Neuro-Fuzzy based Identification of Meat Spoilage using an Electronic Nose

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***Abstract*—Freshness and safety of muscle foods are generally considered as the most important parameters for the food industry. The performance of a portable electronic nose has been evaluated in monitoring the spoilage of beef fillet stored aerobically at different storage temperatures (0, 4, 8, 12, 16 and 20°C). An adaptive fuzzy logic system model that utilizes a prototype defuzzification scheme has been developed to classify beef samples in their respective quality class and to predict their associated microbiological population directly from volatile compounds fingerprints. Results confirmed the superiority of the adopted methodology and indicated that volatile information in combination with an efficient choice of a modeling scheme could be considered as an alternative methodology for the accurate evaluation of meat spoilage.**

Keywords-neurofuzzy systems; neural networks; meat spoilage; prediction; classification

I. INTRODUCTION

The resolution of the Uruguay Round of the General Agreement on Tariffs and Trade (GATT) in 1995, recognized public health risk as the only basis for restrictions of international trade in food. Beef is one of the commercially viable and widely consumed muscle foods throughout the world. Although it is a good food source for proteins and other essential nutrients, it is also an ideal substrate for the growth of both spoilage and pathogenic microorganisms. The current practice to assure the safety of meat still relies on regulatory inspection and sampling regimes. Meat industry however needs rapid and non-destructive sensing methods for quantification of these indicators in order to determine suitable processing procedures for their raw material and to predict the remaining shelf life of their products [1].

Rapid and non-invasive methods based on analytical instrumental techniques, such as Fourier transform infrared spectroscopy (FTIR) [2] and Raman spectroscopy [3] have been considered for their potential in meat quality assessment. In the past two decades, awareness about the food safety from the point of specific pathogenic bacteria has considered the need for a rapid and accurate detection system for microbial spoilage by checking the volatile organic compounds (VOCs) generated by these microorganisms [4]. The electronic nose (enose) is a system initially created to imitate the function of human nose. There are three primary components in an electronic nose: an array of chemical gas sensors with broad and partly overlapping selectivity that measure volatile compounds, a signal preparation system, and a pattern recognition system [5].

One of the earliest research studies in the application of enose to meat quality analysis was conducted by Balasubramanian, where the changes in the headspace of vacuum packaged beef strip sides vaccinated with *Salmonella typhimurium* were evaluated using a metal oxide based enose [6]. The prediction of total viable counts (TVC) in chilled pork using an enose using support vector machine (SVM) has been investigated [7]. Enose has been also used for the development of a prediction model to detect the content of pork in minced mutton. The adulteration issue is an important problem for food safety [8].

The main objective of this paper is to associate acquired volatile fingerprints (snapshots) of odour profile with beef spoilage during aerobic storage at various temperatures (0, 4, 8, 12, 16 and 20 °C) through the development of an advanced intelligent-based decision support system. Datasets related to enose data as well as the associated microbiological analysis (*i.e.* TVC) from beef fillets, were provided by the Agricultural University of Athens, Greece. The achievement of this objective, however, involves the implementation of a number of sub-tasks, related to data analysis. Due to the multi-variable nature of enose data, a dimensionality reduction algorithm was applied on the data used for training purposes. The robust PCA (RPCA) scheme has been utilized to obtain principal components that are not influenced much by outliers [9].

In this study, a MIMO Adaptive Fuzzy Logic System (AFLS) model that utilizes a prototype defuzzification scheme has been developed to classify beef samples to one of three quality classes (*i.e.* fresh, semi-fresh, and spoiled) based on their biochemical profile provided by the enose dataset. The same model simultaneously predicts the microbial load (as total viable counts) on meat surface. The proposed AFLS model differs from conventional fuzzy rule-table approaches which utilize the "look-up table" concept. In the proposed scheme, the number of memberships for each input variable is directly associated to the number of rules, hence, the "*curse of dimensionality*" problem is significantly reduced. Results from AFLS are compared against models based on an MIMO MLP,

ANFIS, PLS and non-linear regression models. Such comparison is considered as an essential practice, as we have to emphasize the need of induction to the area of food microbiology, advanced learning-based modelling schemes, which may have a significant potential for the rapid and accurate assessment of meat spoilage.

