# An Asymmetric Neuro-Fuzzy Model for the Detection of Meat Spoilage

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***Abstract*—In food industry, quality and safety parameters are direct related with consumers' health condition. There is a growing interest in developing non-invasive sensorial techniques that have the capability of predicting quality attributes in real-time operation. Among other detection methodologies, Fourier transform infrared (FTIR) spectroscopy has been widely used for rapid inspection of various food products. In this paper, an advanced clustering-based neurofuzzy identification model has been developed to detect meat spoilage microorganisms during aerobic storage at various temperatures, utilizing FTIR spectra. A clustering scheme has been utilized as an initial step for defining the fuzzy rules while an asymmetric Gaussian membership function has been used in the fuzzification part of the model. The proposed model not only classifies meat samples in their respective quality class (i.e. fresh, semi-fresh and spoiled), but also predicts their associated microbiological population directly from FTIR spectra. Results verified the superiority of the proposed scheme against the adaptive neuro-fuzzy inference system, multilayer perceptron and partial least squares in terms of prediction accuracy.**

***Keywords—Neuro-fuzzy systems, neural networks, meat spoilage, sensors, clustering.***

## I. INTRODUCTION

In the past few decades, meat industry has enormously flourished, due to the continuing growth of worldwide demand for improved food quality [1]. Interest in meat quality is determined by the effort to supply the consumer with a consistent high quality product at a reasonable price. Such realization is linked with the accurate assessment of meat quality utilizing modern techniques for quality evaluation [2]. However, the shelf life of meat is low and the consumption of spoiled meat products could cause serious health hazards. Beef, as one of the most commercially consumed muscle foods, although is a good food source for proteins and other vital nutrients it is also considered as an ideal substrate for the growth of pathogenic microorganisms and consequently spoilage. Currently, meat safety is mainly relied on regulatory inspection and sampling protocols. Additionally, although a plethora of chemical and microbiological methods have been proposed for the detection and measurement of bacterial meat spoilage, the majority of them are considered as time-consuming processes [3]. Meat industry however needs rapid analytical methods and in the past such analysis had been carried out through the usage of high-performance liquid chromatography (HPLC) and gas chromatography-mass spectrometry [4]. The majority of these methods are however invasive and the introduction of accurate and non-destructive sensing technologies to detect the spoilage bacteria as well as pathogenic bacteria with a high degree of dependency in food products is highly desirable. Various rapid, non-invasive methods based on analytical instrumental techniques, such as Fourier transform infrared spectroscopy (FTIR) [5], Raman spectroscopy [6], hyperspectral imaging [7] and electronic nose technology [8] have been explored for their potential as reliable "meat quality" sensors. The "mechanism" of these approaches is based on the assumption that the metabolic activity of micro-organisms on meat, results in biochemical changes, with the simultaneous formation of metabolic by-products, which could contribute to spoilage. The quantification of these metabolic activities is associated to a unique "signature", providing thus information about the type and rate of spoilage [9]. Over the last few years, FTIR has been considered as a very important tool in food analysis. The application of chemometric-based techniques to associate FTIR spectral data with meat spoilage is not new and it has been investigated in the past [10]. However, the main focus on those studies was related only to the detection of bacterial spoilage, in terms of microbiological analysis. FTIR spectral data collected directly from the surface of meat were verified that they could be used as biochemical interpretable "signatures", in an attempt to obtain information on early detection of microbial spoilage of chicken breast and rump steaks [11]. A number of partial least squares (PLS) models and simple multilayer neural networks (MLP) have been investigated to correlate, not only spectral data from FTIR spectroscopy analysis with beef spoilage and its associated total viable bacteria counts-TVC, but also to associate spectral data with quality classes defined by sensory assessment of the samples [12]. Recently, two advanced machine learning methodologies based on adaptive fuzzy logic systems (AFLS) [13] and on Extended Normalized Radial Basis Functions Neural Networks [14] have been proposed, utilizing the same dataset used earlier in [12]. These two simulation studies demonstrated the effectiveness of the detection approach based on FTIR spectroscopy which in combination with an appropriate machine learning strategy could become an effective tool for monitoring meat spoilage. The main objective of this paper is to associate FTIR spectral data with beef spoilage during aerobic storage at various temperatures

