Determining the Aging of Cheese from Sheep's Milk by "Electronic Nose" Multi-sensor System

Todor Todorov*, Stefan Ivanov*, Toshko Nenov* and Marta Seebauer**

* Technical University of Gabrovo, Gabrovo, Bulgaria

**Óbuda University/Alba Regia Technical Faculty, Székesfehérvár, Hungary t61@abv.bg, st_ivanov@abv.bg, tgnenov@gmail.com, seebauer.marta@amk.uni-obuda.hu

Abstract— Production of a high quality cheese is a complex and time consuming process requiring exact compliance with the technology of manufacturing. This work presents the results of test of sheep's milk cheese done by "electronic nose" multi-sensor system based on metal oxide gas sensors. Several samples of cheese were measured during different stages of its aging. The collected data is used for training, validation and test of artificial neural network for determining the aging of sheep cheese.

I. INTRODUCTION

Rapid quality control of foods and the determination of their quality during storage time are essential for human health.

For determining of their taste usually is used organoleptic sensory analysis called "flavor analysis." For this purpose is employed a team of well-trained tasters. The essence of tasting process in practice is that the tasters assess the product through their receptors for taste, odor, smell and vision [1]. The disadvantages of this method of assessment are that it is relatively expensive, requires a lot of time and has a rather subjective character.

Another method to diagnose the state of foods is the determining the composition of gases collected from the product by using a classical gas chromatograph [2]. This method is considerably objective and accurate but is characterized by its high costs and long duration of measurements.

The most accurate of all analysis is the method based on examination of the specific protein composition and DNA identification [3]. In this case, like in the first two methods also, serious disadvantages are the high costs, and the need for relatively long time for testing, as well as the requirement for highly trained personnel, and expensive special equipment.

Knowing the working principles of the olfactory organs of biological systems allows the development of technical tools for gas analysis based on gas sensors which are called "electronic nose" and are comparable in efficiency with their biological analogues [4]. The "electronic nose" is multi-sensor system for detection of gaseous substances. Different from traditional sensor systems requiring highly selective sensitive elements, the "electronic nose" uses a set of relatively non-selective gas sensors. The development of "electronic nose" systems is based on the modern technologies in the fields of electronics and special methods for data processing and data fusion [5].

The "electronic nose" is used in the food industry for quality control, monitoring and evaluation of the products freshness, determining of their expiration date and others. Its advantage is based on the fact that it provides the ability to determine the quality of the tested products quickly and with great accuracy [6].

In this work are presented the testing results of cheese from sheep's milk carried out with "electronic nose" multisensor system based on metal oxide gas sensors. Tested samples of cheese were taken during different stages of its aging. Artificial neural network was trained and tested with the collected data to determine the maturity of the sheep cheese.

II. EXPERIMENTAL RESEARCHES AND RESULTS

The metal-oxide gas sensors are particularly suitable for the realization of the "electronic nose" because they have a high sensitivity related to different gases and - in addition to this - they have a very low price. They are used in systems for detection of intentionally added water in milk [7], for analysis and quality control of yoghurt [8], for detection of dangerous bacteria in dairy products [9, 10], etc.

In the experiments was used cheese from sheep's milk. Samples of sheep cheese were obtained directly in production plant and they were taken during the overall period of its aging. The different samples for experiments were taken from 5th, 14th, 21st, 28th and 46th day of the cheese production. The analysis of individual samples was carried out by multi-sensor system of type "electronic nose" based on metal oxide gas sensors as described in [11].

All tested samples for a given period of aging were divided into equal parts in shape and weight and stored in a refrigerator with temperature at about 4°C. Before the measurement of each sample, the "electronic nose" system was turned on for a specified time, to reach by the test chamber and the gas sensor the operating temperature. During the process of measurement the glass container, in which the sample is placed, is maintained at constant temperature of 50°C. Placing the sample in an environment with such a temperature contributes to the separation of a larger quantity of gases which are analyzed by the gas sensors in the upper part of the chamber. The period of measurement for every individual sample is equal. After gathering the results of all sensors and removal of sample it is required a definite time for relaxation of sensors. In the study for every period of aging were carried out six measurements with different samples. Five of the results were used for training of artificial neural network. The results of the rest measurement were used for testing of the trained network. Samples used for every testing were selected by random way.