II. ENOSE SAMPLING AND ANALYSIS

The experimental case study was performed at the Agricultural University of Athens (AUA), Greece. A detailed description of the experimental methodology, as well as the related microbiological analysis of the meat samples, is described in [10]. Briefly, the samples were prepared by cutting fresh pieces of beef into small portions and then packed aerobically in trays that were wrapped with air-permeable plastic film. Samples were stored under controlled isothermal conditions at 0, 4, 8, 12, 16 and 20°C in high precision incubators for up to 434 h, depending on storage temperature, until spoilage was apparent. At the beginning and during storage, after appropriate time intervals, duplicate meat samples were taken for microbiological, sensory and chemical analysis via enose.

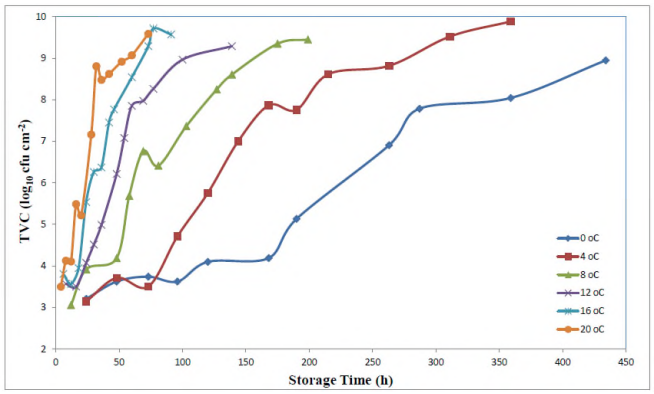

Figure 1. Population dynamics of TVC at various temperatures

In parallel, microbiological analysis was performed, and resulting growth data from agar plate counts were $\log_0$ transformed and fitted to the primary model of Baranyi in order to verify the kinetic parameters of microbial growth (maximum specific growth rate and lag phase duration) [10]. The growth curves of total viable counts (TVC) for beef fillet storage at different temperatures under aerobic conditions are illustrated in Fig. 1.

Additionally, sensory evaluation of meat samples was performed by researchers at AUA, during storage, based on observation of colour and smell before and after cooking [10]. Each sensory attribute was assigned to a three-point scale corresponding to: 1=fresh (acceptable meat quality and the absence of off-flavors); 2=semi-fresh (presence of slight off-flavors but not spoiled); and 3= spoiled (clearly off-flavor development). Odour characteristics of beef fillets, as determined by samples kept frozen and thawed prior to each sensory evaluation, were considered as fresh. Putrid, sweet, sour, or cheesy odours were regarded as indicative of microbial spoilage and classified the samples as spoiled. Bright colours typical of fresh oxygenated meat were considered fresh, whereas a persistent dull or unusual colour rendered the sample spoiled. In total, 210 meat samples were evaluated by a sensory panel and classified into the selected three groups as fresh (n = 48), semi-fresh (n = 72), and spoiled (n = 90).

Libra enose is a compact analytical device used to classify and identify complex odours produced by Technobiochip [11]. The instrument is composed by an array of sensors and a data analysis system. Sensors work like biological receptors and data analysis system allows to transpose information that sensors extract from an odour in an “olfactory image” analogous with our “sensation” of a smell. Libra enose uses a set of eight 20MHz piezoelectric transducers placed in a measuring chamber. Fig 2 illustrates its details. The surface of each transducer is covered by a different poly-pyrrole derivatives layer which forms nonspecific bindings with the compounds of gas mixtures. This nonspecific binding makes sensors non-selective and prohibits them to be poisoned during measurements.