(0, 5, 10, 15, 20 °C) utilizing a further improved hybrid intelligent learning-based prediction system. The same information of FTIR spectra, as well as the correlated microbiological analysis (i.e. total viable counts - TVC) used in [12-13], has been also utilized in this paper. In the current study, an Asymmetric Gaussian Fuzzy Inference Neural Network (AGFINN) which is made up of Asymmetric Gaussian membership functions associated with a clustering scheme, has been developed to predict not only the microbial load (as TVC) on meat surface, but also to simultaneously classify beef samples to one of three quality classes, based on their biochemical profile provided by FTIR spectral information. The proposed MIMO AGFINN system utilizes the centre of average method as a defuzzification method and unlike the Adaptive Neuro Fuzzy Inference System (ANFIS) and AFLS model, it includes a clustering component which defines the number of fuzzy rules. In the AGFINN model, the main issue of "*curse of dimensionality*" is considerably minimized, as for each input variable, the number of membership functions (MF) is equal to the number of fuzzy rules. Thus, in this scheme the number of fuzzy rules is independent from the number of input variables, creating thus a novel "multi-dimensional inspired" rule layer, in contrast to ANFIS's architecture. Despite the widespread usage of the standard symmetric Gaussian membership functions, AGFINN alternatively utilizes an asymmetric membership function. It has been considered from literature, that variability and flexibility features are higher in asymmetric Gaussian functions compared to the standard one. Thus, such function could partition input space more effectively [15].

Results from AGFINN are compared against models based on AFLS, ANFIS, MLP and PLS [13]. 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. Such an accurate assessment prediction could allow a more efficient management of products in the food chain.

## II. FTIR SAMPLING AND ANALYSIS

The FTIR experimental case was performed at the Agricultural University of Athens, Greece, and information related to FTIR spectra, as well as the correlated microbiological analysis (*i.e.* total viable counts - TVC) from beef fillets, was provided to the first author for research purposes. A description of the experimental methodology as well as the related microbiological analysis of the meat samples is described in [12]. FTIR spectral information was used as a way to obtain metabolic "signatures" of beef fillet samples during storage in aerobic conditions at five different storage temperatures (0, 5, 10, 15, and 20 $^{\circ}$C ). Typical FTIR spectral data in the range of $1800-1000\text{cm}^{-1}$ collected from fresh, semi-fresh and spoiled beef fillet samples stored at 0, 10 and 20 $^{\circ}$C respectively are shown in Fig. 1. Due to the multi-variable nature of FTIR data, a principal component analysis (PCA) was applied on spectral data used for training purposes. PCA scheme was implemented in MATLAB (R2018a), with the aid of PLS_Toolbox (ver. 8.7, Eigenvector.com). For this particular experimental case study, although the total variance (100%) of the dataset was explained by 34 principal components (PCs), only the first five PCs were associated with the 98.25% of the total variance, as shown in Table I.

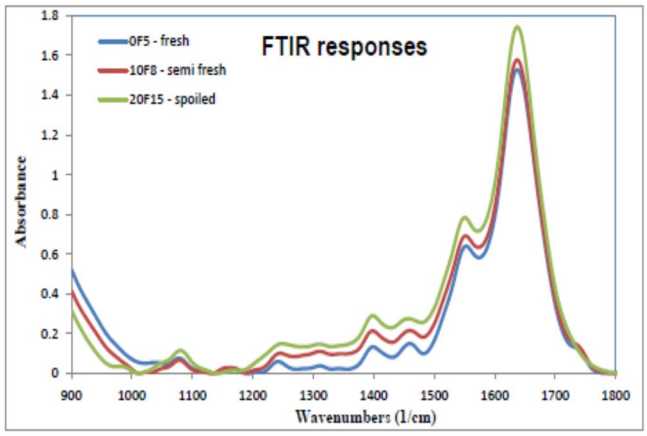


Fig. 1. FTIR spectra collected from beef samples

The variability (%) of the first three PCs is dominant to the overall contribution and this is also illustrated from a visualization of the first three orthonormal principal component coefficients for each variable, and the principal component scores for each observation in a single plot, as shown at Fig. 2.

