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COMPARISON OF ARTIFICIAL NEURAL NETWORK AND MATHEMATICAL MODELS FOR DRYING OF APPLE SLICES PRE-TREATED WITH HIGH INTENSITY ULTRASOUND

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Abstract

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In this paper, an artificial neural network model was compared to the traditional regression models for drying food materials. High intensity ultrasound with amplitudes set to 25%, 50%, 75% and 100% of maximal was used for the treatment of apple slices of different thicknesses. After 7 min of treatment, samples were dried in the infrared drier at two different temperatures. The four most frequently used regression models for drying available in the literature were fitted based on experimental data, and their usability was tested on different experimental sets. For the creation of back-propagation neural network, 3 input parameters were used (amplitude of ultrasound, sample thickness and drying temperature) together with one output (moisture content). After training and the validation of networks, statistical analysis was conducted, based on the mean square error and correlation coefficient, the best network was selected. After the assessment of networks and statistical results, neural networks showed excellent fitting to experimental data, independently of the input parameters obtained in experiments. This is opposed to standard regression models, which had excellent fit to just one set of experimental data, and show inadequate fit even with small-introduced changes in one or more input parameter.

Key words: apple, artificial neural network, drying, mathematical model, ultrasound

Introduction

Drying of food materials on a large scale depends on the proper control of drying operation, drying time, temperature, air velocity and other parameters, such as water content and mass of material (Ježek et al., 2006; Ježek et al., 2008). The performance and characteristics of convective dryers are usually determined following a series of experiments on various temperatures and air velocities (Movagharnejad et al., 2007). Mathematical models based on such experimental data combine the effects of all parameters, and different combinations and coefficients (Togrul, 2005). The performance and characteristics of convective dryers are usually determined by performing a series of experiments on various temperatures and air velocities (Movagharnejad, 2007). The design of drying operations needs accurate models for drying which are simple and fast to use, so that optimal parameters can be calculated, instead of those based on a series of time-consuming experiments (Evin, 2011; Mrkic et al., 2002).

Rapid drying to low moisture is critical, and the search for further improvements to conventional drying processes have resulted in experiments with high intensity ultrasound before or during the drying phase (Brnčić et al., 2010; Bankole et al., 2005). Combining the drying process and high-intensity ultrasound pre-treatment leads to even more complex, expensive and time- and money-consuming experiments, which benefit from the implementation of quality mathematical models? The drying process, which includes ultrasonic treatment with intensities over 10 W/cm^2 is suitable for changing the physical and chemical properties of fruit, and as such should be carefully modelled to minimise the loss of food quality and process costs (Dujmić et al., 2012; Bosiljkov et al., 2011). Testing and setting up a system based on previous experimental data using regression models is standard prac-

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tice in laboratory and industry settings, but it has some serious limitations in the complex drying setup, primarily with regard to the number of variables used (usually two: moisture content and drying time) (Menlik et al., 2010). Current empirical mathematical models of correlation between drying time as an input parameter and water content as an output parameter have excellent predictions for the single, specific experiment. Some of the most commonly used drying models are presented in Table 1, and are discussed in the experimental section of this paper. The introduction of any modification to the drying parameters leads to an inability of the previously established empirical model to fit new experimental data; as a result, there is no such model to satisfy the whole range of drying conditions. Based on only one input parameter, existing models are not adequate for industrial control of air-drying processes (Hernandez-Perez et al., 2004).

Artificial neural networks (ANN) can overcome this limitation, and when correctly used can incorporate data from the all input variables, giving values for one or (rarely) more output variables (Afaghi et al., 2001). Neural networks, as massive parallel-distributed information processing systems, are modelled based on biological neural networks, taken from research on artificial intelligence. Such models have the ability to set weights to each unit or each neuron in the network (Chaylan et al., 2010). Those properties of heuristic models do not require parameters of physical models and can learn just from experimental data, even when handling complex systems with nonlinear interactions between multiple decision variables (Lertworasirikul and Tipsuwan, 2008). This enables multiple variable inputs with different levels of significance, which, after training, give values for the relevant output variable. The most popular networks for the process modelling of food drying are multi-layer perceptrons. Those networks consist of identical neurons organised in layers, with connections between every unit in adjacent layers (Hussain et al., 2002). In a typical back propagation feed-forward network, inputs are fed to the input layer consisting of the same number of neurons. Output values from the input layer propagate through neurons in the hidden layer, based on the weight of each neuron and using non-linear sigmoid, hyperbolic tangent or just simple linear transfer functions (Hernandez-Perez et al., 2004). Finally, after going through one or more hidden layers, data are fed to the output layer and the result is transformed and forwarded to output variables. This structural method of propagation was accepted as the most stable, and is preferred over other types of networks. The next step after the forward pass is the backward pass, in which errors from the output layer are sent back to the input layer; during this step, weights and interconnections were adjusted with the goal of minimising the error and identifying the best fit to experimental data (Erenturk and Erenturk, 2007). After the training phase of network, validation with fresh set of data and testing of network performance is performed, to ensure minimal error and prevent over-fitting.