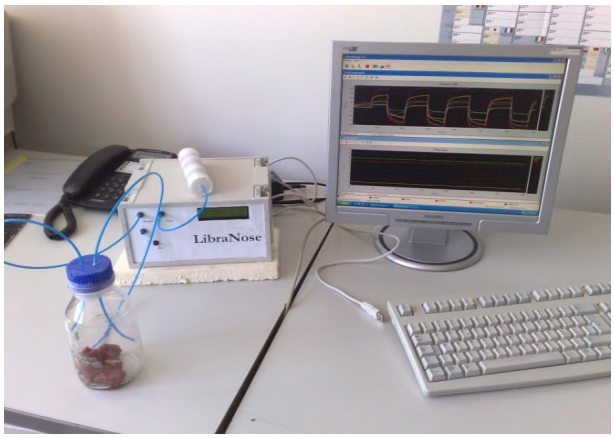

Figure 2. Libra Electronic Nose

The device can be quickly reused after a short cycle of cleaning using clean filtered air obtained via a carbon active filter. The measuring chamber is held at a constant temperature during the measurements by a thermostatic electronic system. A flow system formed by a micro-electric valve and a micro-pump conveys the gas sample to the measuring chamber in a controlled, by the connected computer, way.

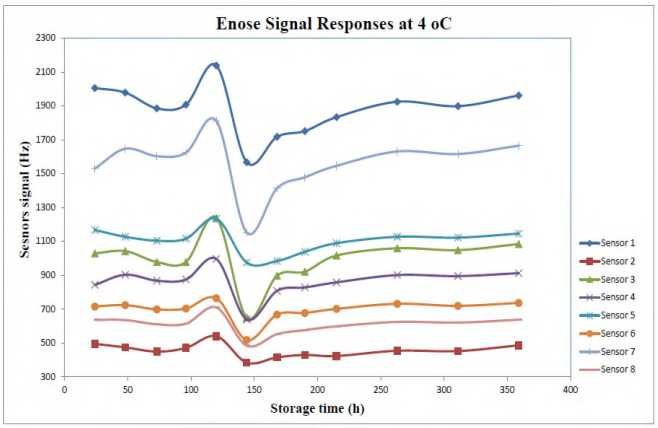

Figure 3. Enose responses during storage of beef fillets at 4°C

For each measurement, a beef fillet sample of 5 g was introduced inside a 100 ml volume glass jar and left at room temperature (20°C ±2°C) for 15 min to enhance desorption of volatile compounds from the meat into the headspace. Pre-processing of the data obtained from enose sensors is required to obtain the "olfactory image" of the sample. This process involves extracting certain significant characteristics from the sensor response curves in order to produce a set of data that can be processed by the recognition system of the enose. Different features can be extracted and used depending on the characteristics of the enose used such as the type of sensors adopted, and the stability of the responses of the latter to the reference gas, to variations in humidity and temperature levels. The responses of all sensor signals classes for meat samples stored at 4°C are shown in Fig. 3. Considering that each measurement can be represented as a point in an 8-dimensional space, a dimensionality reduction algorithm has been applied on those enose data used for training purposes. The robust PCA (RPCA) scheme has been utilized to obtain principal components that are not influenced much by outliers. RPCA scheme was implemented in MATLAB, with the aid of PLS_Toolbox (ver. 8.0 Eigenvector.com).

TABLE I. ROBUST PCA SCHEME

PCs	Robust PCA		
	Eigenvalue	Prop. %	Cum. prop. %
1	7.17e+004	71.45	71.45
2	1.11e+004	21.88	93.34
3	2.40e+003	4.11	97.45
4	9.47e+002	1.55	99.01
5	2.70e+002	0.50	99.50

For this particular experimental case study, the first four principal components (PC) were associated with the 99% of the total variance, as shown in Table I. These specific PCs were extracted and utilized as inputs to the various simulation models developed for this specific case study.