TABLE I. RESULTS OF PCA SCHEME

| PCs | PCA | | |
|---|---|---|---|
| | Eigenvalue | Prop. % | Cum. prop. % |
| 1 | 190.080 | 70.925 | 70.925 |
| 2 | 48.083 | 17.941 | 88.867 |
| 3 | 12.754 | 4.759 | 93.626 |
| 4 | 7.215 | 2.692 | 96.318 |
| 5 | 5.194 | 1.938 | 98.256 |
| 6 | 1.807 | 0.674 | 98.930 |
| 7 | 1.070 | 0.399 | 99.329 |

Thus, only the first five principal components from the PCA scheme were used as inputs to the various simulation models developed for this specific case study.

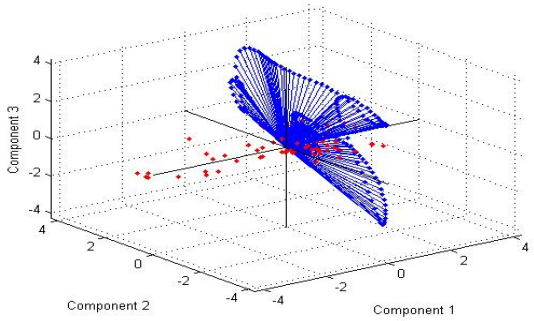


Fig. 2. 3-D plot for the first three principal components

In parallel, microbiological analysis was performed, and resulting growth data from plate counts were $\log_{10}$ transformed and fitted to the primary model of Baranyi & Roberts in order to verify the kinetic parameters of microbial growth (maximum specific growth rate and lag phase duration) [12]. The population dynamics of total viable counts

(TVC) for beef fillet storage at different temperatures, under aerobic conditions, is illustrated in Fig. 3.

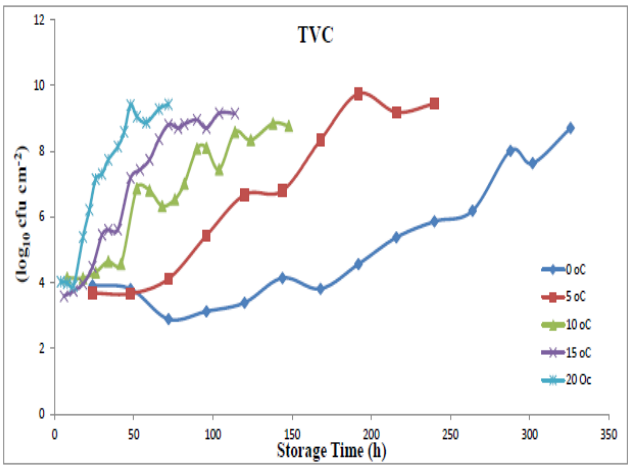


Fig. 3. Growth curves of TVC at various temperatures

## III. ARCHITECTURE OF AGFINN

In this paper we propose a connectionist model of fuzzy system in the form of a feed-forward multi-layer network, which can be trained using an iterative algorithm. The proposed AGFINN design is illustrated by a traditional MIMO structure, shown in Fig. 4, which includes also a clustering initialization step.

