Effects of temperature and immersion time on rehydration of osmotically treated pork meat

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Summary

The aim of this work was to investigate the changes in osmotically treated pork meat during rehydration process, using artificial neural network approach, compared to second order polynomial model (obtained using response surface methodology). Meat samples were osmotically treated in two different solutions: (1) sugar beet molasses and (2) saccharose-NaCl solution, at temperature of (23 ± 2) °C for 5 h. After being osmotically treated, meat samples were rehydrated at three constant temperatures (20 °C, 40 °C and 60 °C) during four different immersion durations (15 min, 30 min, 45 min and 60 min), and afterwards examined for mass and volume gain (dV), and for rehydration percentage (R). The maximum R was observed for 20 °C and 60 min (24.1% and 26.2% for solution 1 and 2, respectively), while the maximum dV was observed at 40 °C and 30 min (16.1% and 22.6% for solution 1 and 2, respectively). Second order polynomials used for prediction of R and dV showed good accuracy compared to experimental results (coefficient of determination, r^2, ranged between 99.171–93.665), while the best of five artificial neural network models gained r^2 in the range of 0.992– 0.995 for R, and in the range of 0.976–0.988 for dV, for samples treated in solution 1 and 2.

Keywords

rehydration; osmotic treatment; pork meat; artificial neural network

Meat represents a cellular system with great biochemical and structural complexity, created by a network of muscular fibres surrounded by connective tissue. One of the most important constituents of meat is water [1, 2]. Physicochemical, sensory and technological properties of fresh meat are related to water content. Water is held in myofibrils, functional proteins of meat, but also it may exist in the intracellular space between myofibrils and sarcoplasm [3]. The technique of dehydration is probably the oldest method of food preservation practiced by mankind [4]. Osmotic treatment (OT) is a non-thermal process that implies food material immersion in hypertonic solution. The difference of the chemical potential between the material and the solution promotes two main fluxes: efflux of water from the material to the osmotic solution, and influx of soluble solids from the osmotic solution to the material. As osmotic agents, saccharose and salts (such as NaCl) are often used. Previous research [5] showed that the process of osmotic treatment positively influenced the microbiological profile and safety of osmo-treated pork meat, while the preliminary sensory analysis showed that meat processed in this manner had satisfactory sensory characteristics. The use of sugar beet molasses during OT improved the nutritional profile of pork meat, causing that the chemical composition after OT got to the optimum range for human health. Sugar beet molasses is an excellent medium

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for OT, primarily due to the high dry matter (80%) and the specific nutrient content (approximately 51%, saccharose, 1% raffinose, 0.2% glucose and fructose, 5% proteins, 6% betaine, 1.5% nucleosides, purine and pyramidine bases, organic acids and bases), which provide high osmotic pressure in the solution [6].

In OT processes, heat and mass transfer flows can modify physicochemical properties of the material such as chemical composition [7], mechanical properties [8, 9], volume and porosity. The quality of the dehydrated product depends on the extent of these changes. Regarding the changes in volume and porosity, high shrinkage and low porosity lead to products with poor rehydration capability [10]. Furthermore, the changes in volume and dimensions must be considered for modelling the mass transfer during OT [11, 12]. Volume changes during OT take place mainly due to compositional changes and mechanical stresses associated to mass fluxes. These changes were analysed as variations in the volumes of solid, liquid and gas phases of the food material during the process [13], and were correlated with changes in moisture content and weight reduction [14], or with water loss [15]. Structural parameters such as sample volume, specific dimensions and porosity are closely related not only to food behaviour in mass transfer processes, but also to other aspects such as food sensory and physical properties.

Dehydrated products need to be rehydrated before consumption or further processing [16]. During rehydration, absorption of water into the tissue results in an increase in the mass. Simultaneously, leaching out of solutes (saccharose, acids, minerals, vitamins) also occurs, and both phenomena are influenced by the nature of the product and conditions employed for rehydration [17, 18]. A study of rehydration kinetics can be used to ascertain the net extent of injuries sustained by any material during rehydration and any other processing step prior to it [19]. Rehydration is influenced by several factors, grouped as intrinsic factors (such as product chemical composition, pre-drying treatment, product formulation, drying techniques and conditions and by the post-drying procedure) and extrinsic factors (such as composition of immersion media, temperature and hydrodynamic conditions) [16].

The literature is inconsistent on rehydration characteristics with regard to food-to-water ratio, temperature of rehydration, level of agitation and procedure for the determination of moisture content [19]. Rehydration can be considered as a measure of the injury to the material caused by drying and OT [20]. It was shown [21] that the volume changes (swelling) of biological materials are often proportional to the amount of absorbed water. It is generally accepted that the degree of rehydration is dependent on the degree of cellular and structural disruption. In some studies that considered food structure in the process modelling, changes in sample volume were explained in terms of water loss throughout the process [22]. The time needed to reach the minimum volume was determined with a proposed equation [13]. The initial shrinkage period was observed to be followed by a swelling period.