III. AFLS ARCHITECTURE

With the continuously growing demand for models for complex systems inherently associated with nonlinearity, high-order dynamics and imprecise measurements, there is need for a relevant modeling environment. During the last decade, neuro-fuzzy network (NF) approaches have gained considerable interest for solving real world problems. The proposed MIMO AFLS scheme consists of an alternative defuzzification approach, the area of balance (AOB), and its structure is shown in Fig. 4 [12]. In this architecture, the fuzzy basis layer consists of fuzzy basis nodes for each rule. A fuzzy basis node has the following form:

$$\varphi_m(\bar{x}) = \frac{\mu_m(\bar{x})}{\sum_{l=1}^{L} \mu_l(\bar{x})} \quad (1)$$

where $\varphi_m(\bar{x})$ is the normalised fuzzy basis node for rule m and $\mu_m(\bar{x})$ is the firing output of rule m. Since a product-inference is utilized, the fuzzy basis node $\mu_m(\bar{x})$ is in the following form:

$$\mu_m(\bar{x}) = \prod_{i=1}^{n} \mu_{F_i^m}(x_i) \quad (2)$$

Where, n denotes the number of input variables and $\mu_{F_i^m}(x_i)$ is the membership function of the i^{th} input of rule m. In the proposed scheme, a "Gaussian-shape" membership function has been employed, thus $\mu_{F_i^m}(x_i)$ has the following form:

$$\mu_{F_{ii}^m}(x_i) = \exp\left[-\frac{(x_i - c_i^m)^2}{2(b_i^m)^2}\right] \quad (3)$$

where c_i^m and b_i^m are the centre and spread parameters of the membership function i^{th} input of the m^{th} rule. The "centroid of area" (COA) defuzzification method returns the centroid of the area formed by the consequent membership function, the membership value of its rules and the max-min or max-product inference. COA's good performance is however come with a high computational cost. The overall output of the AFLS system utilizes Kosko's method with product inference [13].

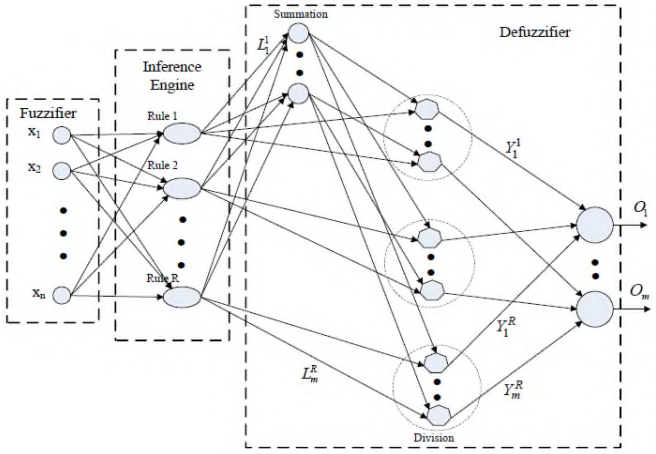

Figure 4. AFLS with AOB scheme

The calculation of the output, y, is defined as

$$y_p = \frac{\sum_{m=1}^{M} \mu_m L_p^m y_p^m}{\sum_{m=1}^{M} \mu_m L_p^m} \quad (4)$$

where y_p is the p^{th} output of the network, μ_m, the membership value of the m^{th} rule, L_p^m the spread parameter of the membership function in the consequent part of the p^{th} output of the m^{th} rule and y_p^m the centre of the membership function in the consequent part of the p^{th} output of the m^{th} rule [12]. The gradient descent learning algorithm scheme has been used to update its various parameters. The update equations for y_p^m, L_p^m, c_i^m and b_i^m are:

$$y_p^m(n+1) = y_p^m(n) + m_y[y_p^m(n) - y_p^m(n-1)] - \eta_y \frac{\partial J}{\partial y_p^m}|_n \quad (5)$$

$$L_p^m(n+1) = L_p^m(n) + m_L[L_p^m(n) - L_p^m(n-1)] - \eta_L \frac{\partial J}{\partial L_p^m}|_n \quad (6)$$

$$c_i^m(n+1) = c_i^m(n) + m_c[c_i^m(n) - c_i^m(n-1)] - \eta_c \frac{\partial J}{\partial c_i^m}|_n \quad (7)$$