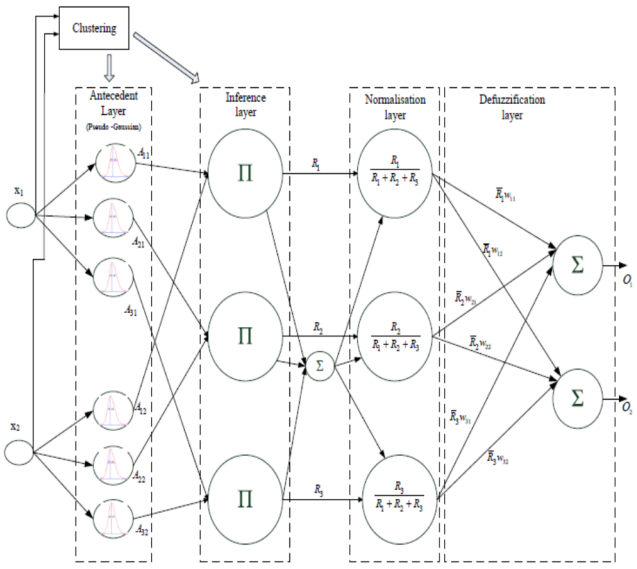


Fig. 4. Structure of AGFINN system

The gradient descent (GD) algorithm has been used as a learning scheme, while AGFINN's output is calculated via a "centre average" (CA) defuzzification method. The first three layers $L_1$, $L_2$ and $L_3$ are associated to the premise part (i.e. IF part) of a fuzzy systems, while layer $L_5$ relates to the equivalent consequent part (i.e. THEN part). Layer $L_4$ represents the normalization layer, and is applied to the outputs from $L_3$. In this paper, centres derived from the clustering method were used for the initialization for the centres of fuzzy MFs. Based on AGFINN's architecture the number of fuzzy rules equals the number of clusters. In addition, the spread parameters for each MF $\sigma_{ij}$ are initialized based on the following equation

$$\sigma_{ij} = \left( \sum_{k=1}^{n} u_{ik} (x_{kj} - c_{ij})^2 \Big/ \sum_{k=1}^{n} u_{ik} \right)^{1/2} \quad (1)$$

In the above equation, elements in matrix $\mathbf{U}$, correspond to the MFs of input $\boldsymbol{x_k}$ from the $i^{th}$ cluster, as they were derived from the clustering scheme.

### A. Clustering-based Initialization

The applied clustering algorithm at layer $L_2$ consists of two stages [16]. In the first stage, a method similar to Learning Vector Quantization (LVQ) algorithm generates crisp c-partitions of the data set. The number of clusters c and the cluster centres $v_i$, $i = 1,...,c$, obtained from this stage are used by Fuzzy c-means (FCM) algorithm in the second stage. The first stage clustering algorithm determines the number of clusters by dividing the learning data into these crisp clusters and calculates the cluster centres which are the initial values of the fuzzy cluster centres derived the second stage algorithm. If we consider that $\boldsymbol{X} = [\boldsymbol{x}_1,...,\boldsymbol{x}_n] \in R^{np}$ be a learning data, then the first cluster is created starting with the first data vector from X and the initial value of the cluster centre is taking as a value of this data vector. Then other data vectors are included into the cluster but only these ones which satisfy the following condition

$$\|x_k - v_i\| < D \quad (2)$$

where $x_k \in X$, $k = 1,...,n$ and $v_i$, $i = 1,...,c$ are cluster centres, $V = [v_1,...,v_n] \in R^{cp}$, the constant value D is fixed at the beginning of the algorithm. Cluster centres $v_i$ are updated for each cluster (i.e., $i = 1,...,c$) according to the following equation

$$v_i(t+1) = v_i(t) + \eta_t (x_k - v_i(t)) \quad (3)$$

where $t = 0, 1, 2, ...$ denotes the number of iterations, $\eta_t \in [0,1]$ is the learning rate and it is decreasing during the execution of the algorithm (depending on the number of elements in the cluster). At the end of first stage, the number of clusters c is defined, while the dataset is divided into the clusters. In addition, the values of cluster centers $v_i$ $i = 1,...,c$, which can be used as initial values for the second stage clustering algorithm, are calculated. In the second stage, the classic fuzzy c-means algorithm has been used to optimize the values of cluster centers.

