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ARTIFICIAL NEURAL NETWORK AS THE TOOL IN PREDICTION RHEOLOGICAL FEATURES OF RAW MINCED MEAT

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ABSTRACT

Background. The aim of the study was to elaborate a method of modelling and forecasting rheological features which could be applied to raw minced meat at the stage of mixture preparation with a given ingredient composition.
Material and methods. The investigated material contained pork and beef meat, pork fat, fat substitutes, ice and curing mixture in various proportions. Seven texture parameters were measured for each sample of raw minced meat. The data obtained were processed using the artificial neural network module in Statistica 9.0 software.
Results. The model that reached the lowest training error was a multi-layer perceptron MLP with three neural layers and architecture 7:7-11-7:7. Correlation coefficients between the experimental and calculated values in training, verification and testing subsets were similar and rather high (around 0.65) which indicated good network performance.
Conclusion. High percentage of the total variance explained in PCA analysis (73.5%) indicated that the percentage composition of raw minced meat can be successfully used in the prediction of its rheological features. Statistical analysis of the results revealed, that artificial neural network model is able to predict rheological parameters and thus a complete texture profile of raw minced meat.

Key words: artificial neural nets, minced meat, rheological properties, rheology of food

INTRODUCTION

A neural network is a powerful data modelling tool that is able to capture and represent complex input/output relationships. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. The true power and advantage of neural networks in their ability to represent both linear and nonlinear relationships and in their ability to learn these relationships directly from the data being modelled. Traditional linear models are simply inadequate when it comes to modelling data that contains nonlinear characteristics [Rai et al. 2005].

An artificial neural network technique was used to predict the rheological properties of dough from the torque developed during mixing. Dough rheological properties were determined using traditional equipment such as farinograph and extensigraph. The back propagation neural network was designed and trained with the acquired mixer torque curve (input) and the

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measured rheological properties (output) [Ruan et al. 2003].

A neural networks were developed for predicting flavour intensity in blackcurrant concentrates from gas chromatographic data on flavour components in sorbent extracts from blackcurrant concentrates varying in season, geographical origin and processing technology [Baccorh et al. 2002].

Fuzzy classifier and a neural network are proposed for the classification of wine distillates for each of two distinct features of the products namely the aroma and the taste. The fuzzy classifier is based on the algorithm while the neural system is a feedforward multilayer network which is trained using the back-propagation method. The results show that both fuzzy and neural classification systems performed remarkably well in the evaluation of the aroma and the taste of the products [Raptis et al. 2000].

Neural network and fuzzy logic models were proposed to model the textural changes of dry peas cooked at different temperatures. The neural network model consistently produced the best fit to the experimental data, and the first-order-reaction kinetic model [Xie et al. 1998].

Non-destructive, image-based method was evaluated for predicting mechanical properties of fried, breaded chicken nuggets. A multiple-layer feed-forward neural network was established to predict the three mechanical parameters. The correlation coefficients of the predicted results with those from mechanical tests were above 0.84 [Qiao et al. 2007].

NRaw minced meat is a mixture of many components with different chemical composition and mechanical properties and therefore it is difficult to model its rheological features. Raw minced meat texture depends on the material used and proportions of basic components as well as technological processes applied during production (chopping, mincing).

In order to control the structure and quality of products formed from raw minced meat it is necessary to recognize rheological features of raw material. Optimization of a technological process and raw material composition ensure obtaining a product of desired rheological and sensory properties. On that basis one can be able to forecast raw material behaviour during processing as well as rheological properties of products and thus conduct technological processes with efficiency. Expectations of consumers towards product quality cause that food technologists need to search for methods of food quality improvement in order to obtain acceptable products.

If one would like to predict rheological features of food products at various stages of processing, it is indispensable to recognize their rheological models composed of mechanical analogues of ideal materials. Through mathematical calculations it may be revealed if a given sample undergoes creep, stress relaxation and retardation as long as we know its modulus of elasticity in shear and viscosity modulus.

Mathematical analysis of possible raw minced meat composition at three levels of meat content gives 5832 combinations. Therefore, a methodology need to be used which could optimize the selection of percentage content of raw minced meat ingredients.