Table 1
Experimental models for drying of food material

Model name	Model equation
Page	$MR = \exp(-kt^n)$
Henderson - Pabis	$MR = a \cdot \exp(-kt)$
Logarithmic	$MR = a \cdot \exp(-kt) + c$
Approximation of diffusion	$MR = a \cdot \exp(-kt) + (1-a) \cdot \exp(-kbt)$

In this paper, empirical models for drying of food materials will be fitted to the experimental data gathered using ultrasonic pre-treatment and drying of apple slices. Models will be compared to the modelled artificial neural network and the best one will be chosen based on statistical analysis.

Materials and Methods

Fresh Golden delicious apples (Fragaro, Croatia) were peeled and cut into slices of 5×5 cm with thicknesses of 0.25 and 0.5 cm. Approximately 50±1 g of apple slices were immersed in 200 mL of distilled water, in a 250 mL glass. The starting temperature of distilled water was 22°C and the humidity was constant during all experiments. An ultrasonic probe with a 40 mm radius was immersed 1 cm below the water surface. Ultrasonic equipment (UP-200S, dr. Hielscher, Germany) with variable amplitude and pulse settings had a theoretical maximal output power of 200 W, with a fixed frequency of 24 kHz. Amplitudes were set at 25, 50, 75 and 100% of the maximum. The maximal cycle was used during all experiments. Processing of liquid with immersed samples using high-intensity ultrasound was performed for 7 minutes. The reference sample was immersed in water for 7 minutes, without ultrasonic treatment. After processing, apple slices were put in an infrared dryer and moisture analyser (Mettler LJ-16, Switzerland), with drying temperatures set to 55°C and 65°C. During the experimental run in an infrared dryer, the mass of the samples was recorded every minute, until no significant difference between ten subsequent readings was observed.

Statistical analysis was conducted and mathematical models, together with models of the neural network, were produced in Statistica 9 (Statsoft, USA) software. For each run, absolute moisture (X/X_0) was calculated based on equation 1 and calculation of the parameters for selected models for describing the drying behaviour of food materials was conducted based on the experimental data.

$$\frac{X}{X_0} = MR = \frac{M - M_e}{M_0 - M_e} \; , \tag{1}$$

where M_e is equilibrium moisture content and M_0 is the starting moisture content.

Using nonlinear estimation with user-specified regression and least squares minimisation, Page, logarithmic, Henderson and Pabis, as well as an approximation of diffusion equations were fitted to the experimental data. Based on mean square error and correlation coefficient, the best model is selected and compared to the neural network model.

A multi-layer perceptron was selected as the relevant network type for training with experimental data. Selected input variables were amplitude of ultrasound, thickness of slices and drying temperature, with water content as the output variable, as presented in Figure 1.

In order to estimate the dynamic drying behaviour, values for input variables were randomly collected from the experimental dataset and divided into three partitions. The first set (70% of data) was used as training data for neural networks and the second set (20% of data) was used for validation of networks and evaluation of network quality during the training phase. The third set (10% of data) was used as new data for testing network performance, and consequently, this partition is never used in training. One hidden layer was selected as adequate and the starting number of neurons was set as half of the sum of the input and output neurons (Farkas et al., 2000). An increase of neurons in the network is conducted until the fitting error reaches a satisfactory level, which prevents over-learning of the network and inadequate fit to validation data.

To account for the effect of other drying variables besides amplitude of ultrasound and to compare models with neural network, constants in drying models were regressed against slice thickness and drying temperature using multiple regression analysis. Combinations with the highest R-value were included in the final model, ensuring the best possible fit to all of the gathered experimental data.