### B. AGFINN: Learning analysis

The clustering pre-processing step practically indicates the generation of the fuzzy rules base. Thus, fuzzy rules can be formulated by the following equation:

$$\text{IF } (x_1 \text{ is } U_1^i \text{ AND....AND } x_q \text{ is } U_q^i) \text{ THEN } y_k = \sum_{j=1}^{c} w_{kj} R_j \quad (4)$$

where $U$ are the sets derived from the c-partition of training data X and $R_c$ are the fuzzy normalized rules [17]. The proposed configuration of AGFINN scheme is thus illustrated as:

**Layer 1:** Nodes at this stage simply forward input variables $x_1, x_2, ..., x_n$ to $L_2$.

**Layer 2:** This is premise part in a fuzzy IF-THEN structure, which utilizes an asymmetric Gaussian MF with the following form

$$A_{ij} = \exp\left(-\frac{1}{2}\left(\frac{x_i - c_{ij}}{\sigma_{ij}^{left}}\right)^2\right) U\left(x_i; -\infty, c_{ij}\right) + \exp\left(-\frac{1}{2}\left(\frac{x_i - c_{ij}}{\sigma_{ij}^{right}}\right)^2\right) U\left(x_i; c_{ij}, \infty\right) \quad (5)$$

$$where \;\; U\left(x_i; a, b\right) = \begin{cases} 1 \;\; if \;\; a \le x_i < b \\ 0 \;\; otherwise \end{cases}$$

The MF in the above equation includes two types of spreads, namely $\sigma_{ij}^{left}$ and $\sigma_{ij}^{right}$ respectively, which modify the traditional Gaussian MF to a rather non-symmetric style that can provide different output characteristics, as shown in Fig. 5.

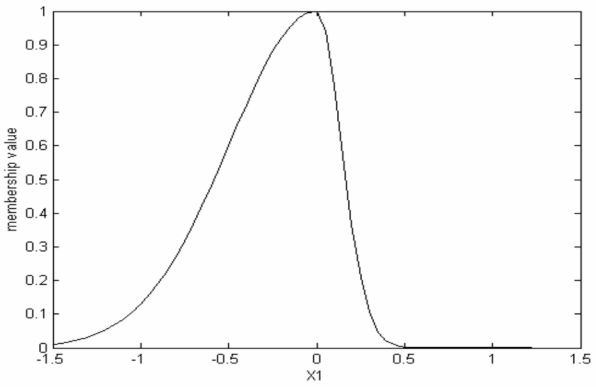


Fig. 5. Structure of Asymmetric MF

Following the clustering stage, an initial value for spread ( $\sigma_{ij}^{init}$ ) has been calculated. As AGFINN utilizes two spreads, one located at the left of the initial centre parameter and one at the right, both spreads are initialized as $\sigma_{ij}^{init} / 2 = \sigma_{ij}^{left} = \sigma_{ij}^{right}$ . Thus, during the first iteration of the training process, the total spread of any asymmetric MF has been equalled to $\sigma_{ij}^{total} = \sigma_{ij}^{left} + \sigma_{ij}^{right}$ . Upon the arrival of any input variable from $L_1$, its position (left/right) against the specific centre parameter for each MF needs to be recorded via a specific MF index allocated for each MF. This index is then used in the backward learning phase to update that particular spread parameter. The value of this index is then updated accordingly to any new input arrival from $L_1$. During forward training phase, $\sigma_{ij}^{total}$ is used as the spread used in the Gaussian function which has the specific form

$$A_{ij} = \exp\left(-\frac{\left(x_i - c_{ij}\right)^2}{2b_{ij}^2}\right) \quad (6)$$

where $b_{ij} = \sigma_{ij}^{total}$ , $i$ represent the number of MF/rules, while $j$ denotes the specific input variable. During the backward learning phase, a new spread $\sigma_{ij}^{new}$ value is calculated via the GD learning method. Based on the information stored at that specific MF index, either the left or right spread is updated as $\sigma_{ij}^{left\ or\ right} = \sigma_{ij}^{new} / 2$ . For the next iteration step, in the forward training phase, the spread parameter will be equal again as $\sigma_{ij}^{total} = \sigma_{ij}^{left} + \sigma_{ij}^{right}$ , incorporating however the relative adjustment of one of its components.