Response surface methodology (RSM) is an effective tool for optimizing a variety of food processes including rehydration [23]. The main advantage of RSM is the reduced number of experimental runs that provide sufficient information for statistically valid results. The RSM equations describe effects of the test variables on the observed responses, determine test variables interrelationships and represent the combined effect of all test variables in the observed responses, enabling the experimenter to make efficient exploration of the process. In case of food processes, nonlinear models are more suitable due to variability and nonlinear behaviour 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.

Artificial neural network (ANN) models recently gained momentum for process modelling and control. ANN models are recognized as a good tool for dynamics modelling 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 [24]. Due to the complexity of the rehydration process, several authors recommended the use of ANN for modelling mass transfer kinetics during the rehydratation process [25, 26]. Nevertheless, few works have been done on the application of ANN to model the rehydration process. Also, no study was published on the effect of process conditions on rehydration percentage (R) and volume changes (dV) of pork meat.

The aim of here presented article was to investigate the effects of temperature and processing time on the mass transfer phenomena during rehydration of pork meat, that were OT in sugar beet molasses or, saccharose solutions, to model R and dV, as a functions of the process variables. The performance of five ANN models was compared with the performance of second order polynomial (SOP) models.

MATERIALS AND METHODS

Fresh pork (*Musculus triceps brachii*; 24 h post mortem) was bought in local butcher store and transported to the laboratory, where it was held at about 4 °C for 1–2 h. The muscles were trimmed of external fat and connective tissues, and manually cut into approximately (1 × 1 × 1) cm cubes with a sharp sterile knife. Meat samples were osmotically treated at (23 ± 2) °C for 5 h in a solution of sugar beet molasses (soluble solid content 80.00 $kg \cdot l^{-1}$) – solution 1, and in saccharose-salt solution in distilled water (1 200 g of saccharose and 350 g of NaCl diluted in 1 litre of distilled water) – solution 2. The solution to sample mass ratio was 10 : 1 for both cases, to avoid significant dilution of the medium by water removal, which would lead to local reduction of the osmotic driving force during the process [27, 28]. Meat cubes were fully immersed and held in the solution using stainless wire mesh. Experiment was carried out using laboratory glasses (volume V = 500 ml each). On every 5 min, meat samples in osmotic solutions were stirred with hand-held agitator in order to induce sample-solution contact and provide better homogenization of the osmotic solution. After being removed from the osmotic solution, samples were gently blotted with a tissue paper in order to remove excessive solution from the surface, and then they were analysed.

Rehydration

Osmotically treated meat samples were rehydrated by immersing meat cubes in water bath at three different constant temperatures (20 °C, 40 °C and 60 °C). The samples were withdrawn from the bath at different immersion periods (15 min, 30 min, 45 min and 60 min) and were weighed after being blotted. Finally, rehydration percentage R was calculated as:

$$R = \frac{(M_t - M_0)}{M_0} \times 100 \quad (1)$$

where M_t and M_0 is the sample mass at time t (rehydrated samples) and at start of rehydration (t = 0, dried samples), respectively.

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 (Instrumentaria Sutjeska, Zagreb, Croatia).

Percentage of volume changes dV was calculated as:

$$dV = \frac{(V_t - V_0)}{V_0} \times 100 \quad (2)$$

where V_t and V_0 is the sample volume at time t (rehydrated samples) and at start of rehydration (t = 0, dried samples), respectively.

All sample dimensions (width, height and depth) of meat cubes were measured before and after rehydration using digital caliper, and approximate volume was calculated.

ANOVA and response surface methodology

Before modelling by ANN, it is recommended to make some statistical data analysis, like analysis of variance (ANOVA) to check the significant effect of the input variables over the output, and to justify the use of ANN model by coefficient of determination r^2. This is recommended in particular in the case when relatively small number of experimental measurements are being used for ANN model development. The RSM method was selected to estimate the main effect of solution type (solution 1 or 2) on mass transfer variables during the rehydration of pork meat cubes. The independent variables were rehydration time (t) of 15 min, 30 min, 45 min and 60 min, and temperature (T) of 20 °C, 40 °C and 60 °C. The dependent variables were the responses: rehydration percentage of the samples treated with solution 1 or 2 (Y_1 and Y_2, respectively), and volume changes of the samples treated with solution 1 or 2 (Y_3 and Y_4, respectively). The accepted experimental design included 3 × 4 = 12 experiments. All models were fitted to the response surface generated by the experimental design [29]. The following SOP model was fitted to the data:

$$Y_k = \beta_{k0} + \beta_{k1}T + \beta_{k2}t + \beta_{k11}T^2 + \beta_{k22}t^2 + \beta_{k12}Tt \quad (3)$$

where β_{k0}, β_{ki}, β_{kii}, β_{kij} are constant regression coefficients. The significant terms in the model were found by ANOVA for each response.

