Artificial neural network model of pork meat cubes osmotic dehydration

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Abstract

Mass transfer of pork meat cubes *(M. triceps brachii)*, shaped as 1×1×1 cm^3, during osmotic dehydration (OD) and under atmospheric pressure was investigated in this study. The effects of different parameters, such as concentration of sugar beet molasses (60–80 mass%), temperature (20–50 °C), and immersion time (1–5 h) in terms of water loss (*WL*), solid gain (*SG*), final dry matter content (*DM*), and water activity (a_w), were investigated using experimental results. Five artificial neural network (ANN) models were developed for the prediction of *WL*, *SG*, *DM*, and a_w in OD of pork meat cubes. These models were able to predict process outputs with coefficient of determination, r^2, of 0.990 for *SG*, 0.985 for *WL*, 0.986 for a_w, and 0.992 for *DM* compared to experimental measurements. The wide range of processing variables considered for the formulation of these models, and their easy implementation in a spreadsheet calculus make them very useful and practical for process design and control.

Keywords: mass transfer, osmotic dehydration, pork meat, sugar beet molasses, neural network.

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Many traditionally techniques and their combinations, such as salting, drying, cooking, smoking and marinating, are used to prevent spoilage of meat and its products by reducing its water content. A common step in these processes is placing product (meat) in contact with a concentrated solution (salt, sugar, acids, seasonings, etc.) [1,2].

One of the potential preservation techniques for producing products with low water content and improved nutritional, sensorial and functional properties is osmotic dehydration (OD). During OD, partial removal of water content, from plant or animal tissue, is achieved by osmotic pressure difference between product and hypertonic solution, which are in direct contact. Mass transfer is caused by a difference in osmotic pressure: water outflow from product to solution, solute transfer from solution into the product, and leaching out of the products own solutes [3]. OD is an environmentally acceptable method, with its ultimate aim for keeping the initial characteristics of the final product, also material gentle drying method, which received considerable attention because of the low processing temperature, low waste material and low energy requirements [4,5]. Water removal in liquid form, usage of mild temperatures and osmotic solution reusing are the main advantages of OD process in comparison with other drying treatments [6–9].

The mass transfer mechanism and quality of final product are affected by many factors such as composition and concentration of osmotic agents, immersion time of the product in the solution, agitation/circulation of osmotic solution, operating temperature, nature and thickness of food material and pre-treatment, size and shape of the product, osmotic solution to pork meat mass ratio, agitation level, material porosity, type of osmotic agent and processing pressure [10–14].

Osmotic dehydration (OD) is recognized as a pre-treatment step to pork meat drying processes such as air-drying, microwave or freeze-drying, to improve the nutritional, sensorial and functional properties of pork meats, reduce heat damage and minimize their color and flavor changes [14].

Previous research [15] has shown that the process of osmotic dehydration has positively influenced the microbiological profile and food safety of osmodehydrated pork meat, while preliminary sensory analysis has shown that meat processed in this manner has satisfactory sensory characteristics. Also, the use of sugar beet molasses during OD improves the nutritional profile of pork meat, the chemical composition of which, after the process of OD, is in the optimal range for human health [16].

OD of pork meats is based on placing the meat into a concentrated aqueous solution, so that water is removed from the pork meat and the solutes diffuse from the solution into the meat tissue. There is also an

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observable minor flow of solutes from pork meat to solution [13]. The existence of those simultaneous and opposite fluxes is one of the main difficulties for modeling OD kinetics [17].

Great effort has been spent in developing models for predicting the mass transfer kinetics of OD at atmospheric pressure. It is very difficult to develop a mathematical model capable of including all of the factors involved in the process. Mechanistic and empirical approaches have been proposed by many authors [18,19]. Mechanistic approaches describe the underlying phenomena by means of various mechanisms; some authors have used Fick's law of diffusion [20–22] and some other authors proposed models based on the knowledge about cellular physiology of tissues [20,23,24]. Physicochemical, sensory and technological properties of fresh meat are related with water content [25]. Water is held in myofibrils, functional organelles of meat, but also it may exist in the intracellular space between myofibrils and sarcoplasm [26]. Meat represents a cellular system with great biochemical and structural complexity, created by a network of muscular fibers surrounded by connective tissue.

Empirical models are developed from experimental data. Their uses are limited because they are only capable of representing data at conditions similar to those on which such models were developed [27]. However, recent work has shown that the empirical models give a reasonable fit to experimental data and can successfully predict mass transfer mechanism [28]. Also, the main advantage of an empirical modeling approach is that it has a capability to learn from experimental data. Many authors have used a simplified version of the non-steady state form of Fick's law to model OD mechanism. The empirical models, which these authors proposed, considered proportionality relationships between a concentration parameter and the square root of time [29–31]. In these models, simultaneous water and solute transfer is resolved to a simple transfer of water or solute, which is inefficient as far as the technological control of both dewatering and impregnation effects are concerned [32].

