MATHEMATICAL MODELLING OF THE MECHANICAL PROPERTIES OF FOUR VARIETIES OF BRINE PICKLES USING NEURAL NETWORKS

– Research paper –

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Abstract: The study assesses the impact of selected fruit properties and the souring process parameters on the mechanical properties of four varieties of field cucumbers (Śremianin, Śremski, Polan and Izyd) harvested from 2014 to 2016. The analyses focused on the changes in the values of the puncture strength parameters of the peel and the mesocarp, the deformation from the moment of puncture and the energy needed to puncture the peel and the mesocarp of the selected cucumber varieties relative to the year of harvest, fruit size, type of brine, puncture location and souring time. Neural networks were used to model the relationships studied. Sensitivity analysis of the obtained models showed that the length fraction had the greatest impact on the puncture strength and the energy needed to puncture the peel and the mesocarp. On the other hand, deformation was most affected by the souring time and the brine composition.

Keywords: cucumber, puncture strength, neural modelling, sensitivity analysis

INTRODUCTION

Cucumbers are firmly rooted in culinary traditions worldwide (Murcia et al., 2009). In addition to the mass consumption of fresh cucumbers, a significant portion of the overall crop is used to produce cucumber preserves or gherkins, which are pickled in a brine, vinegar or other solutions (Jahangiri et al., 2016; Mukherjee et al., 2013; Sotiroudis et al., 2010). The consumption of fresh and preserved cucumbers offers significant health benefits. This fruit contains a number of nutrients, including minerals, vitamins B and C, and folic acid (Guiné et al., 2014; Turkmen et al., 2005).

The factor that largely determines the course of the lactic fermentation process is the endemic microflora found on the fruit. The changes in its composition can potentially affect the souring process (Garcha and Natt, 2012). The addition of NaCl to the brine results in faster growth of mesophilic and G+ lactic bacteria of the genus *Lactobacillus* while limiting the development of undesirable microflora. It also reduces osmotic

pressure, and this leads to enriched nutrient contents in the brine. A souring process carried out properly in an anaerobic environment takes a lot of time because diffusion is slow. In addition to the large amounts of lactic acid, the process results in the production of smaller amounts of acetic acid, acetaldehyde, butanediol, diacetyl and carbon dioxide (Franco et al., 2012; Brasca et al., 2007).

The souring process is not the same for all cucumber varieties. The usefulness of varieties is determined by their sensory and mechanical parameters (Manuwa and Muhammad, 2011; Kashaninejad et al., 2006). The texture of the fruit is a very important feature determining the potential to preserve the flavour and the durability of the final product, and this is a basic property commonly evaluated by consumers. As an important quality parameter, it significantly affects customers' preferences and perceptions (Vicente et al., 2007).

In the era of dynamic agricultural development, understanding the mechanical properties of plant material is extremely important. In the fruit and vegetable processing industry, an important role is played by fast and effective methods enabling the assessment of the potential of plants from the

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viewpoint of their further processing (Moradi et al., 2020). The quality of the raw material is determined during all stages of growth from the selection of the appropriate farming conditions to effective harvesting. To meet the requirements of today's economy and to produce high-quality raw material, appropriate instrumental methods should be used (Eboibi and Uguru, 2017; El-Garniany and Albaloushi, 2015).

An examination of mechanical properties constitutes the basic instrumental measurement of the texture and elasticity of the biological material tested (Miraei et al., 2016). It includes a number of mechanical tests that use compressive, cutting and tensile forces. Strength tests are used to measure the force-deformation-time interactions and other physical parameters directly related to them (Bourne, 2002; Harker et al., 2002).