Database preparation

The mean ± standard deviation (SD) values of the experimentally measured process variables and desired outputs are given in Tab. 1. StatSoft Statistica ver. 10 (StatSoft, Tulsa, Oklahoma, USA) was used to randomly divide the collected data into two groups: training data (80%) and testing data (20%). Testing data set was used to examine the network generalization capability. To improve the behaviour of ANN, both input and output data were normalized [30, 31], according to Eq. 4:

$$x_{i\,norm.} = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \quad (4)$$

where x_i is i-th case, with measured temperature (T) and immersion time (t), and R and dV from Tab. 1. Normalized variables gained values in the range of 0–1, and had no physical meaning.

Tab. 1. Experimental data for rehydration of pork meat cubes.

Case No.	T [°C]	t [min]	R_1 [%]	R_2 [%]	dV_1 [%]	dV_2 [%]
1	20	15	11.1 ± 0.7^{b}	9.3 ± 0.5^{d}	3.6 ± 0.1^{b}	4.6 ± 0.2^{b}
2	20	30	20.0 ± 1.1^{d}	17.4 ± 0.7^{f}	6.0 ± 0.1^{e}	5.4 ± 0.1^{b}
3	20	45	20.2 ± 1.2^{d}	23.2 ± 1.1^{g}	4.1 ± 0.1^{b}	7.3 ± 0.1^{d}
4	20	60	24.1 ± 0.9^{g}	26.2 ± 0.4^{h}	14.9 ± 0.7^{a}	9.6 ± 0.7^{a}
5	40	15	5.5 ± 0.3^{e}	2.0 ± 0.1^{e}	3.7 ± 0.1^{b}	10.1 ± 0.2^{a}
6	40	30	8.6 ± 0.3^{f}	4.4 ± 0.2^{c}	16.1 ± 0.7^{a}	22.6 ± 1.0^{g}
7	40	45	12.7 ± 0.9^{b}	5.4 ± 0.1^{c}	16.2 ± 0.7^{a}	16.0 ± 0.7^{e}
8	40	60	11.3 ± 0.2^{b}	7.9 ± 0.3^{d}	16.3 ± 1.3^{a}	9.3 ± 0.2^{a}
9	60	15	-7.4 ± 0.3^{a}	-8.0 ± 0.2^{b}	16.1 ± 0.5^{a}	9.1 ± 0.4^{a}
10	60	30	-7.9 ± 0.1^{a}	-8.8 ± 0.4^{b}	8.5 ± 0.2^{f}	18.9 ± 0.5^{f}
11	60	45	-9.4 ± 0.7^{ac}	-11.1 ± 0.4^{a}	-0.7 ± 0.02^{d}	5.8 ± 0.1^{b}
12	60	60	-10.9 ± 0.7^{c}	-12.0 ± 0.6^{a}	-10.0 ± 0.7^{c}	-7.4 ± 0.2^{c}

Values with the same letter in superscript are not statistically different, $p < 0.05$ (post-hoc Tukey's HSD test).
T – temperature, t – time, R_1 – rehydration of meat treated in solution 1, R_2 – rehydration of meat treated in solution 2, dV_1 – volume change of meat treated in solution 1, dV_2 – volume change of meat treated in solution 2.

Artificial neural network modeling

In this article, a multi-layer perception models (MLP) that consisted of one input layer, one hidden layer and one output layer, which is the most common, flexible and general-purpose kind of ANN, was evaluated [31]. It is necessary to perform a trial and error procedure, until a good network behaviour is obtained, and it is also necessary 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 a problem of local minima [31]. The number of weights 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. The ANN procedure of StatSoft Statistica was used to model ANN, and the number of hidden nodes varied from 4 to 8, 2 inputs and 4 outputs, with 32 to 60 weight coefficients (depending on the number of hidden nodes). Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm, implemented in StatSoft Statistica's evaluation routine, was used for ANN modelling. The information passes between layers through a "transfer" or "activation" functions. This function is typically nonlinear for hidden layers and linear for the output layer. In most applications, hyperbolic tangent function behaves better as compared to other functions [31, 32]. Coefficients associated with the hidden layer (both weights and biases) are grouped in matrices W_1 and B_1. Similarly, coefficients associated with the output layer are grouped in matrices W_2 and 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 [33, 34]:

$$Y = f_1[W_2 f_2(W_1 X + B_1) + B_2] \tag{5}$$

Weights (elements of matrices W_1 and 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 [32–35], according to the sum of squares (SOS) and BFGS algorithm, used to speed up and stabilize convergence [30]. 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 ver. 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 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 and *SOS* were used as parameters to check the performance of ANN. The ANN model can be implemented using an algebraic system of equations, to predict R and dV, by substitution of the corresponding weights and biases, and coefficients matrices in Eq. 5. This step can be easily achieved in some spreadsheet calculus (Microsoft Office Excel 2007, Microsoft, Redmond, Washington, USA).