Figure 1. Signal levels from sensors for five measurements of sheep cheese

The data that were used to train the neural network are shown in the following figures.

Fig.1 shows the data from five measurements on five different aging periods of sheep cheese.

In the results presented in Fig.1 can be observed the differences in the reactions of six sensors (GGS 1330, GGS 2330, GGS 3330, GGS 4330, GGS5330 and GGS 7330) according to different periods of aging of sheep cheese. The results show that there is a good repeatability in the responses of sensors for the five subsequent measurements of cheese samples.

Fig.2 presents the data about the averaged measurements of each cheese sample. The figure clearly shows the trend of changing responses of the sensors. The most informative in this case are the sensors GGS 3330 and GGS 4330. These two sensors demonstrate the best expressed changes in the response of sensors to the period of aging of the cheese.

Fig.3 shows the averaged data for each of the five different periods of aging of sheep cheese.

When the data of five measurements for each stage of aging are averaged, the responses from the gas sensors have very definite changes for the different periods. From the results it can be concluded that when signals from five sensors (GGS 1330, GGS 2330, GGS 3330, GGS4330, and GGS 8330) are observed then for good separation for different periods of aging of the cheese can be marked. The best separation for the different periods of aging was produced by the signals of three sensors (GGS 3330, GGS4330, GGS4330, GGS4330).



Figure 2. Averaged values of signals from sensors for measurement of five samples of sheep cheese



Figure 3. Averaged values from the signals of sensors for the five measurements of each period of aging of sheep cheese

The trend in the responses of the sensors is very clear. The differences in the levels of the sensors are directly related to the period of aging of the cheese.

III. ARTIFICIAL NEURAL NETWORK FOR ANALYZE OF AGING OF CHEESE FROM SHEEP'S MILK

To determine the quality of sheep cheese in accordance with the level of its aging was trained an artificial neural network. The Levenberg-Marquardt algorithm was used as training algorithm. The structure of the neural network consists of 3 inputs, one hidden layer with 10 neurons and one neuron in the output layer. The transfer function of the neurons in hidden layer is tangent sigmoid function and a linear function is used for the neuron in the output layer.

The data for training of neural network were five of the six samples of sheep's cheese with varying degrees of aging. After the data obtained from all sensors were analyzed, only data from three sensors - GGS3330, GGS4330 and GGS8330 were selected for training of the neural network while these three sensors had the best reaction depending on the degree of aging of sheep cheese.

Before the training of a neural network, a polynomial approximation was used to generate additional points that lie on approximated data curves. A second order polynomial process was used for approximation. Fig.4 shows the dependences for the three sensors which were received by the approximation.



Figure 4. Approximated data from three sensors for determining of the time of aging of sheep cheese



Figure 5. Results of a neural network training for determining of the time of aging of sheep cheese

After the training, the performance of the neural network has been verified with testing data. The test results are presented on Fig.5.

The comparison between the expected time and the time received on the neural network output (Fig.6) it can be seen that the neural network was trained successfully and there is no big discrepancy between the expected and received time. The error that occurs in this case is about 10 minutes, which is negligible for a period of aging which is measured in days and weeks.

The work of the trained neural network was tested with input data which has random noise added with maximum amplitude of 50mV.

Fig.7 presents the relation between the expected time of aging and the resulting time generated by the neural network with presence of noise in the input data.

The proper functioning of neural network except with the simulated data was checked with testing data, which have not participated in the training process of the network.

When the neural network was tested its response determined successfully submitted data for different aging periods. Fig.8 illustrates the distribution of neural networks response to the testing data in the three-dimensional space using for visualization data from two sensors.