**Layer 3:** This layer represents the "classic" fuzzy rules layer. The multiplication has been used as a fuzzy AND operation, thus output has the following form:

$$R_i = \prod_j^n A_{ji}(x_j) \quad (7)$$

In this proposed architecture, the number of rules is the same as the number of clusters.

**Layer 4:** At this normalization layer, each normalized rule is calculated by:

$$\overline{R_i} = \frac{R_i}{\sum_{j=1}^{c} R_j} \quad (8)$$

**Layer 5:** Finally, this is the consequent stage of the AGFINN scheme, which has the following form

$$O_i = \sum_{j=1}^{c} w_{ij} \overline{R}_j \quad (9)$$

AGFINN's training involves the usage of the gradient descent (GD) algorithm for the parameters' tuning for AGFINN scheme. During, this phase, correction signals are calculating from the AGFINN's output backward to the premise part of the model and all network's parameters are adjusted. Thus, the weights at the defuzzification layers are updated as:

$$W_{ki}(t+1) = W_{ki}(t) + \eta_w \Delta W_{ki} \quad (10)$$

The $c_{ij}$ and $b_{ij}$ parameters of the proposed membership function are tuned via the following equation

$$c_{ij}(t+1) = c_{ij}(t) - \eta_c \left(\frac{\partial E}{\partial c_{ij}}\right)$$
$$b_{ij}(t+1) = b_{ij}(t) - \eta_b \left(\frac{\partial E}{\partial b_{ij}}\right) \quad (11)$$

where $\frac{\partial E}{\partial c_{ij}}$ and $\frac{\partial E}{\partial b_{ij}}$ are the components extracted from the following chain rule configuration:

$$\frac{\partial E}{\partial c_{ij}} = \frac{\partial E}{\partial O}\frac{\partial O}{\partial R_i}\frac{\partial R_i}{\partial A_{ij}}\frac{\partial A_{ij}}{\partial c_{ij}}$$
$$\frac{\partial E}{\partial b_{ij}} = \frac{\partial E}{\partial O}\frac{\partial O}{\partial R_i}\frac{\partial R_i}{\partial A_{ij}}\frac{\partial A_{ij}}{\partial b_{ij}} \quad (12)$$

All learning rates parameters ($\eta_w, \eta_c, \eta_b$) in our simulation have been set with a constant value of 0.15. The partial derivative components in Eq. 12 are then calculated as

$$\frac{\partial A_{ij}}{\partial c_{ij}} = \left[\exp\left(-\frac{(x-c_{ij})^2}{2b_{ij}^2}\right)\right]' =$$
$$\left[\exp\left(-\frac{(x-c_{ij})^2}{2b_{ij}^2}\right)\right]\cdot\left(-\frac{(x-c_{ij})^2}{2b_{ij}^2}\right)' = \quad (13)$$
$$= A_{ij}\cdot\left(-\frac{1}{2b_{ij}^2}\left((x-c_{ij})^2\right)'\right) = A_{ij}\cdot\left(\frac{1}{b_{ij}^2}(x-c_{ij})\right)$$