In case of food processes, nonlinear models are more suitable due to variability and nonlinear behavior of natural products. In addition, many production processes involve fluctuation in process conditions, and rely to a great extent on the skill and experience of operators. Therefore, artificial neural network (ANN) models recently have gained momentum for process modeling and control. ANN models are recognized as a good tool for dynamics modeling because they do not require parameters of physical models, have an ability to learn the solution of problems from a set of experimental data, and are capable to handle complex systems with nonlinearities and interactions between decision variables [28].

Due to the complexity of the osmotic dehydration process, several authors have recommended the use of ANN for modeling mass transfer kinetics during the OD process [19,28,33]. Nevertheless, little work has been done on the application of ANN to model OD process. Also, there was no study on the effect of OD conditions on water loss and solid gain of pork meat.

The kinetics of water removal and solid gain is greatly influenced by the type of osmotic agent. Ternary aqueous solutions containing salt and sugar are common osmotic agents for food dehydration [1,34]. Salt solutions, because of their influence on water activity depression, are widely used in traditional meat processing, but there are several advantages if ternary water/salt/sugar solutions are being used as immersion solutions [35,36]. The presence of a second solute maintains a high transfer potential favorable to water loss, and at the same time by the presence of sugar, salt impregnation is hindered [36]. High salt concentrations decrease the water holding capacity, which contributes to meat dehydration and shrinkage while there is no swelling of muscle fibers or myofibrils [26,37].

Sugar beet molasses is an excellent medium for osmotic dehydration, primarily due to the high dry matter (80%) and specific nutrient content. The specific chemical composition (approximately 51% sucrose, 1% raffinose, 0.25% glucose and fructose, 5% proteins, 6% betaine, 1.5% nucleosides, purine and pyramidine bases, organic acids and bases) and high content of solids (around 80%) provide high osmotic pressure in the solution, therefore molasses appears to be an excellent osmotic medium [38].

Althought sugar beet molasses is rarely used in human consuption, few reaserches showed that sugar beet molasses can be successfully incorporated to various food (bread and bakery products [39] and meat products [40,41]) without drastic impairment of sensory properties.

The application of OD in food industry has many advantages: improvement of texture, flavor and color, no chemical pretreatment, energy efficiency, providing stable and quality product [42].

The amount of solid uptake by the tissue during OD process is significant but it can be reduced with edible films (starch, pectins, agar-agar, etc. [43]). For this reason, the objective of future studies will be investigation of solid gain reduction by starch coatings.

The specific objective in this study was to investigate the effect of process parameters (solute concentrations, process temperatures and immersion time) on mass transfer in the OD process of pork meat. Five ANN models were developed to predict water loss, *WL,* and solid gain, *SG*, and also water activity, a_w, and final moisture content, *DM*, for the OD process of the pork meat. The performance of ANN was also compared with the performance of multiple linear regression (MLR) models.

EXPERIMENTAL

Material

Pork meat (*M. triceps brachii*) was purchased just before use. Initial moisture content of the fresh meat was 72.83%. Before the osmotic treatment, fresh meat was cut into cubes, dimension of nearly 1×1×1 cm^3. Sugar beet molasses solution, with inital dry matter content of 85.04%, was obtained from the sugar factory Pećinci, Serbia. Distilled water was used for dilution of solutions. Sugar beet molasses was diluted to concentration of 60, 70 and 80 mass%. The sample to solution ratio was 1:5 (w/w). The process was performed in laboratory jars at temperature of 20, 35 and 50 °C with agitation on every 15 min under atmospheric pressure. After 1, 3 and 5 h the samples were taken out from osmotic solutions to be lightly washed with water and gently blotted to remove excessive water. All experiments were repeated three times.

Dry matter content of the fresh and treated samples was determined by drying the material at 105 °C for 24 h in a heat chamber until constant weight was achieved (Instrumentaria Sutjeska, Croatia). All weight measurements were carried using precision scale (Kern PLS 310-3F with accuracy ±0.001 g) in accordance to AOAC Official Method 950.46 [44]. Water activity (a_w) of the osmotic dehydrated samples was measured using a water activity measurement device (Testo 650, Germany) with an accuracy of ±0.001 at 25 °C. Soluble solids content of the molasses solutions was measured using an Abbe refractometer, Carl Zeis, Jenna, at 20 °C.

