, M., Baharlooei, A., Ahmadi, H. (2009): Modeling Drying Kinetics of Pistachio Nuts with Multilayer Feed-Forward Neural Network, *Dry Technol* 27(10), 1069-1077.

Ozcep, F., Yildirim, E., Tezel, O., Asci, M., Karabulut, S. (2010): Correlation between electrical resistivity and soil-water content based artificial intelligent techniques, *Int J Phys Sci* 5(1), 47-56.

Phanphanich, M., Mani, S. (2009): Drying characteristics of pine forest residues, *BioResources* 5(1), 108-121.

Premi, M., Sharma, H.K., Sarkar, B.C., Singh, C. (2010): Kinetics of drumstick leaves (*Moringa oleifera*) during convective drying, *Afr J Plant Sci* 4(10), 391-400.

Prlić Kardum, J., Sander, A., Skansi, D. (2001): Comparison of Convective, Vacuum and Microwave Drying of Chlorpropamide, *Dry Technol* 19, 167-182.

Rai, P., Majumdar, G.C., DasGupta, S., De, S. (2005): Prediction of the viscosity of clarified fruit juice using artificial neural network: a combined effect of concentration and temperature, *J Food Eng* 68(4), 527-533.

Raisul Islam, Md., Sablani, S.S., Mujumdar, A.S. (2003): An Artifical Neural Network Model for prediction of Drying Rates, *Dry Technol* 21(9), 1867-1884.

Rayaguru, K., Routray, W. (2010): Effect of drying conditions on drying kinetics and quality of aromatic *Pandanus amaryllifolius* leaves, *J Food Sci Technol* 47(6), 668-673.

Reis, R.C., Barbosa, L.S., Lima, M.L., Reis, J.S., Devilla, I.A., Acheri, D.P.R. (2011): Mathematical modeling of drying kinetics of pepper Cumari do Pará, *Rev Bras Eng Agric Ambient* 15(4), 347-353.

Roberts, J.S., Kidd, D.R., Padilla-Zakour, O. (2008): Drying kinetics of grape seeds, *J Food Eng* 89, 460-465.

Sacilik, K. (2007a): Effect of drying methods on thin-layer drying characteristics of hull-less seed pumpkin (Cucurbita pepo L.), *J Food Eng* 79(1), 23-30.

Sacilik, K. (2007b): The Thin-Layer Modelling of Tomato Drying Process, *Agric Conspec Sci* 72(4), 343-349.

Saeed, I.E. (2010) Solar drying of roselle (*Hibiscus sabdariffa* L.): Effects of drying conditions on the drying constant and coefficients, and validation of the logarithmic model, *Agric Eng Int: CIGR Journal* 12(1), 167-181.

Sander, A., Prlić Kardum, J., Glasnović, A. (2010): Drying of Solids; Estimation of the mathematical model parameters, *Can J Chem Eng* 9999(1), 1-8.

Sant´Ana Silva, A., dos Santos Melo, K., Alves, N.M.C., da Silva Fernandes T.K., de Almeida Farias P. (2009): Thin layer drying kinetics of ´apple´ banana on a fixed bed dryer, *Rev Bras Prod Agroind* 11(2), 129-136.

Sawhney, R.L., Pangavhane, D.R., Sarsavadia, P.N. (2009): Drying Studies of Single Layer Thompson Seedless Grapes. In: International Solar Food Processing Conference, Indore, India, pp.1-19.

Sharma, G.P., Verma, R.C., Pathare, P. (2005): Mathematical modeling of infrared radiation thin layer drying of onion slices, *J Food Eng* 71, 282-286.

Thakur, A.K., Saharan, V.K., Gupta, R.K. (2010): Drying of Perlette grape under different physical treatment for raisin making, *J Food Sci Technol* 47(6), 626-631.

Topuz, A. (2010): Predicting moisture content of agricultural products using artificial neural networks, *Adv Eng Softw* 41(3), 464-470.

Tunde-Akintunde, T.A., Afon, A.A. (2010): Modeling of hot-air drying of pretreated cassava chips, *Agric Eng Int: CIGR Journal* 12(2), 34-41.

Vega, A., Fito, P., Andrés, A., Lemus, R. (2007): Mathematical modeling of hot-air drying kinetics of red bell pepper (var. Lamuyo), *J Food Eng* 79, 1460-1466.

Vega Galvez, A., Tello Ireland, C., Lemus Mondaca, R. (2007): Mathematical simulation of drying process of Chilean gracilaria (*Gracilaria* chilensis), *Ingeniare Rev Chil Ing* 15(1), 55-64.

Vega-Galvez, A., Uribe, E., Perez, M., Tabilo-Munizaga, G., Vergara, J., Garcia-Segovia, P., Lara, E., Di Scala, K. (2011): Effect of high hydrostatic pressure pretreatment on drying kinetics, antioxidant activity, firmness and microstructure of Aloe vera (Aloe barbadensis) Miller gel, *LWT-Food Sci Technol* 44, 384-391.

Wang, Z., Sun, J., Chen, F., Liao, X., Hu, X. (2007): Mathematical modelling on thin layer microwave drying of apple pomace with and without hot air pre-drying, *J Food Eng* 80, 536-544.

Yadollahinia, A.R., Omid, M., Rafiee, S. (2008): Design and fabrication of experimental dryer for studying agricultural products, *Int J Agric Biol* 10, 61-65.

Zomorodian, A.A., Dadashzadeh, M. (2009): Indirect and Mixed Mode Solar Drying Mathematical Models for Sultana Grape, *J Agric Sci Technol* 11(4), 391-400.

Zomorodian, A., Moradi, M. (2010): Mathematical Modeling of Forced Convection Thin Layer Solar Drying for Cuminum cyminum, *J Agric Sci Technol* 12, 401-408.

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