Statistical analysis and verification of the experiments

ANOVA and RSM were performed using StatSoft Statistica for Windows, ver. 10 programme. The model was obtained for each dependent variable (or response) where factors were rejected when their significance level was less than $p < 0.05$. Post-hoc Tukey's honest significant difference (HSD) test at a significance level of $p < 0.05$ were calculated to show significant differences between different samples. The same programme was used for generation of graphs and contour plots. The graphs of the responses with significant parameters were super-imposed to determine optimum drying conditions and were plotted on optimization graphics.

RESULTS AND DISCUSSION

After relatively short time (15 min), significant weight and volume gains were observed for both treatments. Process temperature was the most significant variable affecting final dry matter content and rehydration kinetics. At the end of rehydration process, conducted at 20 °C and 40 °C, a significant recovery in mass was observed, although the values were lower than for fresh meat. As the result of OT, the ruptured and shrunken meat tissue had a reduced own ability to absorb water. Rehydration percentage at 20 °C for solution 1 was 24.1%, and for solution 2 was 26.2%. However, rehydration at 40 °C brought a higher mass gain in case of solution 1 (11.3%) compared to solution 2 (7.9%). Results obtained at 60 °C were negative, which means that rehydration did not take place. The best conditions for meat rehydration were obtained using a temperature of 20 °C and time of 60 min. Volume of samples increased almost linearly with the weight increment.

Tab. 2. ANOVA table, showing sum of squares.

Term	DF	R_1	R_2	dV_1	dV_2
T	1	1543.0^{*}	1680.3^{*}	26.9^{**}	0.03^{ns}
t	1	39.4^{*}	62.0^{*}	5.1^{ns}	49.7^{**}
T^2	1	55.8^{*}	0.5^{ns}	160.4^{*}	163.5^{*}
t^2	1	9.1^{**}	2.2^{ns}	2.6^{ns}	138.7^{*}
$T \times t$	1	66.2^{*}	125.0^{*}	357.3^{*}	158.0^{*}
Error	6	14.3^{ns}	5.3^{ns}	30.5^{ns}	8.3^{ns}
r^2		99.2	99.2	91.5	93.7

T – temperature, t – immersion time, r^2 – coefficient of determination, DF – degrees of freedom, R_1 – rehydration of meat treated in solution 1, R_2 – rehydration of meat treated in solution 2, dV_1 – volume change of meat treated in solution 1, dV_2 – volume change of meat treated in solution 2.
* – significant at $p < 0.05$ level, ** – significant at $p < 0.10$ level, ns – not significant,

ANOVA and RSM results

The ANOVA study was conducted prior to ANN to determine the influence of process variables (temperature and treatment time) on R and dV of pork meat cubes in solution 1 and 2. The experimental data used for the analysis were derived from the experimental design. Tab. 1 shows the response variables as a function of independent variables for the analysis. ANOVA table (Tab. 2) shows the calculation regarding the developed SOP models, Eq. 3, when the experimental data were fitted to a response surface, and it exhibits the significant independent variables and their interactions. It also shows the significant effects of independent variables on the responses and which of the responses were significantly affected by the varying treatment combinations.

The calculation of R for samples treated by solution 1 was significantly affected by all process variables, temperature and treatment time, at $p < 0.05$ level. It was noticed that the calculation of R was most affected by linear term of processing temperature in SOP model. The impact of temperature was dominant, as seen by temperature's quadratic term, and also by the cross-product term, which were more influential than both linear and quadratic term of rehydration time in SOP model calculation. The quadratic term of rehydration time in SOP model was significant at $p < 0.10$ level. The calculation of R for meat samples treated by solution 2 was mostly affected by linear term of processing temperature (significant at $p < 0.05$ level). The quadratic terms for both temperature and rehydration time were found statistically insignificant, while the interchange term was found more influential than the linear term of rehydration time, in SOP model calculation. Both of these terms were significant at $p < 0.05$ level.

The calculation of dV for samples treated in solution 1 were significantly affected by interchange term and by quadratic term of temperature in SOP model, significantly at $p < 0.10$ level, while linear term affected dV calculation statistically significantly at $p < 0.10$ level, in SOP model calculation. All other sources were statistically insignificant. The temperature terms were found dominant, but mostly nonlinearly, which can be observed on the contour plots. The calculation of dV for samples treated in solution 2 was most affected by linear and quadratic terms of processing time in SOP model (significant at $p < 0.05$ and $p < 0.10$ level, respectively). The quadratic term of temperature and cross product term were found statistically significant at $p < 0.05$ level, while all other terms were found statistically insignificant, in SOP model calculation.