Osmotic dehydration

In order to describe the mass transfer kinetics of the OD, experimental data from three key process variables are usually obtained: moisture content, change in weight and change in the soluble solids. Using these, water loss, *WL*, solid gain. *SG*, were calculated for different solutions and processing times [3]:

$$WL = \frac{m_i z_i - m_f z_f}{m_i} \quad \left[\frac{\text{g}}{\text{g fresh sample}}\right] \tag{1}$$

$$SG = \frac{m_f s_f - m_i s_i}{m_i} \quad \left[\frac{\text{g}}{\text{g fresh sample}}\right] \tag{2}$$

where m_i and m_f are the initial and final weight (g) of the samples, respectively; z_i and z_f are the initial and final mass fraction of water (g water/g sample), respectively; s_i and s_f are the initial and final mass fraction of total solids (g total solids/ g sample), respectively. The mass loss during osmotic dehydration can be evaluated by subtracting *SG* from *WL*. The moisture content in dry matter at any time can be calculated by dividing subtract of initial water present, and water loss, with initial dry solids. Similarly, the solid content, on dry basis at any time, can be calculated as the ratio of subtract of initial dry solids and solid gain with initial dry solids.

Analysis of variance and multiple linear regression modeling

It is recommended to perform some statistical analysis of data, like analysis of variance (ANOVA) to check the significance of the effect of the input variables over the output, before modeling ANN, and to justify the use of ANN model by r^2. First order polynomials (FOP) regression formula was used for modeling, and StatSoft Statistica software was used for data correlating and ANOVA evaluation of linear regression coefficients.

Artificial neural network modeling and database preparation

The mean values of the experimentally measured independent variables and desired outputs are given in Table 1. StatSoft Statistica 10 was used to randomly divide collected data into three groups: training data (60%), cross validation (20%) and testing data (20%). The cross-validation data set was used to test the performance of the network while training was in progress as an indicator of the level of generalization and the time at which the network had begun to over train. Testing data set was used to examine the network generalization capability.

To improve the behavior of the ANN, both input and output data were normalized according to Eq. (3):

$$q_{i\,\text{norm.}} = \frac{q_i - \min(q_i)}{\max(q_i) - \min(q_i)} \tag{3}$$

where q_i is *i*-th case, with measured temperature, *T*, immersion time, *t*, and sugar beet molasses concentration, *C* and *WL*, *SG*, *DM* and a_w from Table 1. Normalized variables gain values in the range of 0 to 1, and have no physical meaning.

In this article, a multi-layer perceptron model (MLP) that consisted of one input layer, one hidden layers and one output layer, which is the most common, flexible and general-purpose kind of ANN was evaluated [45].

It is necessary to make a trial and error procedure, until a good network behavior is obtained, also to choose the number of hidden layers, and the number of processing elements (also called "neurons") in the hidden layer(s). It is advisable to use just one layer, because the use of more layers could lead to the problem of local minima [45].

Table 1. Experimental data for the MLR and ANN modeling

Run No.	T / °C	t / h	C / mass%	WL, g/g f.s.	SG, g/g f.s.	a_w	DM / %
1	20	1	80	0.23	0.08	0.91	37.18
2	20	3	80	0.41	0.12	0.89	50.28
3	20	5	80	0.47	0.14	0.88	56.53
4	20	1	60	0.24	0.09	0.91	39.19
5	20	3	60	0.37	0.12	0.89	48.45
6	20	5	60	0.42	0.15	0.89	53.87
7	20	1	70	0.24	0.07	0.91	38.83
8	20	3	70	0.40	0.11	0.89	50.93
9	20	5	70	0.46	0.13	0.87	56.29
10	35	1	80	0.28	0.08	0.87	43.42
11	35	3	80	0.47	0.14	0.85	60.64
12	35	5	80	0.52	0.16	0.81	66.72
13	35	1	60	0.29	0.10	0.91	43.36
14	35	3	60	0.42	0.14	0.87	54.33
15	35	5	60	0.46	0.15	0.88	58.25
16	35	1	70	0.27	0.08	0.90	42.84
17	35	3	70	0.43	0.13	0.88	56.62
18	35	5	70	0.47	0.15	0.86	61.23
19	50	1	80	0.39	0.15	0.88	50.59
20	50	3	80	0.55	0.17	0.83	65.56
21	50	5	80	0.58	0.21	0.80	71.11
22	50	1	60	0.33	0.12	0.89	47.78
23	50	3	60	0.45	0.15	0.87	58.11
24	50	5	60	0.48	0.16	0.87	61.06
25	50	1	70	0.38	0.12	0.88	49.53
26	50	3	70	0.50	0.15	0.86	61.67
27	50	5	70	0.55	0.16	0.85	67.21

The first estimate of the processing elements (PE) number can be obtained from the following equation [27,46]:

$$m = n(x+1) + y(n+1) \tag{4}$$

where x and y represent the number of input and output PE, respectively, n is the number of PE in the hidden layer and m is the number of weights (connections between layers) in the neural network; m can be taken as the number of training exemplars divided by 10. Some suggestions regarding the number of hidden neurons are as follows: this number should be between the size of the input layer and the size of the output layer, it should be 2/3 the size of the input layer, plus the size of the output layer, or it should be less than twice the size of the input layer.