The aim of this study was to elaborate a modelling and forecasting tool for rheological features of raw minced meat at the stage of mixture preparation. The technique used was artificial neural network (ANN) which was trained for recognizing and prediction of seven parameters connected with rheological characteristics of raw minced meat.

MATERIAL AND METHODS

The investigation was conducted on pork meat without bones (I class), beef meat without bones (I class) with fat, fat substitutes (starch and dietary fibre), curing brine as described in the Polish norm PN-A-82117:1997 and water in the form of ice.

Detailed characteristics of the material was as follows:

- Pork ham without bones of natural light-pink colour with firm, elastic muscle tissue, smell characteristic of raw pork meat, without any symptoms of getting spoiled as well as without fat tissue (PN-65/A-82000, PN-A-82014). The meat did not have any defects and was refrigerated at 276.15°K (3°C) until the analysis.
- Beef leg meat of natural light-red colour, with firm, elastic muscle tissue, smell characteristic of raw beef meat, without any defects, symptoms of getting spoiled or fat tissue (PN-65/A-82000, PN-A-82014).

- Pork fat in pieces of 0.04 m trick, white matt colour with cream shade, damp and slightly sticky to the touch (PN-85/A-85800).
- Fat substitutes: soluble dietary fibre, analytically pure $(C_6H_{10}O_5)_n$–162.10 g·mol^{-1} produced by Chempur and bamboo dietary fibre.
- Crumbled ice from tap water of hardness at the level of 14-20 dh, produced in SD 23 WS-6 Simag ice maker with the efficiency of 28 kg of ice per 24 hours. Before adding to raw minced meat the ice was crumbled to cubes with equivalent diameter about 0.005 m.
- Curing mixture: solution containing 11% of NaCl and 1.5% of curing brine. The curing brine conformed to standards described in the norm PN--A-82023:2000. Then, the mixture was made up to 1000 ml with water (87.5%) in a flask and added to raw minced meat at the stage of mincing in the amount of 20% by mass.

Raw minced meat was analysed at three levels of ingredient content. Each sample weighted 1 kg. The ratio of pork to beef amounted to 100% (dashed line in Figure 1), 50% (dash double-dot line in Figure 1) and 0% (continuous line in Figure 1).

Pork fat constituted 10, 15 or 20% of the total raw minced meat mass. Meat was cured with the use of curing mixture in the quantity of 10, 15 and 20% by mass. In order to reduce the content of pork fat, it was partly substituted by potato starch and dietary fiber produced from bamboo, which constituted 10, 15 or 20% of the pork fat mass. The addition of water in the form of crumbled ice was at the level of 10, 15 and 20% of the total raw minced meat mass.

The components of raw minced meat (i.e. pork, beef and pork fat) originated from a slaughter done on Saturday and were bought cooled on Monday. After preparing the raw minced meat it was formed to a block 0.04 × 0.04 m and then analysed.

Crumbled meat and pork fat were minced in a meat processing equipment M-8 with the total power 370 W and efficiency 40 kg·h^{-1} through sieves with mesh size 0.008, 0.006 and 0.0045 m. Then, a 1 kg weight portion was mixed in a 5 l bowl of Clatronic KM 2718 food processor. First, the meat and pork fat were mixed