Research on the mechanical properties of fruit makes it possible to optimize the harvesting, transport, storage and processing of the raw material (Hashemi and Khaneghah, 2017; Hashemi et al., 2017; Bargel and Neinhuis, 2005). Many authors have emphasized the importance of considering mechanical properties when designing systems for sorting, classifying or storing fruit and vegetables (Gorzelay et al., 2017; Jahangiri et al., 2016; Arendse et al., 2014; Mousavizadeh et al., 2010; Sahin and Samnu, 2006; Kang et al., 2002).

Field cucumbers are anisotropic, which is why instrumental tests should be conducted regularly and comprehensively. By testing the mechanical properties of raw material, it is possible to evaluate its quality, firmness and hardness, i.e., the properties that determine its potential for processing (Sakata et al., 2011; Sakurai et al., 2005). Because cucumbers are characterized by different values of puncture parameters within a single fruit, it is not easy to describe their properties simply by conducting a basic puncture test (Xiaoyi et al., 2013; Kohyama et al., 2009; Fleming et al., 1995).

Mathematical modelling is of great importance in food industry. It helps to simulate many complex processes and sometimes to understand better their nature. Mathematical models can be used for optimization and, hence, decrease the costs for a variety of processes. Mathematical modelling includes two types of models: empirical (based on experimental data) and theoretical (based on the

equations governing the phenomena). Compared with theoretical models, empirical models are considered to be easier to develop and more accurate (Moradi et al., 2020). There have been many applications of empirical modelling in the food industry reported in prior literature. A dimensionless method was used for the modelling of the physical and mechanical properties of cucumbers (Moradi et al., 2020), the terminal velocity of cantaloupe (Moradi et al., 2019) and the convective drying of tuberous crop (Sandoval-Torres et al., 2017). One of the very interesting techniques useful for empirical modelling is artificial neural networks (ANN). This artificial intelligence tool enables one to produce mathematical models with high accuracy based on empirical data sets. ANNs were employed for the prediction of the viscoelastic behaviour of pomegranate (Saeidirad et al., 2013) and for the prediction of the mechanical properties of horticultural products (Mollazade et al., 2013). For many years, neural networks were treated as a “black box” and successfully employed as a tool for solving classification, prediction and regression tasks. However, there are several methods for determining the contribution of independent input variables in an ANN model. These methods can be used to achieve a better understanding of complex, real-world relationships described by a neural model (Pentoś, 2016).

Biological materials are subject to various static and dynamic stresses related to harvesting, handling, loading, transport, sorting and storage. As a result of these technological processes, fruit undergoes mechanical damage, which is manifested as external and internal defects of the cellular structure of the tissues. Mechanical damage reduces the commercial value of the raw material and its capacity for processing. Therefore, this study was designed to assess the various mechanical properties of four cucumber varieties. The obtained models may prove to be a useful tool when designing and optimizing the procedures used in the harvesting, transporting or processing of cucumbers. The sensitivity analysis based on the network models provides additional information about the relationships of fruit parameters and souring process parameters with the mechanical properties of brine pickled cucumbers.

MATERIALS AND METHODS

Characteristics of the research material

The research material comprised the fruits of four varieties of field cucumbers (Śremianin, Śremski,

Polan and Izyd) harvested from experimental plots located in Rzeszów (southern Poland - 50°02'01"N 22°00'17"E). Hand-picked samples of fresh cucumbers were brought to the Mechanical Analysis Laboratory of the University of Rzeszów,

where they were washed and packed in properly labelled bags. Cucumbers were divided into length fractions before packing. Fraction I and Fraction II comprised fruit that were 3.5-5.0 cm and 5.5-7.5 cm in length, respectively.

Characteristics of the souring process

Before the souring process was initiated, the cucumbers were pre-selected in order to exclude the specimens that were damaged, affected by diseases or had incorrect colouring. Then, the remaining fruit were subjected to the souring process in glass jars with a capacity of 0.9 l and a twist-off cap. Until the start of the turbulent fermentation, the jars were kept at room temperature, after which they were transferred to a room with a temperature of 5°C. The chemical composition of the brines used in the souring process is presented in Table 1.