In this work, the ANN procedure of StatSoft Statistica was used to model the ANN, and the number of hidden nodes varied from n = 5 to 9 (proposed by StatSoft Statistica's ANN module), there were x = 3 inputs, and y = 4 outputs, and m = 44 to 76 weight coefficients (depending on n).

Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm, implemented in StatSoft Statistica's evaluation routine, was used for ANN modeling. The information is transferred, between the layers through a "transfer" or "activation" functions. This function is typically nonlinear for hidden layers and linear for the output layer. Most common nonlinear activation functions, used in StatSoft Statistica ANN calculation are logistic sigmoid and hyperbolic tangent functions (also exponential, sine, softmax and Gausian). In most applications, the hyperbolic tangent function behaves better as compared to other functions [45,47].

Coefficients associated with the hidden layer (both weights and biases) are grouped in matrices $\mathbf{W}_1$ and $\mathbf{B}_1$. Similarly, coefficients associated with the output layer are grouped in matrices $\mathbf{W}_2$ and $\mathbf{B}_2$. If Y is the matrix of the output variables, f_1 and f_2 are transfer functions in the hidden and output layers, respectively, and X is the matrix of input variables, it is possible to represent the neural network, by using matrix notation, as follows [27,46]:

$$Y = f_1(\mathbf{W}_2 f_2(\mathbf{W}_1 X + \mathbf{B}_1) + \mathbf{B}_2) \quad (5)$$

Weights (elements of matrices $\mathbf{W}_1$ and $\mathbf{W}_2$) are determined during the training step which updates them using optimization procedures to minimize the error function between network outputs and experimental outputs [27,47,48], according to the sum of squares (SOS) and BFGS algorithm, used to speed up and stabilize convergence [50]. The goodness of fit, between experimental measurements and model calculated outputs, represented as ANN performance (sum of r^2 between measured and calculated *WL*, *SG*, *DM* and a_w for each ANN) and also the sum of SOS between measured and calculated *WL*, *SG*, *DM* and a_w, during training, testing and validation steps, are determined. The values of r^2 between experimentally measured and ANN outputs, for training, testing and validation steps, for each output variable (*WL*, *SG*, *DM* and a_w) have also been calculated. The SOS between the experimental and the network predicted values was used as the iteration termination criterion, as StatSoft Statistica's default. As soon as the cross-validation *SOS* starts to increase, the training step is terminated; otherwise, the training step ends after a fixed number of epochs or training cycles.

Training, testing and system implementation

The StatSoft Statistica 10 commercial software was used to develop the ANN model. The training step was started, after ANN architecture was defined. The training process was repeated several times in order to get the best performance of the ANN, due to a high degree of variability. It was accepted that the successful training was achieved when learning and cross-validation curves (*SOS* versus epochs) approached to zero.

Testing was carried out with the best weights stored during the training step; correlation coefficient *r*, and *SOS* were used as parameters to check the performance of the ANN.

The ANN model can be implemented using an algebraic system of equations, to predict *WL*, *SG*, *DM* and a_w, by substitution of the corresponding weights and coefficients matrices in Eq. (5). This step can be easily achieved in some spreadsheet calculus (Microsoft Office Excel, for instance).

RESULTS AND DISCUSSION

Analysis of variance

Analysis for variance (ANOVA) was conducted for linear model of input and output variables (FOP), and output variables were tested against the impact of input variables. Table 2 shows significant effects ($p < 0.05$) of all variables, and r^2 between experimentally measured and models calculated *DM* and *WL* were found to be very acceptable. All four variables considered in the ANOVA analysis were used for the ANN modeling, in spite of the fact that some works have been carried out by changing one of these variables and finding some effect over *WL* or *SG* [14].

Processing elements (PE) in hidden layer

The optimum number of hidden nodes was chosen upon minimizing the difference between predicted ANN values and desired outputs, using *SOS* during testing as performance indicator (Table 3). Results of *WL*, *SG*, a_w and *DM* during testing with five to nine PE in the hidden layer are presented in Table 3. Used MLPs are marked according to StatSoft Statistica's notation, MLP followed by number of inputs, number of neurons in the hidden layer, and the number of outputs. According to ANN performance, from Table 3 (sum of r^2 for all variables in one ANN), it was noticed that the optimal

Table 2. The ANOVA table, showing the significance of the effect of the input variables on each of the output variables in MLR model

Factor	WL	*p*	*SG*	*p*	a_w	*p*	*DM*	*p*
Time	0.175	1.29E-11	0.014	8.37E-09	0.008	1.47E-06	1414.562	9.52E-13
Temperature	0.056	4.16E-07	0.009	5.99E-07	0.005	1.68E-05	567.129	7.00E-09
Concentration	0.010	7.52E-03	0.000	3.31E-01	0.004	1.27E-04	78.699	3.10E-03
Error	0.026	–	0.004	–	0.004	–	165.832	–
r^2	0.888	–	0.824	–	0.773	–	0.916	–