$$b_i^m(n+1) = b_i^m(n) + m_b[b_i^m(n) - b_i^m(n-1)] - \eta_b \frac{\partial J}{\partial b_i^m}|_n \quad (8)$$

where, J_k the objective function is defined as:

$$J_k = \frac{1}{2}\sum_{p=1}^{P}(y_p(\bar{x}_k) - d_p(\bar{x}_k))^2 \quad (9)$$

with P the number of outputs, d_p the desired response of the p^{th} output, and $y_p(\bar{x}_k)$ defined as in Eq. 4. The $\bar{(\ )}$ symbol denotes that all training data needs to be normalised. The initial centre, c_i^m and y_p^m are randomly selected from the k^{th} training pattern, x_i^k and d_p^k respectively. The initial spread parameter, b_i^m, is determined by

$$b_i = \frac{\max(x_i) - \min(x_i)}{N} \quad (10)$$

where b_i is a spread parameter of the i^{th} input of all rules and N is the number of rules. The initial spread parameter, L_p^m, has been set to 0.75 and is adjusted during training. All modelling schemes have been implemented in MATLAB (ver. R2014a, Mathworks.com).

IV. Results & Discussion

A machine learning approach based on the proposed AFLS model has been adopted in order to create a dual model acting as an efficient classifier, in an effort to classify meat samples in three quality classes (fresh, semi-fresh, spoiled) and simultaneously as a predictor. Its structure consists of an input layer which contains six input nodes (i.e. storage temperature, sampling time, and the values of the first four principal components). The inclusion of additional factors such as temperature and sampling time is considered as essential under the condition that such information is available [14].

The output layer consists of two nodes, corresponding to the predicted quality class (fresh, semi-fresh, spoiled) of meat samples and the related microbiological attribute, respectively. The initial enose dataset was divided into a training subset with approx. 66.5% of the data, and a testing subset with the remaining 33.5% (i.e. 70 samples). As both output parameters are not independent, in the sense that quality class is related to microbiological counts and vice versa, a model that combines both these measurements have been considered to be desirable. The real challenge in this paper is to propose a new learning-based structure which could be considered as a benchmark method towards the development of efficient intelligent methods in food quality analysis. For this reason, produced results are compared against the PLS and nonlinear regression technique, which are considered as well-recognized tools in chemometric analysis. In addition, AFLS's prediction results are compared with those obtained by a MIMO MLP network and adaptive neuro-fuzzy inference system (ANFIS) identification models. Such schemes have become popular modelling techniques in food science and technology in recent years. After many trials, it has been found that only 16 rules are necessary for the proposed AFLS model to achieve an acceptable performance for this particular experiment. The number of membership functions for each input variable is directly associated to the number of rules, hence, each input signal is "distributed" through Gaussian functions with different centres and widths to every rule node via a product operator.

The classification accuracy of the model was determined by the number of correctly classified samples in each sensory class divided by the total number of samples in the class. The performance of the model for the prediction of TVC for each meat sample was determined by the bias (Bf) and accuracy (Af) factors, the mean relative percentage residual (MRPE) and the mean absolute percentage residual (MAPR), and finally by the root mean squared error (RMSE) and the standard error of prediction (SEP) [12].

TABLE II. Confusion Matrix for AFLS acting as classifier

True class	Predicted class (AIR)			Row total (n_i)	Sensitivity (%)
	Fresh	Semi-fresh	Spoiled		
Fresh ($n = 16$)	15+1(marginal)	0	0	16	100
Semi-fresh ($n = 24$)	1+1(marginal)	20	2	24	83.33
Spoiled ($n = 30$)	0	0	30	30	100
Column total (n_j)	18	20	32	70	
Specificity (%)	88.88	100	93.75		
Overall correct classification (accuracy): 94.28%					