Table 1. Chemical compositions of the brine

Name	Addition per 100 kg of cucumbers (%)		
	Brine A	Brine B	Brine C
NaCl water solution	5	5	5
Fresh dill, umbel stalks	3	3	3
Horseradish root	0.5	0.5	0.5
Garlic	0.4	0.4	0.4
Black pepper grains (Galeo)	0.15	0.15	0.15
Bay leaf (Galeo)	0.0	0.01	0.01
Allspice (Galeo)	0.15	0.15	0.15
Cherry leaves	-	0.01	0.01
Currant leaves	-	0.05	0.05
Probiotic (yogurt bacteria)	-	-	0.3

Measurement of the mechanical properties

The cucumbers were punctured with a punch probe, $\phi = 5$ mm in diameter, using a Zwick/Roell Z010 testing machine (ZwickRoell GmbH & Co. KG, Germany). The device comprises a base, a measuring head on which a transducer with a tensometric element is located and a movable beam with the digital reader. During the measurement, the head sends a signal reflecting the puncture strength to the digital reader and the printer cooperating with the machine, which automatically records the results. The measurements were carried out separately for each length fraction with 36 replications for each variety. The tests involved fresh fruit and brine-pickled cucumbers on the 10th, 30th, 60th and 90th day of the pickling process and were performed in three locations: the root of the petiole and the central and end parts of the fruit (Figure 1).

The following parameters were applied during the tests of mechanical properties:

- $F_v = 2$ N (initial force),
- $V_1 = 40$ mm/min (approach and return speed of the measuring beam with a digital reader), and
- $V_2 = 20$ mm/min (speed of the measuring beam with digital sensor during the measurement).

During the measurement, the computer cooperating with the machine registered the maximum puncture strength of the peel and the mesocarp F_{max} [N], the maximum deformation L_{max} [mm] and the energy needed to puncture the skin and the mesocarp W [mJ].

Figure 1. Places of the application of the punch probe

Artificial neural networks

Artificial neural networks are techniques based on biological nervous systems. ANNs consist of simple processing elements (artificial neurons). To build an ANN, artificial neurons are arranged in layers. For regression tasks, the most popular ANN architecture is the Multilayer Perceptron (MLP). The MLP is trained using supervised learning algorithms, usually back propagation learning algorithms. For this training process, examples (input data and corresponding target values) are necessary. Based on the vectors from the training data set, the weights of the neurons in the MLP structure are iteratively adjusted to reduce the error between the target values from the training data set (experimental) and the predicted outputs of the network. An MLP comprises at least two layers: an input layer and an output layer. Usually, additional (hidden) layers are placed between the input and output layers to increase the ability of an ANN to model complex, nonlinear relationships. The numbers of nodes in the input and output layers are determined by the numbers of input and output variables of the model, respectively. The number of neurons in the hidden layers is generally determined by a trial and error approach. However, there must be a compromise between the ability to develop a model with acceptable accuracy and avoid overfitting (a perfect fit of the model on the training data with no generalization ability).

In this research, an MLP neural network with a single hidden layer was developed in the Statistica v. 10 software. Each model was composed of five nodes in the input layer and one neuron in the output layer to predict the puncture strength of the peel and the mesocarp F_{max} [N], the deformation L_{max} [mm] and the energy needed to puncture the peel and mesocarp W [mJ]. In the input matrix, one vector is quantitative data (souring time) and four vectors are qualitative data (cucumber variety, chemical composition of brine, fruit size, and puncture location). The experimental data set (3456 vectors for each harvesting year) was divided randomly into training and validation sets at an 80:25 ratio. For each model, the group of 2000 MLP structures with various numbers of neurons in the hidden layer (from 3 to 50), various initial connection weight matrixes, and various transfer functions for the neurons in the hidden and output

layers (sigmoidal, hyperbolic tangent, and exponential) was trained. Based on the criteria of the model accuracy assessment described below, the best architecture for each model was chosen. The MLP structure with one neuron in the output layer is presented in Figure 2.