Figure 6. Time - expected and received from the neural network for the period of aging of sheep cheese



Figure 7. Expected and received from the neural network time for the period of aging of sheep cheese with the presence of noise in the input



Figure 8. Distribution of testing data for the time of aging of sheep cheese

Fig.9 illustrates the time of aging of sheep cheese generated by the neural network with actual testing data. The straight line presents the expected time in days, the other line – the time derived from neural network with applied testing data. The biggest is the deviation in the initial period of aging - 6 days. Increasing the time of aging of the cheese, the deviation decreases and at 46 day the deviation in aging is within one day, which is sufficient to determine the state of the cheese.



Figure 9. Time received by the neural network for the period of aging of sheep cheese



Figure 10. Distribution of error for generated by the neural network results for the period of aging

Fig.10 presents the error for time of aging of sheep cheese achieved from neural network with the actual testing data.

IV. CONCLUSION

The work presents the experimental test of cheese from sheep's milk. The analyzed samples of cheese were taken during different stages of its aging. The analyses were done with the help of multi-sensor system for quality control of food products based on metal oxide gas sensors. Results of this study show significant differences in the responses of gas sensors. They are in direct relation to the period of aging of the various samples of the cheese.

With the data obtained from the tests was trained an artificial neural network. When the neural network was tested with data that have not participated in the training it was found that the error decreases with time and at full aging it is within the range of one day. The cheese has to be qualified at the final stage of its aging and therefore an error of one day is normally and allowable when recognition by neural network is implemented.

Based on the obtained results it can be concluded, that a multi-sensor system could be applied successfully for analyze and determination the aging of cheese from sheep's milk which is commercially available.

References

- G. Zsivanovits, D. Iserliyska, Haracterization of the texture of food products, *New Knowledge Journal of Science*, 2013, pp. 111-115.
- [2] B. Kolb, L. Ettre, Static headspace-gas chromatography, John Wiley&Sons, Inc., Hoboken, New Jersey, 2006.
- [3] D. Kalaidjiev, Genetic and average variability of the coagulation ability of milk, PhD Thesis, Agricultural Academy, Agricultural Institute, Stara Zagora, 2014 (in Bulgarian).
- [4] P. Barlett, J.Elliott, J.Gardner, Electronic Noise and their application in the food industry, *Food Technology*, 1997, vol. 51, No. 12, pp. 248-256.
- [5] T. Pearce, S.Schiffman, H.Nagle, J.Gardner, Handbook of machine olfaction, Wiley/vch Verlag Gmbh & co. Wheinheim, UK, 2003, pp. 138.
- [6] H. Swatland, Effect of connective tissue on the shape of reflectance spectra obtained with a fibre-optic fat-depth probe in beef. *Meat Sci.* 2001, vol. 57, pp.209–213.
- [7] H. Yu, J.Wang, Y.Xu. Identification of Adulterated Milk Using Electronic Nose. *Sens. Mater.*, 2007, vol. 19, pp. 275-285.
- [8] G. Green, A.Chan, R.Goubran. Tracking Food Spoilage in the Smart Home Using Odour Monitoring. in *Proceedings of the 2011 IEEE International Workshop on Medical Measurements and Applications (MeMeA)*, Bari, Italy, 30–31 May 2011, pp. 284–287.
- [9] Z. Ali, W. T. O'Hare, B. Theaker. Detection Of Bacterial Contaminated Milk By Means Of A Quartz Crystal Microbalance Based Electronic Nose. *Journal of Thermal Analysis and Calorimetry*, 2003, vol. 71, pp.155–161.
- [10] S. Benedetti, F.Bonomi, S.Iametti, S. Mannino, M.Cosio. Detection of aflatoxin M1 in ewe milk by using an EN. In Proceedings of the 2nd Central European Meeting 5th Croatian Congress of FTBN, Opatija, Croatia, October 17–20, 2004, pp. 101-105.
- [11] T. Todorov, T. Nenov, S. Ivanov. Multisensor system for quality control of food products, *Automatics and Informatics*. 2014, No 3, pp.41-46 (in Bulgarian).