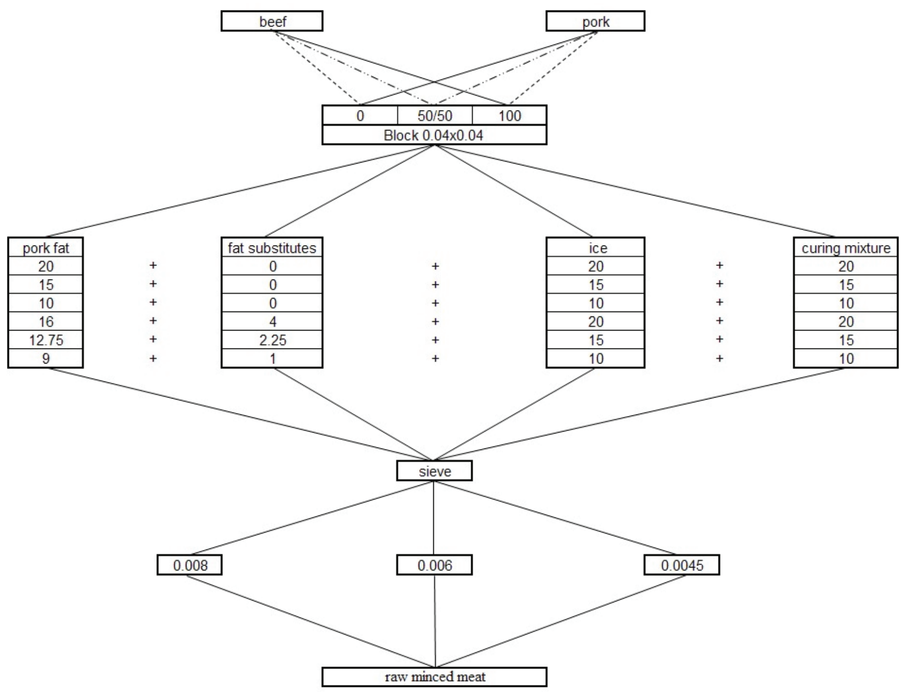

Fig. 1. Percentage composition of raw minced meat at three levels of ingredient content

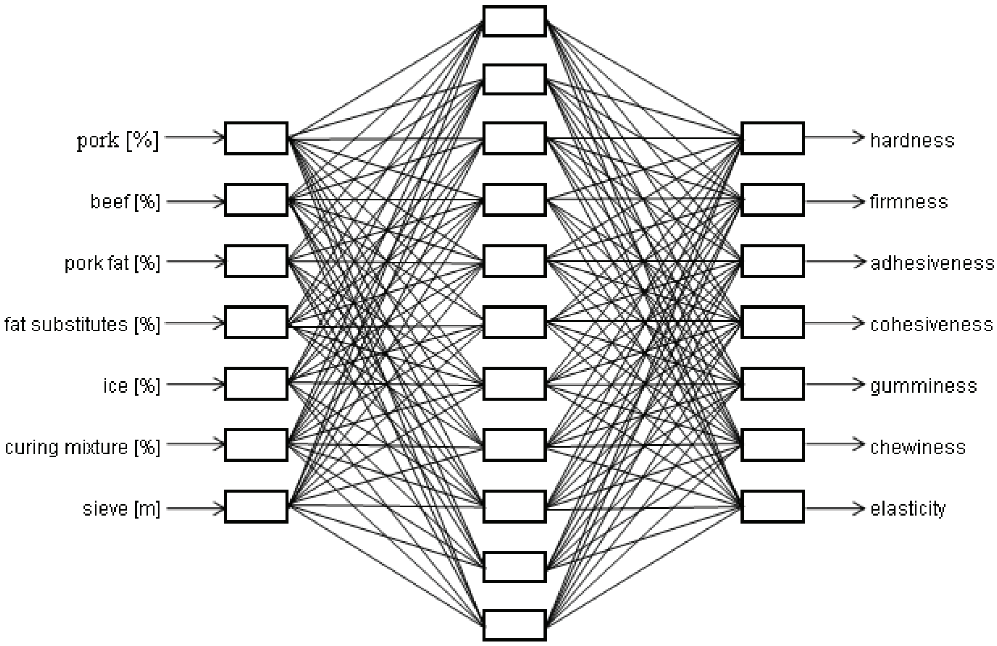

Fig. 2. Architecture of the artificial neural network model MLP 7:7-11-7:7

with ice and then the curing brine and fat substitutes were added. The process of mixing lasted until all the ingredients were evenly distributed. The product obtained was as described in the Polish norm PN-A--82023:2000. Directly after preparation its texture was analysed with the MULTITEST apparatus [Balejko 2003, 2012, www.tz.ar.szczecin.pl] using the TPA test (Texture Profile Analysis). The test consisted of two successive compression ramps to a value of 70% of the unloaded specimen height. Each specimen was sampled 10 times. The following parameters were calculated from the data obtained: hardness, cohesiveness, firmness, gumminess, adhesiveness, chewiness and elasticity [Peleg 1977, Bourne 1978, 1982, Piątek and Dąbrowski 1980, Piggot 1988, Tyszkiewicz et al. 1989, Marsili 1993, Steffe 1996, Pons and Fiszman 1996, Lachowicz and Żochowska 2002, Balejko 2007].