The analysis revealed that the linear terms for R contributed substantially in all cases to generate a significant SOP model. The SOP models for all variables were found to be statistically significant and the response surfaces were fitted to these models. The linear terms of SOP model were found significant, at $p < 0.05$ level, and their influence was the most important in model calculation. On the other hand, non-linear terms in the SOP model for volume changes were found dominant, which was due to complexity of the system and due to its diffusive nature. Also shown in Tab. 2 is the residual variance, where the lack of fit variation represents other contributions except for the first and second order terms. All SOP models had insignificant lack-of-fit tests, which means that all the models represented the data satisfactorily. Also, a high r^2 was indicative that the variation was accounted, and that the data fitted satisfactorily to the proposed SOP model. The r^2 values for R of the samples treated with solution 1 (99.171) and R for those treated with solution 2 (99.220) were very satisfactory and showed good fitting of the model to

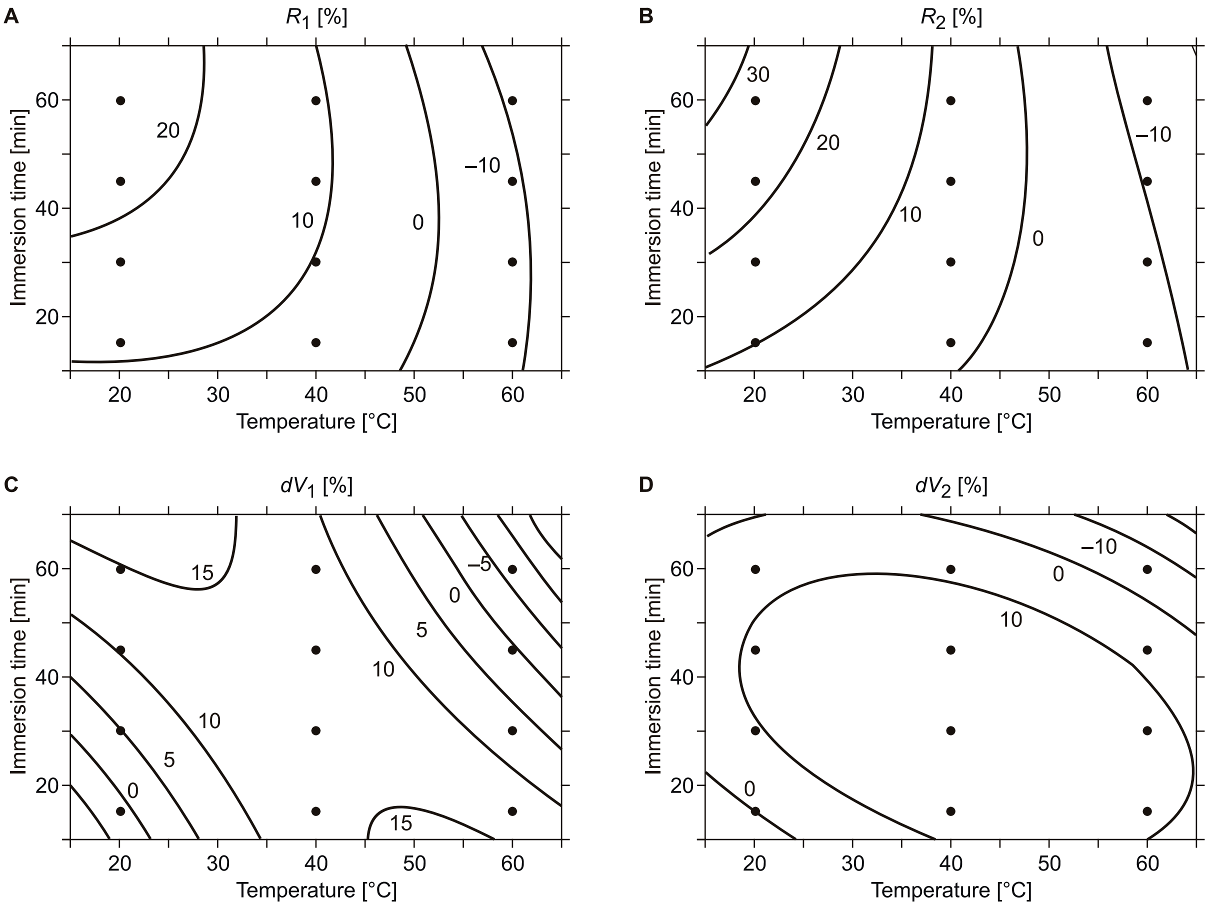

Fig. 1. Contour plots for rehydration and volume changes of pork meat cubes as a function of temperature and immersion time.

A – rehydration of meat treated in sugar beet molasses solution (R_1), B – rehydration of meat treated in saccharose-NaCl solution (R_2), C – volume changes of meat treated in sugar beet molasses solution (dV_1), D – volume changes of meat treated in saccharose-NaCl solution (dV_2).