$$\frac{\partial A_{ij}}{\partial b_{ij}} = \left[\exp\left(-\frac{(x-c_{ij})^2}{2b_{ij}^2}\right)\right]' =$$
$$\left[\exp\left(-\frac{(x-c_{ij})^2}{2b_{ij}^2}\right)\right]\cdot\left(-\frac{(x-c_{ij})^2}{2b_{ij}^2}\right)' =$$
$$= A_{ij}\cdot\left(-\frac{(x-c_{ij})^2}{2}\left(\frac{1}{b_{ij}^2}\right)'\right) = \quad (14)$$
$$A_{ij}\cdot\left(\frac{(x-c_{ij})^2}{b_{ij}^3}\right)$$

$$\frac{\partial R_i}{\partial A_{ij}} = \prod_{lm\neq ij} A_{lm} \quad (15)$$

$$\frac{\partial O}{\partial R_i} = \frac{w_i\left(\sum_{\substack{j=1\\ j\neq i}}^{c} R_j\right) - \sum_{\substack{j=1\\ j\neq i}}^{c} R_j w_j}{\left(\sum_{j=1}^{c} R_j\right)^2} \quad (16)$$

AGFINN model has been implemented using MATLAB (ver. R2018a, Mathworks.com).

## IV. Results and Discussions

A machine learning approach, based on the proposed AGFINN model, has been adopted in order to create a prediction system. The real challenge in this paper is to propose a new and improved 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 with those obtained by AFLS and ANFIS neurofuzzy models as well as against MLP networks and PLS-based regression models. Such schemes have become popular modelling techniques in food science and technology in recent years. The final dataset, consisted of 74 beef patterns, include information from the various storage temperatures, the first five PCs and the sampling times. In this research study, two distinct procedures have been considered. In the first procedure, as the number of observations/samples is small, the separation of the dataset into training and testing subsets (hold-out method) was considered that it would further reduce the number of data and would result in insufficient training of the network. Therefore, in order to improve the robustness of identification process, the leave-1-out cross validation technique was employed to evaluate the performance of the developed AGFINN model.

AGFINN's input layer includes seven input nodes (*i.e.* storage temperature, sampling time, and the values of the five principal components). After many trials, it has been found that only 8 rules are necessary for the proposed model to achieve an acceptable performance for this particular case/experiment. The output layer consists of two nodes, corresponding to the predicted quality class (fresh, semi-fresh, spoiled) of meat samples and the total viable counts (TVC), respectively. As both output parameters are dependent, 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. In order to accommodate both classification and modelling tasks in the same model-structure, the classification task has been modified accordingly. Rather than trying to create a distinct classifier, an attempt has been made to "model" the classes [13]. Initially, values of 10, 20 and 30, have been used respectively, to associate the three classes with a cluster centre. During the identification process, output values of $[5,15]$ were associated to "fresh" class with cluster centre 10, values of $[15.01,25]$ were associated to "semi-fresh" class with cluster centre 20, and finally values of $[25.01,35]$ were associated to "spoiled" class with cluster centre 30. The second output node has been assigned to the total viable counts (TVC).

TABLE II. CLASSIFICATION PERFORMANCE OF AGFINN

| True class | Predicted class | | | Row total | Sensitivity (%) |
|---|---|---|---|---|---|
| | Fresh | Semi-fresh | Spoiled | | |
| Fresh (24) | 22 | 2 | 0 | 24 | 91.66 |
| Semi-fresh(16) | 1 | 15 | 0 | 16 | 93.75 |
| Spoiled (34) | 0 | 1+1 (margin) | 32 | 34 | 94.12 |
| Column total | 23 | 19 | 32 | 74 | |
| **Specificity (%)** | 95.65 | 78.95 | 100 | | |
| **Overall correct classification (accuracy):** 93.24% | | | | | |

The performance of the model in the prediction of TVC for each meat sample was determined by the bias ($B_f$) and accuracy ($A_f$) 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) [13].