Sensitivity analysis

Sensitivity analysis is one of the methods for determining the contribution of the independent input variables in an ANN model. For this research, the sensitivity analysis implemented in the Statistica v. 10 environment was employed to provide information about the relative importance of the input model parameters. In this method, the values of each input variable are replaced by their mean values, which are calculated using the training data set. Then, a quotient of the network error with a certain input changed by its mean value and the network error with the input with its original value is calculated. The error ratio is the variable of importance and enables one to determine the percentages of influence of the input parameters of an ANN model on its output. A similar sensitivity analysis method was used by Hadzima-Nyarko et al. (2011) in the modelling and analysis of the structural damage after an earthquake.

Criteria of models' accuracy assessment

The accuracy of neural models was evaluated based on two criteria, the root mean squared error (RMSE) and the coefficient of correlation (R), which are given by the following equations:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_{pred} - Y_{meas})^2} \quad (1),$$

$$R = \frac{\sum (Y_{meas} - \bar{Y}_{meas})(Y_{pred} - \bar{Y}_{pred})}{\sqrt{\sum (Y_{meas} - \bar{Y}_{meas})^2 \sum (Y_{pred} - \bar{Y}_{pred})^2}} \quad (2),$$

where Y_{pred} is the absolute predicted value, $\bar{Y}_{pred}$ is the average predicted value, Y_{meas} is the absolute measured (experimental) value, and $\bar{Y}_{meas}$ is the average measured value.

An RMSE close to 0 and an R close to 1 indicate the high accuracy of the model at estimating the dependent variable.

Figure 2. Structure of the MLP network

RESULTS AND DISCUSSION

The mechanical characteristics of the fresh fruits of four cultivars of cucumber, namely, Śremianin, Śremski, Polan, and Izyd, are demonstrated in Table 2. The data show that for all mechanical parameters under study, the values are higher for the Izyd and

Śremianin varieties than for the Śremski and Polan varieties. Additionally, slight variations of the puncture strength of the peel and the mesocarp F_{max} [N], the deformation L_{max} [mm] and the energy needed to puncture the peel and mesocarp W [mJ] are observed depending on the harvesting season.

Table 2. Some mechanical properties of the four cucumber varieties (Average $\pm$ SD)

Variety	Strength F_{max} [N]	Deformation L_{max} [mm]	Energy W [mJ]
Year 2014			
Śremianin	29.29 ± 4.43	5.27 ± 1.09	81.62 ± 21.53
Śremski	28.44 ± 4.25	5.04 ± 0.87	76.85 ± 17.51
Polan	26.36 ± 5.12	5.36 ± 0.83	72.22 ± 18.78
Izyd	30.43 ± 6.00	5.63 ± 1.22	85.24 ± 27.60
Year 2015			
Śremianin	32.60 ± 4.50	5.51 ± 1.08	96.06 ± 25.01
Śremski	28.27 ± 3.69	4.68 ± 0.76	73.65 ± 17.97
Polan	28.08 ± 2.86	4.46 ± 0.87	68.20 ± 14.75
Izyd	30.86 ± 4.28	4.91 ± 0.91	81.26 ± 22.23
Year 2016			
Śremianin	29.16 ± 4.32	6.27 ± 1.63	88.93 ± 29.74
Śremski	26.72 ± 4.03	5.11 ± 0.99	72.42 ± 22.33
Polan	27.65 ± 3.94	5.30 ± 1.61	74.56 ± 24.02
Izyd	31.41 ± 5.15	6.14 ± 1.46	97.41 ± 34.69