Tab. 3. Predicted and observed responses at optimum conditions.

Response	R_1 [%]	R_2 [%]	dV_1 [%]	dV_2 [%]
Predicted	24.1	26.2	14.9	9.6
Observed	24.1	26.5	14.6	9.4
SD	0.3	0.5	0.3	0.6
CV	1.5	2.0	2.3	6.6

R_1 – rehydration of meat treated in solution 1, R_2 – rehydration of meat treated in solution 2, dV_1 – volume change of meat treated in solution 1, dV_2 – volume change of meat treated in solution 2, *SD* – standard deviation, *CV* – coefficient of variation.

experimental results (Tab. 2). Volume changes of the samples treated with solution 1 (91.467) and the samples treated with solution 2 (93.665) showed less confident model results, but also showed good fitting of the model and the experimental results. Maximum *R* was achieved when processing time rose (60 min), while temperature was relatively low (20 °C), for meat osmotically treated by both solution 1 and 2, while volume changes seemed to gain their maximum with a mild temperature and the average processing time (40 °C and 30 min). It seems that the low rehydration temperature (20 °C) and long processing time (60 min) could produce a processing optimum, concerning low energy consumption, with long processing time, but also good *R* and increase of sample volume. High temperature should be avoided, due to production expenses, high energy cost, and also degradation of pork meat cubes structure, which were unacceptable, as seen from Tab. 1 (degradation of meat cubes structure, noticed as negative *R*, at higher temperatures).

The contour plots developed from the approximating rehydration and volume change functions are shown in Fig. 1. Both rehydration contour plots showed a rising ridge configuration, with its value maximized at the upper left corner of the plots, with the increase in treatment time, and with minimal processing temperature applied. Volume changes for all samples investigated showed their maxima at the central area of both plots.

Independent experiments were performed at optimal conditions to determine the adequacy of the SOP models. Predicted and observed responses at optimum conditions, with standard deviations and coefficients of variation are presented in Tab. 3. The goodness of fit between experimental measurements and model-calculated outputs, represented as ANN performance (sum of r^2 between measured and calculated *R* and *dV* for each ANN), and also the sum of *SOS* between measured and calculated *R* and *dV*, during training and testing steps, are shown in Tab. 4. As shown in the previous ANOVA tables, the predicted values were comparable to the actual values in the experiment. Very good coefficients of variation (*CV*) of less than 10% for all process variables were calculated. *CV* values higher than 15% for response variables would indicate a statistically minor significance of the SOP model [36]. The low *CV* values of the response variables for *R* indicated the adequacy of our models.

Processing elements 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. Results of *R* and *dV* during testing with four to eight processing elements in the hidden layer are presented in Tab. 4, which shows r^2 between experimentally measured and ANN outputs, for training and testing steps, for each output variable (*R* and *dV*). Used MLP 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 Tab. 4 (sum of r^2 for all variables in one ANN), it was noticed that the optimum

Tab. 4. Artificial neural network summary.

No.	Network name	ANN performance (r^2)		*SOS* (error)		Activation function	
		Training	Testing	Training	Testing	Hidden	Output
1	MLP 2-6-4	0.987	0.988	0.006	0.014	Logistic	Hyperbolic tangent
2	MLP 2-8-4	0.967	0.953	0.024	0.010	Logistic	Hyperbolic tangent
3	MLP 2-8-4	0.943	0.947	0.041	0.032	Exponential	Identity
4	MLP 2-4-4	0.921	0.897	0.149	0.070	Gaussian	Identity
5	MLP 2-6-4	0.979	0.981	0.024	0.030	Logistic	Hyperbolic tangent

MLP – multi-layer perceptron (number of inputs - number of neurons in the hidden layer - the number of outputs), ANN – artificial neural network, r^2 – coefficient of determination, *SOS* – sum of squares.

number of neurons in the hidden layer was six (network MLP 2-6-4, No. 1), when high values of r^2 and also low values of *SOS* were obtained. Also can be noticed that a greater number of processing elements increased the structure complexity and did not improve the network behaviour (during testing step MLP 2-6-4, No. 1, gained $r^2 = 0.987$, $SOS = 0.006$, while MLP 2-8-4, No. 2, gained $r^2 = 0.967$ and $SOS = 0.024$, MLP 2-8-4, No. 3, gained $r^2 = 0.943$ and $SOS = 0.041$). Also, ANN with the same number of hidden neurons, and the same hidden layer activation functions, like No. 1 and No. 5, from Tab. 4, did not necessarily produce the same result, because the input data were randomly divided into training data and testing data groups, as mentioned before. The developed SOP model gained r^2 values slightly lower than those associated with the ANN model. This is in agreement with findings of other authors [32, 35]. Although ANN models are more complex (30–46 weights-bias for *R* and *dV* models, for five different ANN) than SOP models (4 weights-bias for *R* and *dV* models), ANN models perform better because of the high nonlinearity of the developed system.