Table 3. ANN summary

No.	Network name	ANN performance			SOS (error)			Activation function	
		Training	Testing	Validation	Training	Testing	Validation	Hidden	Output
1	MLP 3-6-4	0.879	0.984	0.979	0.050	0.042	0.041	Identity	Logistic
2	MLP 3-7-4	0.915	0.988	0.934	0.032	0.030	0.038	Identity	Identity
3	MLP 3-5-4	0.962	0.984	0.966	0.015	0.040	0.030	Tanh	Exponential
4	MLP 3-5-4	0.956	0.986	0.977	0.016	0.033	0.022	Logistic	Identity
5	MLP 3-9-4	0.968	0.985	0.972	0.011	0.027	0.015	Logistic	Identity

number of neurons in the hidden layer is nine (network MLP 3-9-4), when obtaining high values of r^2 and also low values of *SOS*. Also, it is noticed that a greater number of PE increases the structure complexity does not necessarily improve the network behavior [28], (during testing step MLP 3-9-4 gained r^2 = 0.985, SOS = 0.027, while MLP 3-7-4 gained r^2 = 0.988 and SOS = 0.030, MLP 3-5-4, No 4, gained r^2 = 0.986 and SOS = 0.033).

Simulation and optimization

Process outputs *WL*, *SG*, a_w and *DM* can be calculated by Eq. (5), using matrices W_1 and B_1, and matrices $\mathbf{W}_2$ and $\mathbf{B}_2$, which represent the system, incorporating coefficients associated with the hidden layer (both weights and biases). Output variables are calculated by applying transfer functions f_1 and f_2 (from Table 3) in the hidden and output layers, respectively, onto the matrix of input variables *X* using Eq. (5). The algebraic system of equations is easily evaluated in a spreadsheet (*i.e.*, Microsoft Excel) to predict *WL*, *SG*, a_w and *DM* of OD of pork meat cubes, using Eqn. (6), with shown calculated weights and biases matrices.

$$\mathbf{Y}=\begin{bmatrix} WL \\ SG \\ a_w \\ DM \end{bmatrix},\ \mathbf{X}=\begin{bmatrix} t \\ T \\ C \end{bmatrix},$$

$$\mathbf{W}_1=\begin{bmatrix} 1.639 & 1.202 & 2.450 \\ 1.692 & 1.077 & 1.020 \\ -0.173 & -0.262 & -0.028 \\ 1.606 & 0.716 & 1.367 \\ -0.167 & 1.339 & 0.554 \\ -1.627 & -0.105 & 0.263 \\ 1.667 & 1.468 & 3.409 \\ 2.189 & 0.610 & 1.147 \\ 1.707 & -0.078 & -0.066 \end{bmatrix},\ \mathbf{B}_1=\begin{bmatrix} -0.380 \\ -0.102 \\ -0.113 \\ -0.310 \\ -0.296 \\ -0.358 \\ -0.982 \\ -0.935 \\ -0.740 \end{bmatrix}, \quad (6)$$

$$\mathbf{W}_2=\begin{bmatrix} 0.293 & -0.947 & -1.055 & -0.103 \\ 0.131 & 0.224 & 0.690 & 0.368 \\ 1.077 & 0.966 & -0.562 & -1.055 \\ 0.181 & 0.641 & -0.196 & 0.292 \\ -0.093 & 0.994 & -0.265 & 1.456 \\ 1.503 & -0.039 & -0.152 & -0.307 \\ -0.650 & -1.010 & -0.629 & 0.345 \\ -0.941 & -1.177 & 0.081 & 0.362 \\ 0.366 & 0.461 & 0.605 & 0.860 \end{bmatrix},\ \mathbf{B}_2=\begin{bmatrix} 0.093 \\ -0.237 \\ 0.582 \\ -0.030 \end{bmatrix}$$

ANN models used to simulate experimental OD kinetics (*WL*, *SG*, a_w and *DM*), Figure 1, show simulated curves in comparison with experimental data, for all 5 tested neural networks. Table 3 shows ANN performance data, expressed as the sum of r^2 and sum of SOS, for all variables in one ANN, while Table 4 shows r^2 for each variable (*WL*, *SG*, a_w and *DM*) during training, testing and validation steps. It can be noted that the networks were able to predict reasonably well all process outputs for a broad range of the process variables, shown in Table 1.

The accepted model (MLP 3-9-4) does not work very well at some extreme conditions, as shown in Figure 1, for example, experimental *SG* (targets) and predicted values (outputs) differs the most at the low left and upper right corner of the diagram. This probably happens because *SG* has very small values at these conditions.