Results revealed that the classification accuracy of the AFLS model was very satisfactory in the characterization of beef samples, indicating the advantage of a hybrid intelligent approach in tackling complex, nonlinear problems, such as meat spoilage. The classification accuracy is presented in the form of a confusion matrix in Table II. The model overall achieved a 94.28% correct classification, and 100%, 83.33% and 100% for fresh, semi-fresh and spoiled meat samples, respectively. It is characteristic that no fresh samples were misclassified as spoiled and vice versa, indicating that the biochemical information provided by enose data could discriminate these two classes accurately. Lower percentages were obtained for semi-fresh samples with incorrect classifications in the fresh and spoiled classes. It must be emphasised however that the number of examined samples within each class was not equally distributed, due to the different spoilage rate of beef samples at the different temperatures. The lower accuracies obtained in the semi-fresh class could be also attributed to the performance of the sensory evaluation process, as the difference between "fresh", "semi-fresh" and "spoiled" class is not very obvious sometimes.

An MLP network was also constructed for this case study. The MLP was implemented with two hidden layers (with 12 and 6 nodes respectively) and two output nodes, one for the sensory class and one for the TVCs. The model overall achieved a 91.42% correct classification, with 100%, 79.16% and 96.66% for fresh, semi-fresh and spoiled meat samples, respectively. The related sensitivities represent 5 misclassifications out of 24 semi-fresh meat samples, and one misclassification out of 30 spoiled samples. More specifically for the case of semi-fresh samples, four cases were misclassified as fresh cases, while the remaining one as spoiled. Finally, one spoiled sample was misclassified as semi-fresh.

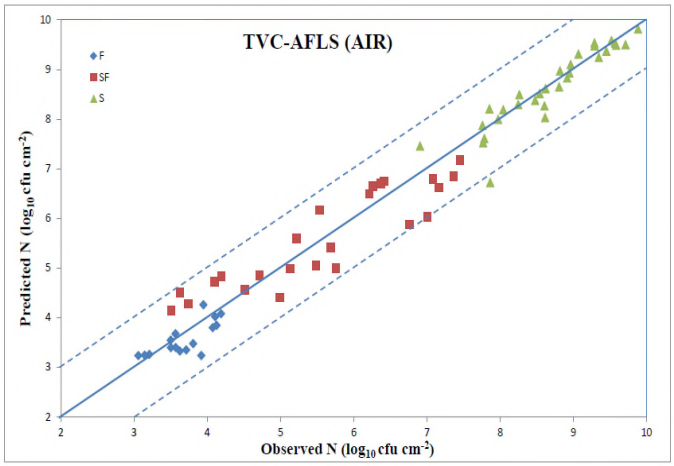

Figure 5. AFLS prediction model for TVC

The plot of predicted (via AFLS) versus observed total viable counts is illustrated in Fig. 5, and shows a very good distribution around the line of equity (y=x), with almost all the data included within the ±1 log unit area. Four (semi-fresh) samples were in the border-line of the ± 1 log unit area, while one sample (spoiled) was placed outside that unit area.

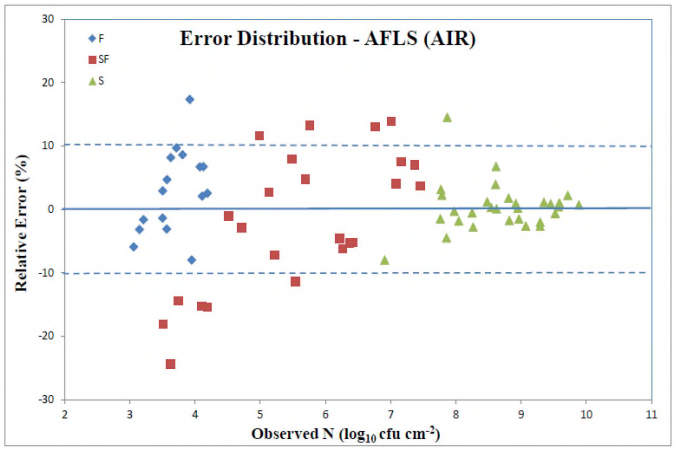

Figure 6. AFLS's Residual Error performance

More specifically, the spoiled "42A3" sample was clearly outside the ± 1 log unit area. "42A3" corresponds to a beef sample stored at 4°C and collected after 168 h of storage. Semi-fresh samples, "39A3", "36A3" and "24A5", "31A1" were placed very close to the borderline. "39A3", "36A3" samples corresponds to beef samples stored at 4°C and collected after 144 h and 120 h of storage respectively. Similarly, "24A5" sample corresponds to a beef sample stored at 8°C and collected after 69 h of storage, while "31A1" corresponds to a beef sample stored at 0°C and collected after 96 h of storage.