Simulation and optimization

Process outputs *R* and *dV*, for samples treated in solutions 1 or 2 (R_1, R_2, dV_1, dV_2), could be calculated by Eq. 6, using matrices W_1 and B_1, and matrices W_2 and B_2, which represented the incorporating coefficients associated with the hidden layer (both weights and biases). Output variables were calculated by applying transfer functions f_1 and f_2 (from Tab. 4) in the hidden and output layers, respectively, onto the matrix of input variables *X* using Eq. 6. The algebraic system of equations was easily evaluated in a spreadsheet to predict *R* and *dV*, for samples of meat treated in solutions 1 or 2, with shown calculated weights and biases matrices.

$$Y = \begin{bmatrix} R_1 \\ R_2 \\ dV_1 \\ dV_2 \end{bmatrix}$$

$$X = \begin{bmatrix} t \\ T \end{bmatrix}$$

$$W_1 = \begin{bmatrix} -5.78 & -2.32 \\ -4.51 & -0.94 \\ -2.53 & -1.56 \\ 0.24 & -2.81 \\ -1.92 & -1.60 \\ 1.44 & 0.26 \end{bmatrix}$$

$$B_1 = \begin{bmatrix} 3.44 \\ 1.78 \\ -1.32 \\ -0.96 \\ 2.97 \\ -0.25 \end{bmatrix}$$

$$W_2 = \begin{bmatrix} -0.32 & 0.94 & 1.79 & -1.13 \\ 0.73 & 1.15 & -0.07 & -0.05 \\ 2.59 & -1.55 & 0.80 & 1.44 \\ -3.38 & 1.46 & 2.00 & 0.34 \\ 3.32 & 1.42 & -2.09 & 1.65 \\ -1.08 & 0.83 & 2.06 & -0.09 \end{bmatrix}$$

$$B_2 = \begin{bmatrix} -0.92 \\ -0.73 \\ -1.77 \\ -0.83 \end{bmatrix} \quad (6)$$

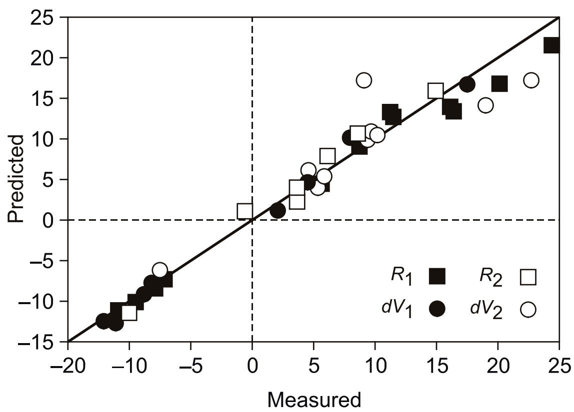

Fig. 2. Comparison of experimentally measured and predicted rehydration percentage and volume changes.

R_1 – rehydration of meat treated in sugar beet molasses solution, R_2 – rehydration of meat treated in saccharose-NaCl solution, dV_1 – volume changes of meat treated in sugar beet molasses solution, dV_2 – volume changes of meat treated in saccharose-NaCl solution.

ANN models used to simulate experimental rehydration kinetics were able to predict reasonably well all process outputs for a broad range of the process variables, shown in Tab. 1. Fig. 2 shows simulated results in comparison with experimental data, for the best neural network (MLP 2-6-4, No. 1). Tab. 4 shows ANN performance data, expressed as the sum of r^2 and sum of *SOS*, for all variables in one ANN. Tab. 5 shows r^2 for each variable (*R* for solution 1 and 2, and *dV* for solution 1 and 2) during training and testing steps. The predicted values were very close to the desired values in most cases, although *dV* prediction was not as good as that for *R* in terms of r^2 value. *SOS* obtained with ANN models were of the same order of magnitude as experimental errors for *R* and *dV* reported in the literature [37, 38].

Mean and standard deviation of residuals were also analysed. The means of residuals were in the range of 0.00–0.02 for *R* and 0.08–1.06 for *dV*, while standard deviations were in the range

Tab. 5. Coefficients of determination between experimentally measured and artificial neural network outputs during training and testing steps.

ANN name	Training				Testing			
	R_1	R_2	dV_1	dV_2	R_1	R_2	dV_1	dV_2
MLP 2-6-4	0.992	0.992	0.983	0.982	0.992	0.995	0.976	0.988
MLP 2-8-4	0.987	0.988	0.946	0.947	0.990	0.988	0.954	0.879
MLP 2-8-4	0.969	0.980	0.911	0.912	0.994	0.996	0.935	0.864
MLP 2-4-4	0.861	0.897	0.943	0.982	0.886	0.845	0.924	0.934
MLP 2-6-4	0.991	0.991	0.980	0.953	0.980	0.982	0.978	0.984

ANN – artificial neural network, MLP – multi-layer perceptron, R_1 – rehydration of meat treated in solution 1, R_2 – rehydration of meat treated in solution 2, dV_1 – volume change of meat treated in solution 1, dV_2 – volume change of meat treated in solution 2.