First, the relationships between the input parameters (cucumber variety, souring time, chemical composition of brines, fruit size, and puncture location) and the output parameters of model (puncture strength of the peel and the mesocarp, deformation and the energy needed to puncture the peel and mesocarp) were modelled separately for each year of harvesting. Then, a model including all experimental data from the years 2014, 2015, and 2016 was developed. The details of models are presented in Tables 3 - 5. The model structure means the number of neurons in each layer of the MLP: input (always 5) – hidden – output (always 1). In the case of strength models, the best ANN architectures are networks containing from 30 to 42 neurons in the hidden layer. For the deformation, the best architectures of models are with 8 – 36 neurons in the hidden layer. For the energy models, the best accuracy was found for architectures with 12 – 44 neurons in the hidden layer. In the case of the strength and deformation models, high accuracy is observed for both the training and validation data sets. The results confirm the generalization capabilities of the models. For the energy models, the accuracy can be considered as acceptable only

for the models developed based on data from one harvesting year. For the model based on all data, the R value is only 0.616. In Figs. 3-5, the performance of the best MLP models for the puncture strength of the peel and the mesocarp F_{max} [N], the deformation L_{max} [mm] and the energy needed to puncture the peel and mesocarp W [mJ] for the validation data set are presented.

Generally, for all mechanical parameters, the accuracy of the model based on data from three harvesting years is lower than the accuracy of the models based on data from one harvesting year. It means that other factors besides the cucumber variety, souring time, chemical composition of brines, fruit size, and puncture location influence the cucumbers' mechanical properties. It is in agreement with the results presented in Table 2 that show that the differences in the mechanical parameters of fresh cucumbers depend on the harvesting year. This phenomenon was reported by Baafi and Safo-Kantanka (2008) who stated that the mechanical, chemical and nutritional properties of the same cucumber variety result from climatic, edaphic and biotic factors.

Table 3. Error metrics of the best model performances: puncture strength of the peel and the mesocarp F_{max} [N]

Harvest year	Model structure	Training		Validation	
		RMSE	R	RMSE	R
2014	5-37-1	4.78	0.848	3.37	0.842
2015	5-30-1	3.05	0.916	2.83	0.912
2016	5-39-1	3.98	0.828	4.05	0.798
2014+2015+2016	5-42-1	4.29	0.753	4.40	0.746

Table 4. Error metrics of best model performances: deformation L_{max} [mm]

Harvest year	Model structure	Training		Validation	
		RMSE	R	RMSE	R
2014	5-8-1	0.11	0.838	0.10	0.859
2015	5-14-1	0.04	0.948	0.04	0.954
2016	5-12-1	0.18	0.733	0.15	0.776
2014+2015+2016	5-36-1	0.11	0.842	0.10	0.858

Table 5. Error metrics of the best model performances: energy needed to puncture the peel and mesocarp W [mJ]

Harvest year	Model structure	Training		Validation	
		RMSE	R	RMSE	R
2014	5-39-1	12.36	0.757	13.64	0.747
2015	5-26-1	10.26	0.833	11.69	0.823
2016	5-12-1	17.36	0.728	16.84	0.776
2014+2015+2016	5-44-1	17.03	0.624	16.71	0.616

Figure 3. Predicted values versus measured values of the puncture strength of the peel and the mesocarp for the validation data set (harvesting year 2015)

Figure 4. Predicted values versus measured values of the deformation for the validation data set (harvesting year 2015)

Figure 5. Predicted values versus measured values of the energy needed to puncture the peel and mesocarp for the validation data set (harvesting year 2015)