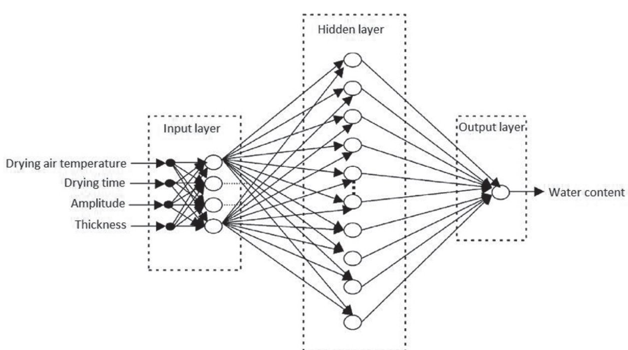

Fig. 1. Model of an artificial neural network based on 4 inputs, a hidden layer with an as yet unknown number of neurons and an output layer, used for fitting of experimental data (based on Erenturk and Erenturk, 2007)

Results and Discussion

Based on the experimentally gathered data, the amplitude of ultrasound has a significant influence on drying time, independently of drying temperature and slice thickness, as presented in Figure 2. Imploding cavitation bubbles and the subsequent release of high temperatures and pressures affected the fruit tissue, changing the structure of the immersed samples. An increase of amplitude leads to an increase in cavitation intensity, which opens pores in the apple samples, and creates new ones. A larger number of pores and the enlargement of existing pores slowed down the sealing of pores during drying, which ensured the faster diffusion of water to the surface of the sample and prolonged the first phase of drying with an almost linear drop in water content. With the increase of amplitude, drying time shortens from 140 min for untreated samples to a minimum of 87 min for samples treated with 100% of maximal amplitude. It is evident that ultrasonic pre-treatment further complicates fitting of empirical mathematical models to experimentally obtained data. Shorter drying times achieved with ultrasonic treatment and different drying curves indicated that models based solely on drying time proved to be unsuitable for use in the prediction and control of the drying process. In Figures 5, 6, 7 and 8, differences between drying curves are evident, as well as the near perfect fit of the empirical model to just one set of the experimental data.

The best empirical correlation for describing the drying behaviour of apple slices is found to be an approximation of diffusion, with $R^2 = 0.99132$ obtained for one specific experiment (Figure 8). In comparison, the best artificial neural network was selected based on the errors in training and testing performances.

MLP with 12 neurons using BFGS 78 algorithm, the logistic transformation function in the hidden layer and the hyperbolic tangent activation function in the output layer had a training error of 0.999375 and an error during the testing phase of 0.999231. A larger number of neurons results in a better fit to training data, but cannot satisfactorily pass the testing phase. Figures 3 and 4 show excellent fit of the ANN model, with predicted and output values fitted independently of the used drying temperature, amplitude or slice thickness. Results show that plots between predicted and experimental water contents in samples were almost a straight line for training and validating processes, with minimal MSE. Excellent prediction of the trained artificial neural network is in accordance with results presented by Hernández-Pérez et al. (2004), Movagharnejad and Nikzad (2007), and Satish and Setty (2005). After the ANN setup, minimal time (in range of few ms) was needed for acquiring of output data based on experimental input values. On-line use of an artificial neural network is thus feasible, which was also reported by Hernández (2009). This also allows the determination of drying time of the samples under the dynamic drying system assisted by ultrasonic pre-treatment.

The correlation coefficients of tested empirical models presented in Table 2 show significantly lower values, indicating that the obtained artificial neural network demonstrates a considerably better fit to the experimental data. The prediction capability of trained ANN is the best of the all of the investigated models independent of the parameters used, which was also reported by Tripathy and Kumar (2008). For the whole range of experiments, maximal error was obtained using the Henderson and Pabis model, with a mean percent er-

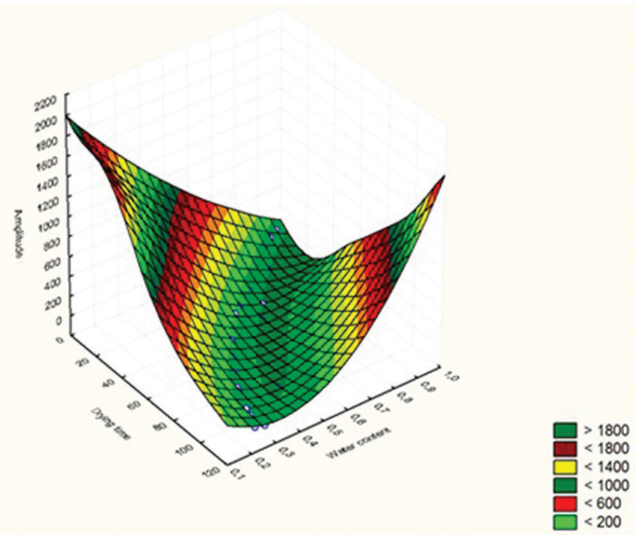

Fig. 2. Dependence of water content in apple samples on drying time and the amplitude of ultrasound based on values gained with an artificial neural network