A more comprehensible picture of the AFLS's prediction performance is however provided in Fig 6 where the % relative error of prediction is shown against the observed microbial population. Based on this plot, data were distributed above and below 0, with approximately the majority of predicted microbial counts included within the ± 10% RE zone. Ten semi-fresh samples however were clearly outside that zone, together with one fresh and spoiled sample.

TABLE III. PERFORMANCE OF AFLS MODEL FOR TVC

Statistical index (AFLS case) AIR	Fresh	Semi-fresh	Spoiled	Overall
Mean squared error (MSE)	0.0722	0.2891	0.0895	0.1540
Root mean squared error (RMSE)	0.2686	0.5376	0.2992	0.3924
Mean relative percentage residual (MRPR %)	2.8938	-1.7546	0.3522	0.2108
Mean absolute percentage residual (MAPR %)	5.7920	9.2045	2.3997	5.5081
Bias factor (B_f)	0.9689	1.0120	0.9957	0.9951
Accuracy factor (A_f)	1.0616	1.0947	1.0246	1.0567
Standard error of prediction (SEP %)	7.2774	9.6081	3.4452	6.0515

The performance of the AFLS model to predict TVCs in beef samples in terms of statistical indices is presented in Table III. Based on the calculated values of the bias factor B_f, it can be assumed that the proposed model under-estimated TVCs in fresh and spoiled samples (B_f <1), whereas for semi-fresh samples over-estimation of microbial population was evident (B_f >1). Such over-estimation was in agreement to the number of semi-fresh samples placed outside the ± 10% RE zone at Fig. 6. Finally, the standard error of prediction (SEP) index is a relative typical deviation of the mean prediction values and expresses the expected average error associated with future predictions. The value of the index was 6.05% for the overall samples, indicating good performance of the network for microbial count predictions. However in the case of semi-fresh samples, the index gave higher values (i.e. 9.6%).

In addition to AFLS, in this research work, an ANFIS model has been developed to predict TVCs. The majority of existing neuro-fuzzy schemes follow the classic Takagi–Sugeno–Kang (TSK) structure, where only one output is enabled. TSK models consist of IF-THEN rules with fuzzy antecedents and mathematical functions in the consequent part. The fuzzy sets partition the input space into a number of fuzzy regions, while the consequent functions describe the system's behaviour in these regions. ANFIS is a classic representative of TSK-based neuro-fuzzy systems. By analysing mapping relationships between input and output data, ANFIS optimises the distribution of membership functions by using a gradient descent algorithm either alone or combined with a least-squares method. The same validation technique, as well as the same training dataset has been utilized also for this case. Under these

conditions, ANFIS performed satisfactory, its performance however was achieved with a high computational cost, by utilizing two membership functions for each input variables and 64 fuzzy rules. Statistical information for ANFIS model is illustrated at Table IV.

TABLE IV. PERFORMANCE OF ANFIS MODEL FOR TVC

Statistical index (ANFIS case) - AIR	**Fresh**	**Semi-fresh**	**Spoiled**	**Overall ANFIS**
Mean squared error (MSE)	0.1858	0.2943	0.1821	0.2214
Root mean squared error (RMSE)	0.4310	0.5425	0.4267	0.4705
Mean relative percentage residual (MRPR %)	-2.3051	0.0791	0.7813	-1.1780
Mean absolute percentage residual (MAPR %)	8.7771	7.9101	3.6923	6.3007
Bias factor (B_f)	1.0162	1.0245	0.9909	1.0081
Accuracy factor (A_f)	1.0924	1.0793	1.0381	1.0644
Standard error of prediction (SEP %)	11.6759	9.6944	4.9139	7.2567