The data obtained were processed using the Automatic Problem Solver implemented in the artificial neural network module in Statistica 9.0 software. The data set included 1050 cases and was divided into three subsets: training (70% of the whole data set), verification (15%) and testing (15%).

RESULTS AND DISCUSSION

The rheological data collected were used in training 1000 neural networks with the backpropagation algorithm. The model that reached the lowest training error was chosen. It was a multi-layer perceptron MLP with three neural layers and architecture 7:7-11-7:7. The explanatory variables were the percentage contents of consecutive raw minced meat ingredients: beef, pork, pork fat, fat substitutes, ice, curing mixture and sieve mesh size.

The MLP model fits the data well. Correlation coefficients between the experimental and calculated values in training, verification and testing subsets were similar and rather high (around 0.65) which indicated good network performance (Fig. 3). Residual normality for linear regression analysis between experimental and calculated data was analysed with the help of probability-probability plots as well as normality tests (Shapiro-Wilk and Kolmogorov-Smirnov). The residues fit the normal distribution (Fig. 4) which also confirmed good quality of the neural network model.

Additionally, relationships between raw minced meat composition and its rheological characteristics

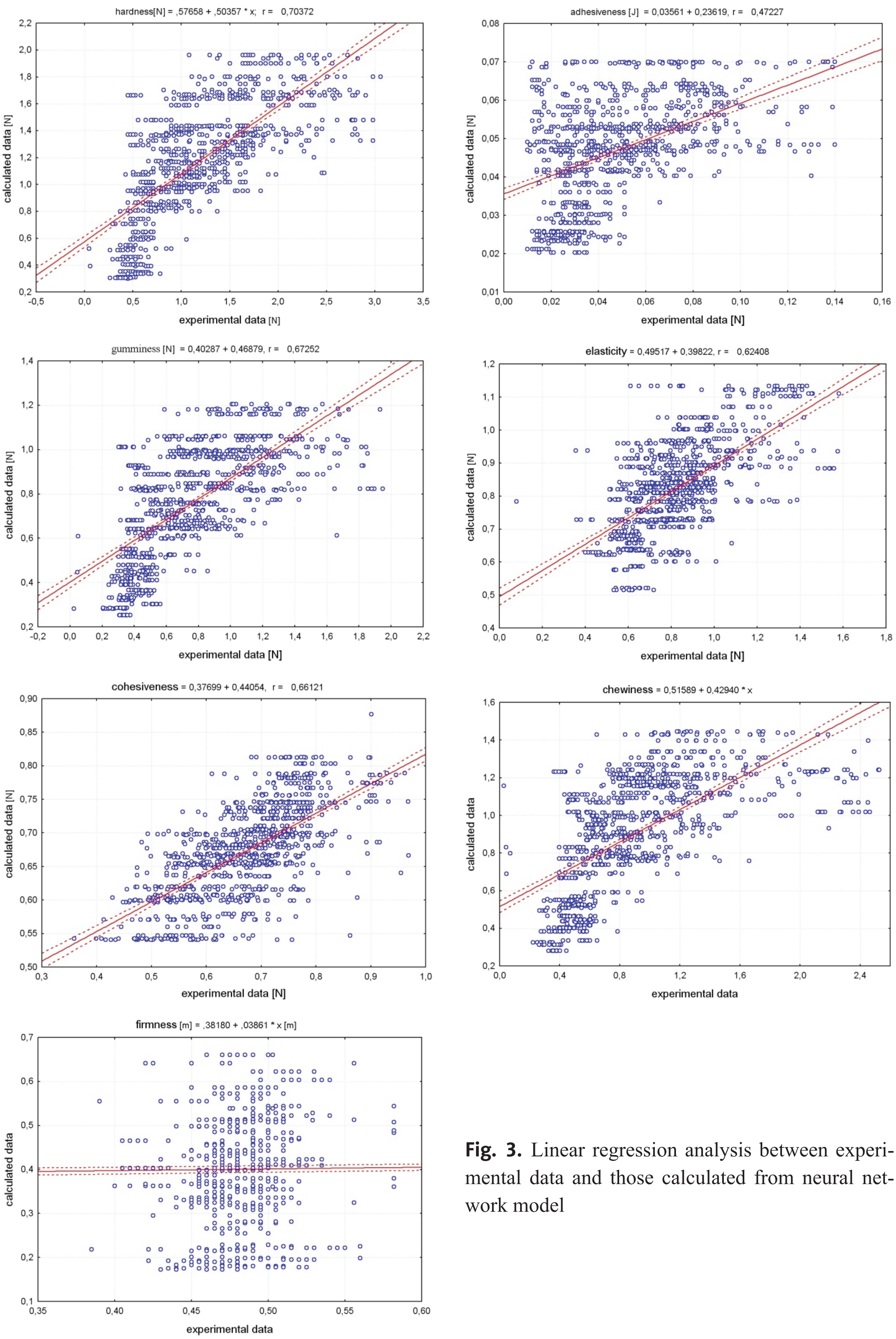

Fig. 3. Linear regression analysis between experimental data and those calculated from neural network model