However, the predicted values were very close to the desired values in most cases, although *SG* and a_w prediction was not as good as that for *WL* and *DM* in terms of r^2 value. *SOS*s obtained with ANN models are of the same order of magnitude as experimental errors for *WL*, *SG*, a_w and *DM* reported in the literature [18,51]. The mean and the standard deviation of residuals have also been analyzed. The mean of residuals were in the range of 0.00–0.02 for *WL*; 0.00–0.01 for *SG*; 0.00 for a_w and 0.09–1.05 for *DM*, while standard deviation were in the range 0.02–0.04 for *WL*; 0.01–0.02 for *SG*; 0.01–0.02 for a_w, and 1.57–3.63 for *DM*.

These results show a good approximation to a normal distribution around zero with a probability of 95% (2·SD) to find residuals below 0.04–0.08 for *WL*; 0.02–0.04 for *SG*; 0.02–0.04 for a_w, and 2.9–7.3 for *DM*, which means a good generalization ability of ANN model for the range of experimental values of *WL*, *SG*, a_w and *DM* shown in Table 1.

MLR model using StatSoft Statistica 10 was also developed, and sum of squares and r^2 values are presented in Table 2. It can be seen that r^2 values are slightly lower than those associated with the ANN model. This agrees with what other authors reported [47,48]. Although ANN models are more complex (44–76 weights-bias for *WL*, *SG*, a_w and *DM* model, for five different ANNs) than linear regression models (4 weights-bias for *WL*, *SG*, a_w and *DM*), ANN models perform better because of the high nonlinearity of the developed system. Tables 2–4 show that ANNs gained much better results, compared to the MLR model, regarding the r^2 comparison between experimental and calculated outputs. r^2 between experimental and MLR model outputs, for *WL*, *SG*, a_w and *DM* , were: 0.888, 0.824, 0.773 and 0.916, respectively, while the best ANN model (MLP 3-9-4) gained: 0.996, 0.967, 0.985 and 0.992 , respectively, during the testing period.

The ANN model allows an extrapolation, by extending the range of process parameters (inputs), but this model was not compared with experimental values beyond the range of variables used in its development due to the lack of experimental information.