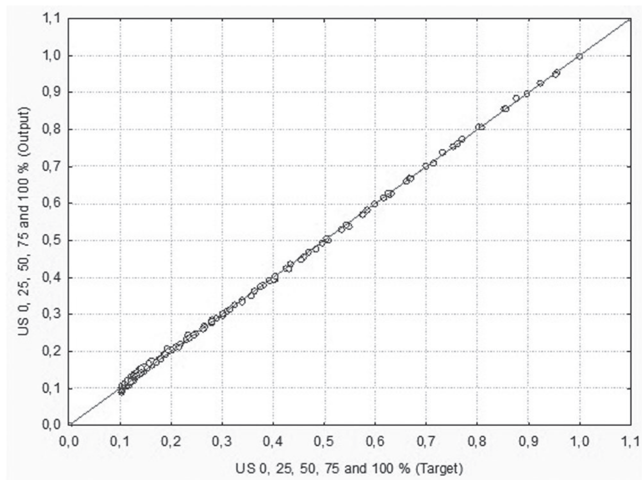

Fig. 4. The ANN predicted and experimental data for water content in apple slices

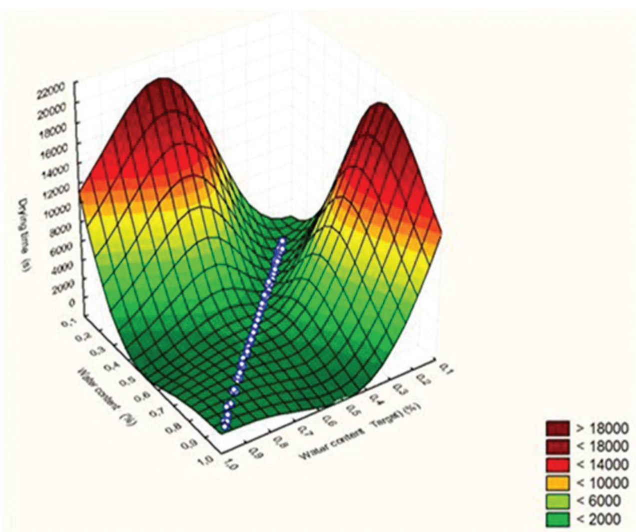

Fig. 3. Predicted and experimental data for changes in water content during drying

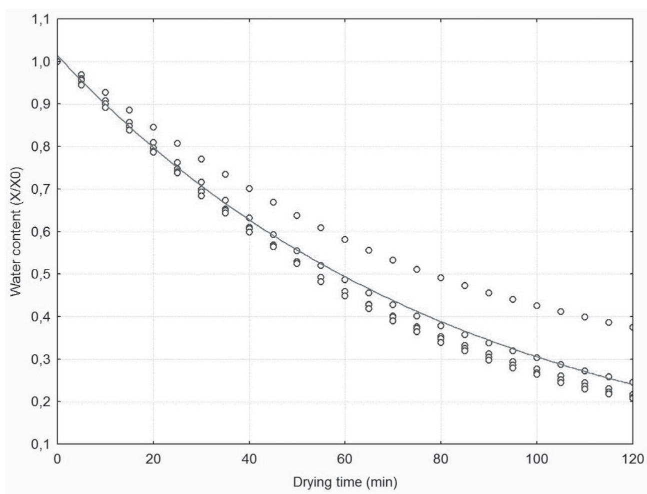

Fig. 5. Henderson and Pabis model fitted to one set of data (25% of amplitude) and compared to 4 other sets of experimental data (without US treatment, 50%, 75% and 100% of maximal amplitude) at 65°C

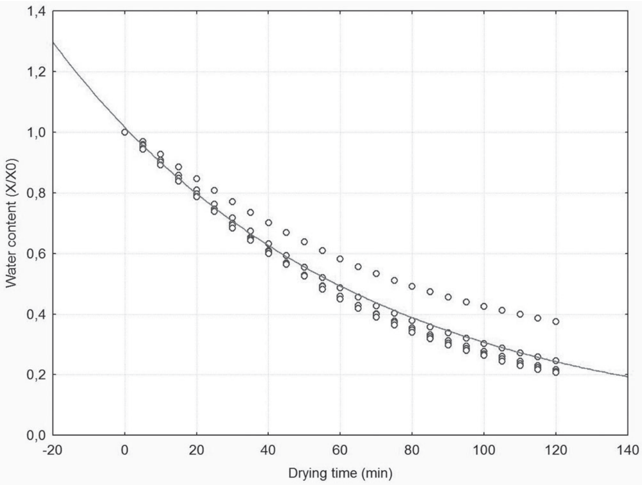

Fig. 6. Logarithmic experimental model fitted to one set of data (25% of amplitude) and compared to 4 other sets of experimental data (without US treatment, 50%, 75% and 100% of maximal amplitude) at 65°C