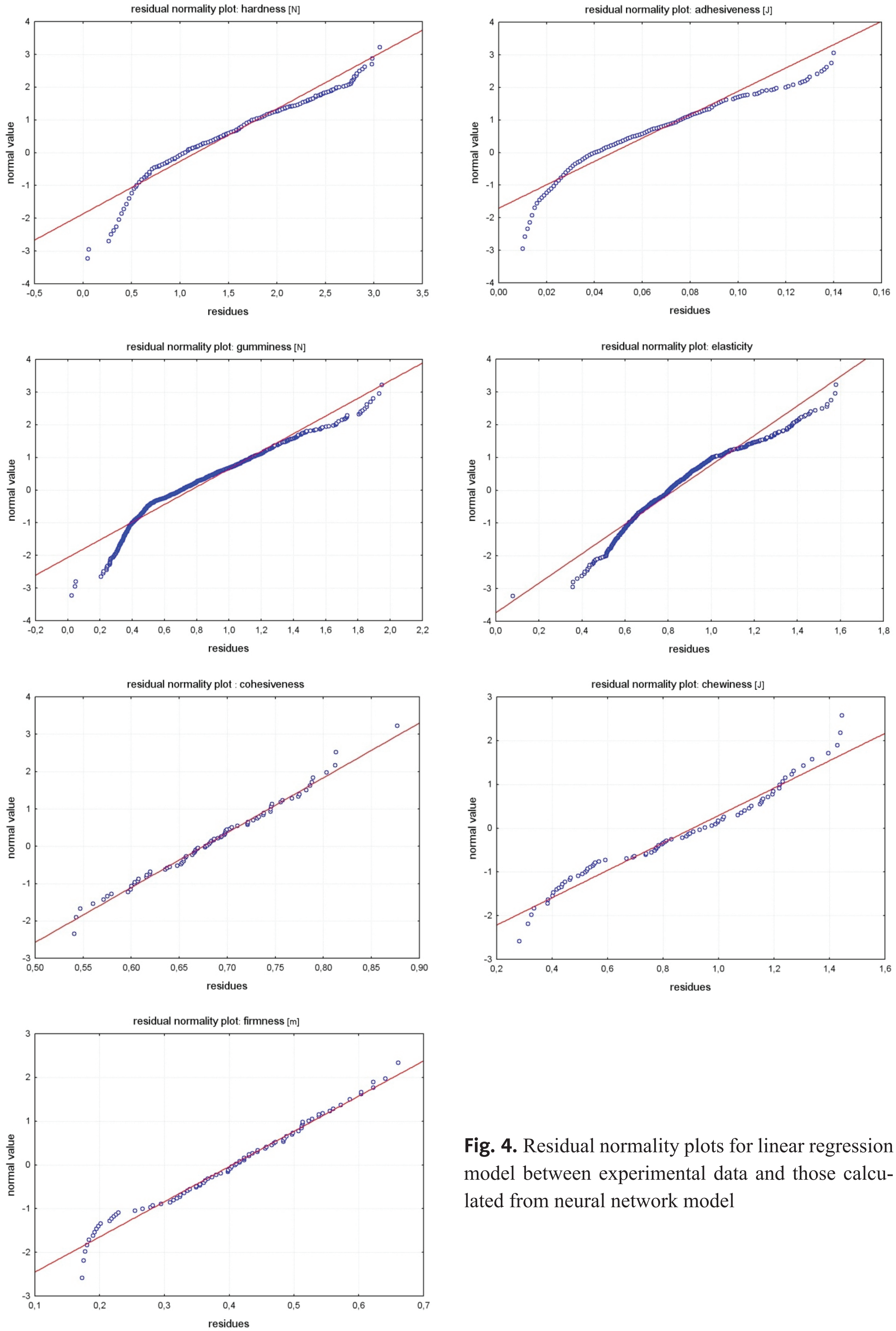

Fig. 4. Residual normality plots for linear regression model between experimental data and those calculated from neural network model

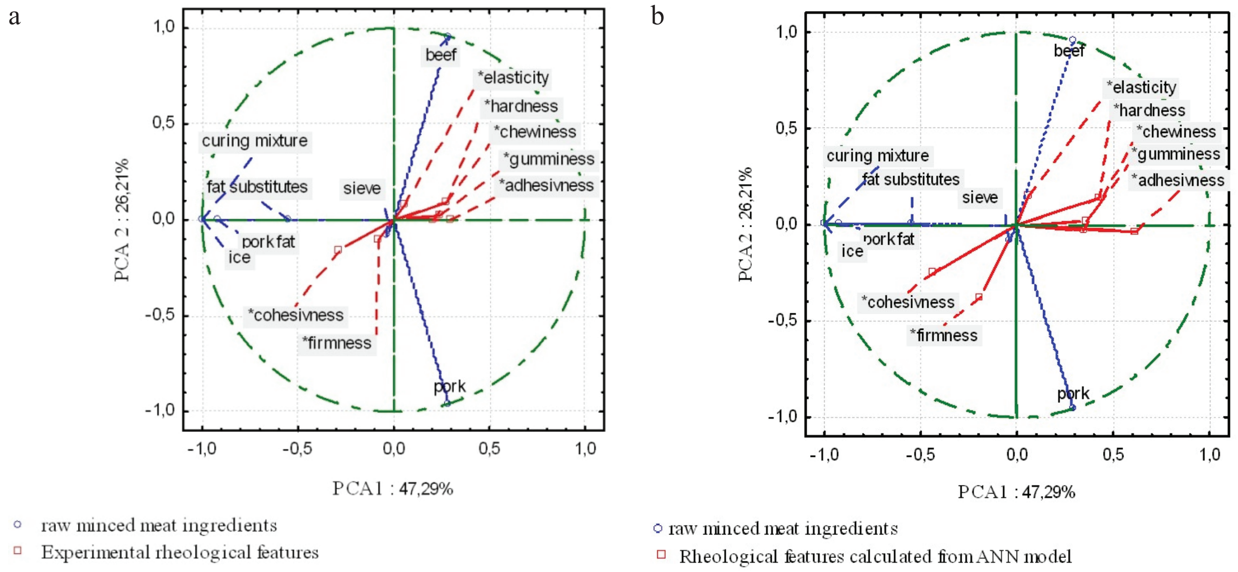

Fig. 5. PCA biplot for experimental rheological features of raw minced meat (a) and those calculated with artificial neural network model (b)

were analysed with the use of principal component analysis PCA (Fig. 5).