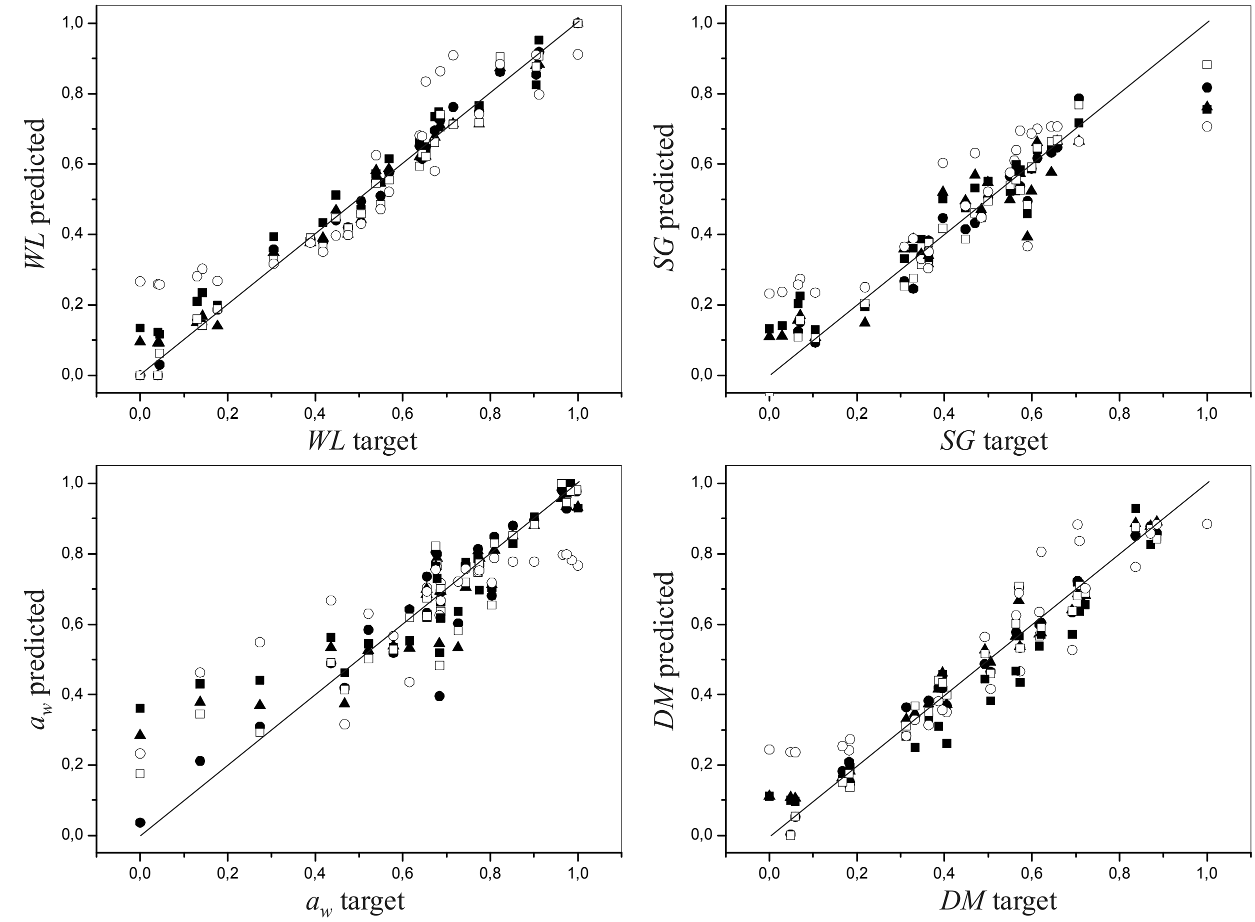

Figure 1. Normalized WL, SG, a_w and DM model prediction performance for: MLP 3-6-4 (■), MLP 3-7-4(●), MLP 3-5-4 (▲), MLP 3-5-4 (□), MLP 3-9-4 (○).

Table 4. r^2 between experimentally measured and ANN outputs, during train, test and validation steps

ANN name	Training				Testing				Validation			
	WL	SG	aw	DM	WL	SG	aw	DM	WL	SG	aw	DM
MLP 3-6-4	0.943	0.900	0.728	0.946	0.971	0.983	0.998	0.983	0.995	0.990	0.949	0.980
MLP 3-7-4	0.942	0.877	0.883	0.958	0.985	0.990	0.986	0.992	0.961	0.967	0.872	0.934
MLP 3-5-4	0.990	0.936	0.932	0.990	0.976	0.989	0.991	0.980	0.999	0.998	0.876	0.992
MLP 3-5-4	0.983	0.913	0.936	0.991	0.990	0.982	0.982	0.991	0.996	0.997	0.930	0.984
MLP 3-9-4	0.990	0.949	0.940	0.994	0.996	0.967	0.985	0.992	0.995	0.991	0.915	0.986

In this work, an attempt was made to optimize the OD process at maximum *WL* and minimum *SG*. The objective function was minimized using Microsoft Excel. Since it is necessary to consider a multi-variable optimization (*WL* and minimum *SG*), a general objective function can be represented by the following expression: $SG + (1 - WL)$, and the optimum can be found using Microsoft Excel's Solver.

Optimum process parameters, for OD in sugar beet molasses solution were: osmotic time of 4 h, molasses solution concentration and temperature of 72% and 45 °C. The predicted responses for the optimum drying conditions in sugar beet molasses solution were: DM of 64.5%, WL in the close vicinity of 0.53, SG about 0.15 and aw in the range of 0.83 to 0.84.

To determine the adequacy of the best ANN model, independent experiments were performed at optimum conditions for validation. Table 5 shows the model validation results. Very good coefficients of variation (CV) of less than 10% for all output variables were calculated. The low CV values for response variables *WL*, *SG*, a_w and *DM,* indicated the adequacy of these models.

Sensitivity analysis

In order to assess the effect of each input variables changes on the output variables a sensitivity analysis was performed. The white noise signals were incorporated by adding or subtracting a Gaussian error of *SD* of 5% and zero mean with 98% probability, *i.e.*, 2.576·*SD* to each input variable [51]. Due to the large number of combinations (three variables in three levels) a full central composite experimental design [52] was used for testing the best performance developed ANN model, which seems to be MLP 3-9-4 (according to Table 3). Table 6 shows the final design with 27 combinations. The complete database (27 points from Table 1) was used, for a total of 27×27 = 729 cases. *SOS* was calculated and compared with the base case, which is comprised of the unperturbed points (*i.e.*, without applying any noise).

Table 5. Predicted and observed output variables, at optimum conditions: time, 4 h, concentration, 72%, temperature, 45 °C

Response	Predicted	Observed	Standard deviation	Coeff. of variation
DM	64.50	64.09	1.04	1.62
WL	0.53	0.52	0.05	9.62
SG	0.15	0.16	0.01	6.25
a_w	0.83	0.82	0.06	7.32

Table 6. The final ANN design with 27 combinations

Essay No.	T / °C	t / h	C / mass%
1	0	0	0
2-9	±1	±1	±1
10-11	0	0	±1
12-13	0	±1	0
14-15	±1	0	0
16-19	0	±1	±1
20-23	±1	0	±1
24-27	±1	±1	0

Figure 2 shows the influence of the input variables on *WL*, *SG*, a_w and *DM*, according to sum of squares, calculated by comparing model predicted values with and without white noise signal applied, according to Table 4. All output variables were most affected by processing time, while the impact of temperature and concentration were also notable.