Mathematical models of cucumbers' mechanical properties have been previously proposed in the literature. Moradi et al. (2019) developed a dimensionless model of the mechanical parameters of three cucumber cultivars common in Iran: Nagin, Shahab, and Shahin. According to the authors' declaration, the accuracy of this model as described by the coefficient of determination $R^2 = 0.9$ may make it useful for real-life applications for designing some unit operations of post-harvesting technologies. There are also some applications of artificial neural networks for the mathematical modelling of various properties of vegetables and fruits. Saeidirad et al. (2013) proposed an ANN model for the viscoelastic behaviour of pomegranates. They developed models of the stress relaxation for three cultivars of pomegranates, namely, Ardestani, Shishekap, and Malas, and achieved high accuracy ($R^2 > 0.99$). Mathematical models for the prediction of the firmness/elasticity of apples, plums, tomatoes, and mushrooms based on an adaptive neuro-fuzzy inference system (ANFIS) were presented by Mollazade et al. (2013). The accuracy of the models as described by the correlation coefficient R for the validation data sets ranged from 0.790 for plums to 0.919 for tomatoes.

Sensitivity analysis

The best MLP models described in Tables 3 – 5 were used for the sensitivity analysis. The sensitivity analysis was performed for the models trained with a data set for a single harvesting year and for all experimental data. The results were converted into the percentage influence of certain input variable on the output parameter of the ANN model and are presented in Figures 6–8.

The results presented in Figures 6-8 show that the percentage influence of each input parameter on the puncture strength of the peel and the mesocarp, the deformation and the energy needed to puncture the peel and mesocarp varies according to the harvesting year. It can be explained by the influence of the other factors on the cucumbers' mechanical parameters that change within seasons. However, generally, the results given by the models based on data for a single harvesting year and three seasons are similar. The highest influence on the puncture strength of the peel and the mesocarp was calculated for the fruit size (more than 40%). The second most influential parameter affecting the puncture strength is the chemical composition of brine (more than 15%). The lowest effect on the puncture strength is observed for the puncture location. The deformation is affected the most by the souring time and brine composition (more than 25%). The influences of the other factors on the deformation are significantly lower. The highest effect on the energy needed to puncture the peel and mesocarp is observed for fruit size. The influences of the other parameters on the energy are generally lower and comparable.

Figure 6. The relative importance of the input variables of the MLP model on the puncture strength of the peel and the mesocarp

Figure 7. The relative importance of the input variables of the MLP model on the deformation

Figure 8. The relative importance of the input variables of the MLP model on the energy needed to puncture the peel and mesocarp

CONCLUSIONS

The study assessed the impact of cucumber parameters, including the variety, size, and the souring process parameters such as the time and chemical composition of the brine, on the selected mechanical properties of the fruit obtained from three different locations. The cucumbers were harvested from 2014 to 2016. The mathematical models based on neural networks were generated using the collected data. The procedure was designed to generate models describing the relationships in question for a specific harvest year and to generate models based on the measurement data acquired during all the three years of the study. In the case of the puncture strength of the peel and the mesocarp and the deformation, as the output

parameters of the models, good quality models were obtained, especially for the years 2014 and 2015 ($R > 0.84$). Likewise, the models based on the three-year data were highly accurate ($R = 0.746$ for puncture force and $R = 0.858$ for deformation). In contrast, the models where the output parameter was the energy needed to puncture the peel and the mesocarp were generally of slightly lower quality. The fact that such models were obtained shows that there are mathematical relationships between the input parameters of the models (souring time, cucumber variety, chemical composition of brine, size fraction, and puncture location) and each of the output parameters (puncture strength of the peel and the mesocarp, deformation, and energy needed to puncture the peel and the mesocarp). For each output parameter, the quality of the models

generated based on one-year data was higher than in the case of the models based on three-year data (except for the deformation identified in 2016). This means that the mechanical parameters of brine pickled cucumbers are influenced by seasonal factors. Sensitivity analysis of the resulting network models has allowed us to find the parameters with the greatest impact on the mechanical characteristics of pickled cucumbers. In the case of

the puncture strength of the peel and the mesocarp and the energy needed to puncture the peel and the mesocarp, it is the size fraction; and in the case of deformation, it is the souring time and chemical composition of the brine. Owing to the relatively good quality of the mathematical models obtained, they can be applied in practice to optimize the cucumber pickling process.

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