The number of explanatory variables was reduced through creating new factors being linear combinations of raw minced meat ingredient contents. The model obtained included two PCA axes and explained 73.5% of the total variance both for experimental data and those calculated from neural network model MLP 7:711-7:7. The highest negative contribution to the first PCA factor had the percentage share of ice and curing mixture. In turn, the content of beef positively contributed to the second PCA axis while the percentage of pork meat – negatively. One can conclude, that cohesiveness and firmness decreased with the content of beef. In turn, firmness increased with the percentage share of pork in raw minced meat.

Table 1. Spearman's rank correlation matrix between experimental rheological features of raw minced meat and those calculated from artificial neural network model

Experimental	ANN						
	hardness N	firmness m	adhesiveness J	cohesiveness	gumminess N	chewiness J	elasticity
Hardness, N	**0.738**	0.260	0.687	–0.528	0.720	0.713	0.279
Firmness, J	0.131	**0.277**	0.062	–0.039	0.141	0.158	–0.009
Adhesiveness, J	0.395	0.095	**0.468**	–0.242	0.399	0.395	0.065
Cohesiveness	–0.468	–0.155	–0.318	**0.672**	–0.357	–0.350	–0.440
Gumminess, N	0.694	0.260	0.682	–0.396	**0.707**	0.704	0.188
Chewiness, J	0.700	0.296	0.687	–0.390	0.716	**0.717**	0.175
Elasticity	0.307	–0.025	0.252	–0.412	0.258	0.238	**0.615**

In order to assess the relationships between experimental rheological data and those calculated from MLP model, the Spearman's rank correlation analysis was used (Table 1).

It revealed very strong positive correlations for hardness (r = 0.738), gumminess (r = 0.707) and chewiness (r = 0.717). Strong relationships were obtained for cohesiveness (r = 0.672) and elasticity (r = 0.614) while for adhesiveness the relationship was at a moderate level (r = 0.468). The only parameter which correlated rather weakly was firmness (r = 0.277).

CONCLUSIONS

Results obtained in this study and its statistical analysis indicate the following conclusions:

1. The usefulness of experimental rheological data in training, verification and testing of artificial neural network models has been proved.

2. High percentage of the total variance explained in PCA analysis (73.5%) indicated that the percentage composition of raw minced meat can be successfully used in the prediction of its rheological features.

3. High correlation between experimental data and those calculated by artificial neural networks indicates that MLP model 7:7-11-7:7 trained with back-propagation algorithm is able to predict texture characteristics of raw minced meat.

REFERENCES

Balejko J., 2003. Opracowanie dynamicznej metody wyznaczania reologicznych właściwości artykułów żywnościowych [Study on dynamic method of food rheological features analysis]. Rozprawy nr 218. Wyd. AR Szczecin [in Polish].

Balejko J., 2007. Reologia żywności [Food rheology]. Wyd. AR Szczecin [in Polish].

Balejko J., 2012. Analysis of rheological features of viscoelastic materials and apparatus for such studies. Patent no: 210484.

Bourne M.C., 1978. Texture profile analysis. Food Technol. 7, 62-66.

Bourne M.C., 1982. Food texture and viscosity: Concept a measurement. Academic Press.

Lachowicz K., Żochowska J., 2002. Wpływ dodatku mięsa dzików na teksturę drobno rozdrobnionych modelowych farszów mięsnych [Influence of wild boar meat addition on the texture of modelling raw minced meat]. Zesz. Nauk. AR Szczec. 2, 81-88 [in Polish].

Marsili R., 1993. Texture and mouthfeel making rheology real. Food Prod. Design. 8, 54.00-58.

Peleg M., 1977. Contact and fracture elements as components of the rheological memory of solid foods. J. Texture Stud. 8, 39-4.008.

Piątek J.W., Dąbrowski K.J., 1980. Instrumentalna ocena tekstury żywności [Instrumental measurement and assessment of food texture]. Przem. Spoż. 34, 419-421 [in Polish].

Piggott J.R., 1988. Sensory analysis of foods. Elsevier Sci. Publ., London.