CONCLUSIONS

An ANN-based model was developed for prediction of *WL*, *SG*, a_w and *DM* of OD of pork meat cubes for a wide range of experimental conditions. The model was able to predict successfully experimental OD kinetics, with ease of implementing it for design and control of OD processes and also the effective use for predictive modeling and optimization of OD processes. As compared to an MLR model, ANN models yield a better fit of experimental data, according to r^2 and SOS, shown in Tables 2–4.

Taking into account that a considerable amount and wide variety of data were used in the present work to obtain the ANN model, and considering that the model turned out to yield a sufficiently good representation of the data, this ANN model can be expected to be very useful in practice for the design and control of OD processes for pork meat cubes. The model could be improved by increasing the database.

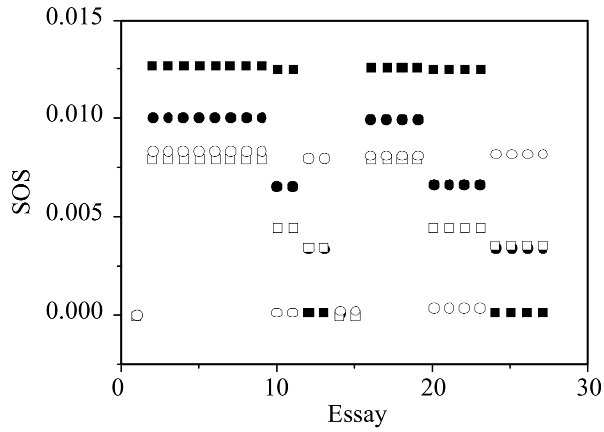

Figure 2. Sensitivity analysis for WL(■) , SG(●), a_w (□) and DM(○).

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IZVOD

MODEL VEŠTAČKE NEURONSKE MREŽE ZA OSMOTSKU DEHIDRATACIJU KOCKICA SVINJSKOG MESA

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(Naučni rad)

Jedna od potencijalno zanimljivih tehnika za očuvanje proizvoda sa niskim sadržajem vode i poboljšanim nutritivnim, senzornim i funkcionalnim svojstvima jeste proces osmotske dehidratacije. Proces osmotske dehidratacije je prihvatljiv metod sa aspekta uticaja na životnu sredinu, čiji je krajnji cilj očuvanje prvobitnih karakteristika gotovog proizvoda, kao i režim sušenja koji ne utiče negativno na materijal. Ovaj proces je privukao značajnu pažnju zbog niskih procesnih temperatura, male količine otpadnog materijala i niskih energetskih zahteva. Modeli veštačkih neuronskih mreža su nedavno u većoj meri počeli da se koriste za modelovanje i kontrolu procesa. Modeli neuronskih mreža su prepoznati kao dobar alat za dinamičko modelovanje jer ne zahtevaju parametre fizičkih modela, imaju mogućnost učenja rešenja problema iz serija eksperimentalnih podataka i mogu da obrađuju kompleksne nelinearne probleme sa interakcijama između odlučujućih promenljivih veličina. Usled kompleksnosti procesa osmotske dehidratacije, više autora je preporučilo modelovanje kinetike prenosa mase tokom procesa osmotske dehidratacije pomoću veštačkih neuronskih mreža. U ovom radu ispitivan je prenos mase pri osmotskoj dehidrataciji kockica svinjskog mesa *(M. triceps brachii),* dimenzija 1×1×1 cm^3. Koristeći eksperimentalne rezultate ispitivan je uticaj različitih parametara, kao što su koncentracija melase šećerne repe (60–80% m/m), temperatura (20–50 °C) i vreme imerzije (1–5 h) na gubitak vlage, prirast suve materije, krajnji sadržaj suve materije i aktivnost vode. Razvijeno je pet neuronskih mreža za predviđanje gubitka vlage, prirasta suve materije, krajnjeg sadržaja suve materije i aktivnosti vode u procesu osmotske dehidratacije kockica svinjskog mesa. Ovi modeli su predvideli procesne izlazne veličine sa tačnošću izraženom preko stepena korelacije sa eksperimentalnim merenjima: r^2 od 0,990 za prirast suve materije i 0,985 za gubitak vlage, 0,986 za aktivitet vode i 0,992 za finalni sadržaj suve materije. Širok opseg procesnih promenljivih veličina razmatranih u konstrukciji ovih modela, kao i njihova laka implementacija u tabelarno izračunavanje čini ih veoma praktičnim za projektovanje i kontrolu procesa.

Ključne reči: Prenos mase • Osmotska dehidratacija • Svinjsko meso • Melasa šećerne repe • Veštačke neuronske mreže