Finally, an MLP network, a PLS and a nonlinear regression model were utilised for TVC prediction. All models were constructed using the same input vector as in the cases of AFLS and the PLS_Toolbox software (Eigenvector.com) in association with MATLAB was used to perform the PLS analysis. Nonlinear regression is often used to model complex phenomena which cannot be handled by a linear model. The XLSTAT software provides such capability through the use of nonlinear regression (NLR) modelling using the nonlinear iterative partial least squares (NIPALS) algorithm. For this specific case, the following 5^{th} order model has been constructed using XLSTAT and achieved a remarkable performance compared to PLS scheme.

$$Y1 = -2.22182 + 0.00140 * X1 + 0.00175 * X2 + 0.00402 * X3 - 0.00712 * X4$$
$$+ 0.96524 * X5 + 0.18783 * X6 + 0.00009 * X2^2 - 000011 * X3^2 - 0.00048 * X4^2$$
$$- 0.25313 * X5^2 - 0.00210 * X6^2 + 0.03667 * X5^3 + 0.00001 * X6^3 - 0.00220 * X5^4$$
$$+ 0.00005 * X5^5$$

Statistical information for both MLP, PLS and NLR models is also illustrated at Table V.

TABLE V. TVC PREDICTION MODELS

Statistical index (MLP, PLS, NLR) - AIR	**Overall MLP**	**Overall PLS**	**Overall NLR**
Mean squared error (MSE)	0.2397	1.8587	0.3819
Root mean squared error (RMSE)	0.4896	1.3633	0.6180
Mean relative percentage residual (MRPR %)	-0.4163	-2.2667	0.0063
Mean absolute percentage residual (MAPR %)	6.2523	20.1221	8.9398
Bias factor (B_f)	1.0002	0.9946	0.9868
Accuracy factor (A_f)	1.0643	1.2126	1.1005
Standard error of prediction (SEP %)	7.5514	21.0263	9.5308

Overall results revealed that prediction accuracy of the AFLS model was better compared with the performances of MLP, NLR and ANFIS, in the characterization of meat samples for this reduced number of samples, indicating again the superiority of this specific MIMO hybrid intelligent modelling approach in tackling complex, nonlinear problems such as the meat spoilage. However, the produced performance from PLS scheme was expected, as it is well known that in modelling of real processes, linear PLS has some difficulties in its practical applications since most real problems are inherently nonlinear and dynamic.

V. CONCLUSIONS

In conclusion, this simulation study demonstrated the effectiveness of the detection approach based on electronic nose which in combination with an appropriate machine learning strategy could become an effective tool for monitoring meat spoilage during aerobic storage at various temperatures. The collected "volatile" data could be considered as biochemical "signature" containing information for the discrimination of meat samples in quality classes corresponding to different spoilage levels, whereas in the same time could be used to predict satisfactorily the microbial load directly from the sample surface. The realization of this strategy has been fulfilled with the development of a MIMO neurofuzzy model which incorporates a prototype defuzzification scheme, while utilising an efficient, compared to TSK-systems, fuzzification layer. In the case of AFLS, the number of memberships for each input variable was directly associated to the number of rules, hence, the "curse of dimensionality" problem was significantly reduced. Classification performance was very good, while overall prediction for TVCs has been considered as very satisfactory, although lower performance was observed especially for the semi-fresh samples. Prediction performances of MLP, NLR and PLS schemes revealed the deficiencies of these systems which have been used extensively in the area of Food Microbiology. There is need to explore further the use of hybrid intelligent systems, and this paper has attempted for the first time to associate enose data with such systems. Further research will be focused in incorporating to the data analysis, specific microbiological data, such as *Pseudomonas* spp., *Brochothrix thermosphacta*, Lactic acid bacteria and *Enterobacteriaceae*.

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