Pons M., Fiszman S.M., 1996. Instrumental texture profile analysis with particular reference to gelled systems. J. Texture Stud. 27, 597-624.

Qiao J., Wang N., Ngadi M.O., Kazemi S., 2007. Predicting mechanical properties of fried chicken nuggets using image processing and neural network techniques. J. Food Eng. 79, 1065-1070.

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

Raptis C.G., Siettos C.I., Kiranoudis C.T., Bafas G.V., 2000. Classification of aged wine distillates using fuzzy and neural network systems. J. Food Eng. 46, 267-275.

Boccorh R.K., Paterson A., 2002. An artificial neural network model for predicting flavour intensity in blackcurrant concentrates. Food Qual. Prefer. 13, 117-128.

Ruan R., Almaer S., Zhang J., 2003. Prediction of dough rheological properties using neural networks. Cereal Chem. 72, 308-311.

Steffe J.F., 1996. Rheological methods in food process engineering. Freeman Press. East Lansing, USA.

Tyszkiewicz S., Baryłko-Pikielna N., Dobrzycki J., Kłosowska D., Jankowski T., Fornal J., Gwiazda S., Poliszko S., 1989. Postęp w analizie żywności. T. 2. Wybrane zagadnienia analizy sensorycznej i fizykochemicznej [Advances in food analysis. Vol 2. Selected issues on sensory and physico-chemical analysis]. Ed. S. Tyszkiewicz. Warszawa [in Polish].

www.tz.ar.szczecin.pl/jb.

Xie G., Xiong R., Church I., 1998. Comparison of kinetics, neural network and fuzzy logic in modelling texture changes of dry peas in long time ccooking. Lebensm. Wiss. Technol. 31, 639-647.

SZTUCZNA SIEĆ NEURONOWA JAKO NARZĘDZIE PROGNOZOWANIA WŁAŚCIWOŚCI REOLOGICZNYCH SUROWYCH FARSZÓW MIĘSNYCH

STRESZCZENIE

Cel. Analiza matematyczna możliwych kombinacji udziału składników farszu w modelu opartym na trzech poziomach zmienności głównego składnika (mięso) daje 5832 wszystkich możliwych rozwiązań. Tak duża liczba kombinacji wymaga użycia narzędzi, które będą w stanie zoptymalizować proces doboru procentowego udziału składników farszu. Celem niniejszej rozprawy jest opracowanie metody pozwalającej na modelowanie i prognozowanie cech reologicznych surowych farszów mięsnych na etapie przygotowania mieszaniny o założonym składzie surowcowym.
Materiał i metody. Materiałem badawczym było mięso wieprzowe i wołowe z udziałem tłuszczu, zamienników tłuszczu w postaci skrobi i błonnika, solanki peklującej o różnym składzie oraz wody w postaci lodu. Instrumentalnie zbadano siedem głównych parametrów tekstury surowych farszów mięsnych. Do prognozowania wykorzystano moduł sztucznej sieci neuronowej programu Statistica 9.0, a zmiennymi objaśniającymi były procentowe zawartości poszczególnych składników farszu oraz średnica oczka sita urządzenia do rozdrabniania.
Wyniki. Na podstawie zgromadzonych danych badawczych przetestowano 1000 sieci neuronowych metodą wstecznej propagacji błędów. Z przetrenowanych na zbiorze danych sieci wybrano cechującą się najmniejszym błędem uczącym. Wybranym modelem sztucznej sieci neuronowej była sieć o architekturze 7:7-11-7:7.
Wnioski. Wysoka korelacja wyników uzyskanych z pomiarów instrumentalnych i wyników uzyskanych z predykcji za pomocą sztucznych sieci neuronowych wykazała, że sztuczna sieć neuronowa 7:7-11-7:7, oparta na architekturze perceptronu wielowarstwowego uczonego metodą wstecznej propagacji błędów, pozwala na prognozowanie parametrów reologicznych surowych farszów mięsnych.

Słowa kluczowe: farsze, reologia, sieci neuronowe, właściwości reologiczne

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