0.02–0.04 for *R* and 0.28–0.64 for *dV*. These results showed 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 *R* and 0.02–0.04 for *dV*, which means a good generalization ability of ANN model for the range of experimental values of *R* and *dV* shown in Tab. 1.

Tab. 6. Central composite design for sensitivity analysis.

Assay No.	Temperature *T* [°C]	Immersion time *t* [h]
1	0	0
2	0	−1
3	0	+1
4	−1	0
5	+1	0
6	−1	−1
7	−1	+1
8	+1	−1
9	+1	+1

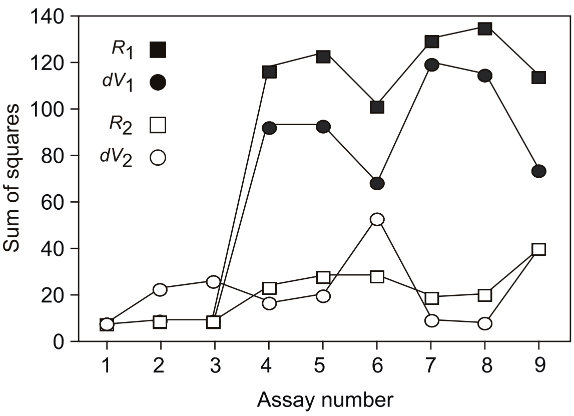

Fig. 3. Sensitivity analysis.

R_1 – rehydration of meat treated in solution 1, R_2 – rehydration of meat treated in solution 2, dV_1 – volume change of meat treated in solution 1, dV_2 – volume change of meat treated in solution 2.

Tab. 2, 4 and 5 show that ANN gained better results than the SOP model, regarding the r^2-based comparison between experimental and calculated outputs. Values of r^2 between experimental and SOP model outputs, for *R* for solution 1 and 2, and *dV* for solution 1 and 2, were: 0.992, 0.992, 0.915 and 0.937, respectively, while the best ANN model (MLP 2-6-4) gained: 0.992, 0.995, 0.976 and 0.988, respectively, during the testing period.

The ANN model allowed 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.

Sensitivity analysis

In order to assess the effect of each input variable changes on the output variables, sensitivity analysis was performed. The white noise signals were incorporated by adding or subtracting a Gaussian error of *SD* = 5% and zero mean with 98% probability, i. e. 2.576 × *SD* to each input variable [39]. A full central composite experimental design [29] was used for testing the best performing ANN model, which seemed to be MLP 2-6-4, No. 1 (according to Tab. 4). Tab. 6 shows the final design with 9 combinations. The complete database (12 points from Tab. 1) was used for a total of 12 × 9 = 108 cases. *SOS* was calculated and compared with the basic case, which comprised unperturbed points (i.e. without applying any noise).

Fig. 3 shows the influence of the input variables on *R* and *dV*, for meat samples treated with solution 1 and 2 , according to sum of squares, calculated by comparing model predicted values with and without white noise signal applied, according to Tab. 5. All output variables were most affected by processing time, while the impact of temperature was also notable.

CONCLUSION

Knowledge of physicochemical properties of food materials is important for an adequate design of food processing as well as for the control and improvement of the quality of the final product. Food shape is one of the main quality attributes perceived by the consumer. Drying process not only increases *dV* but also may cause changes in shape. The maximum rehydration percentage was observed for 20 °C and 60 min (24.1% and 26.2%, for two applied solutions), while the maximum *dV* was observed at 40 °C and 30 min (16.1% and 22.6%, for two applied solutions).

The developed second order polynomial model was used to numerically express *R* and *dV* of pork meat samples after rehydration, osmotically treated in molasses and saccharose-NaCl solution. Samples dehydrated in molasses solution were affected by temperature and treatment time during the rehydration process, while samples treated in saccharose-NaCl solution were most affected by temperature. For both cases of rehydration in two solutions, *R* was most effective with the time increase at relatively low temperatures, while *dV* had its maximum at mild temperatures and at relatively low processing time. ANN-based model was developed for prediction of *R* and *dV* of rehydration of pork meat cubes for a wide range of experimental conditions. The model was able to successfully predict experimental kinetics, with ease of implementing it for design and control of rehydration processes, and also the effective use for predictive modelling and optimization. As compared to SOP models, ANN model yielded a better fit of experimental data. 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 useful in practice for the design and control of rehydration processes for pork meat cubes.

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