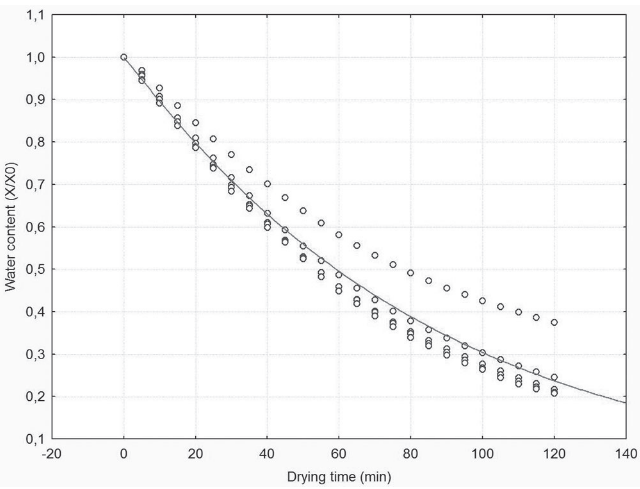

Fig. 7. Page model fitted to one set of data (25% of amplitude) and compared to 4 other sets of experimental data (without US treatment, 50%, 75% and 100% of maximal amplitude) at 65°C

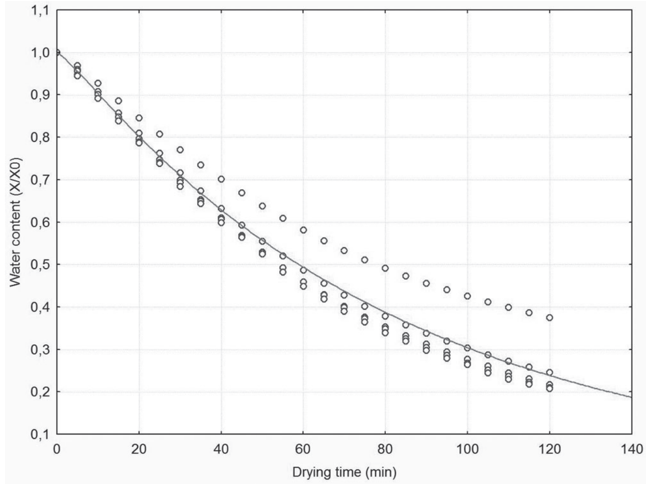

Fig. 8. Approximation of diffusion model fitted to one set of data (25% of amplitude) and compared to 4 other sets of experimental data (without US treatment, 50%, 75% and 100% of maximal amplitude) at 65°C

ror (MPE) of 19.84%. The approximation of diffusion model had the smallest MPE of 13.27%. Those errors are substantially higher than MPE of neural networks, which amounted to just 0.73% because of including the three most significant input variables used in training, instead of just one.

Conclusion

An artificial neural network model with a significantly smaller mean square error compared to empirical models should be the preferred method for accurate describing of drying behaviour. Using the ANN, the application of ultrasound in drying operations can be successfully modelled, as this kind of heuristic network is not strictly limited to specific experiments and allows for a broad range of values for larger numbers of input parameters. All four of the tested empirical models had satisfactory coefficients of correlation above 0.90, but only for one set of data. Compared with ANN and R^2 = 0.999231, empirical models had up to 19.11% higher MSE and

Table 2
Correlation coefficients and mean square errors selected based on multiple regression analysis for experimental models, and compared to the artificial neural network model

Model	Parameters	R^2	MSE
Henderson and Pabis	a=1.01408; k=0.011996	0.952625	$5.24 \cdot 10^{-3}$
Page	k=0.01018; n=1.03412	0.979570	$2.89 \cdot 10^{-4}$
Logarithmic	a=1.00057; k=0.012354; c=0.015823	0.989833	$2.31 \cdot 10^{-4}$
Approximation of diffusion	a=-0.02168; k=0.256448; b=0.047254	0.991032	$9.85 \cdot 10^{-5}$
Artificial neural network		0.999375	$1.18 \cdot 10^{-5}$

could not be considered as good models for the control and prediction of drying using ultrasonic treatment and a wide range of input parameters.

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