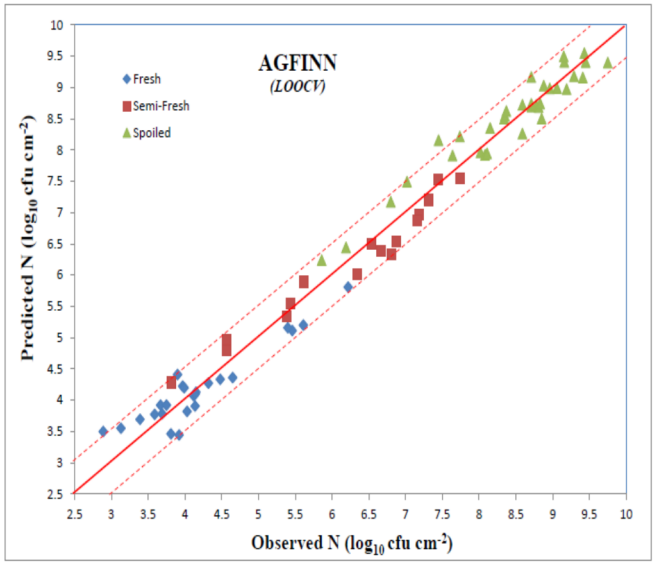


Fig. 6. AGFINN prediction model for TVC

Results revealed that the classification accuracy of the AGFINN model was very satisfactory in the characterization of beef samples, indicating the advantage of a neurofuzzy approach in tackling complex, nonlinear problems, such as meat spoilage. The classification accuracy obtained from AGFINN, is presented in the form of a confusion matrix in Table II. The plot of predicted (via AGFINN) versus observed total viable counts is illustrated in Fig. 6, and shows a very good distribution around the line of equity (y=x), with almost all the data included within the ±0.5 log unit area.

TABLE III. PERFORMANCE OF AGFINN MODEL FOR TVC

| ***Statistical index – AGFINN (leave-one-out)*** | ***Fresh*** | ***Semi-fresh*** | ***Spoiled*** | ***Overall AGFINN*** |
|---|---|---|---|---|
| *Mean squared error (MSE)* | 0.0926 | 0.0769 | 0.0748 | 0.0810 |
| *Root mean squared error (RMSE)* | 0.3043 | 0.2772 | 0.2736 | 0.2846 |
| *Mean relative percentage residual (MRPR %)* | -0.694 | -0.039 | -1.227 | -0.7976 |
| *Mean absolute percentage residual (MAPR %)* | 6.5690 | 4.2171 | 2.8023 | 4.3299 |
| *Bias factor ($B_f$)* | 1.0039 | 0.9991 | 1.0117 | 1.0064 |
| *Accuracy factor ($A_f$)* | 1.0670 | 1.0427 | 1.0280 | 1.0437 |
| *Standard error of prediction (SEP %)* | 7.2716 | 4.4592 | 3.2473 | 4.3313 |

A close inspection reveals some interesting conclusions. Two samples, as shown from Fig. 6, are outside the border line of the ±0.5 log unit area and they are associated to the fresh "0F4" and spoiled "10F14" sample respectively. "0F4" corresponds to a beef fillet, stored at 0ºC and collected after 72h of storage, while "10F14" corresponds to a beef fillet, stored at 10ºC and collected after 104h of storage. The performance of the AGFINN model to predict TVCs in beef samples in terms of statistical indices is presented in Table III.

The SEP rate for fresh samples is shown to be higher compared to semi-fresh and spoiled samples. This is explained by the fact that the ranges of TVCs for both fresh and semi-fresh samples are comparatively close, as shown also from Fig. 6. The distinction between these two classes is more difficult, compared to the case of spoiled samples. In addition to AGFINN model, AFLS, ANFIS, MLP, and PLS models have been implemented developed to predict TVCs [13]. The same leave-1-out cross validation technique, as well as the same training dataset has been utilized also for this case.

TABLE IV. PERFORMANCE OF COMPARABLE MODELS FOR TVC

| **Statistical index leave-one-out** | **AFLS** | **ANFIS** | **MLP** | **PLS** |
|---|---|---|---|---|
| *Mean squared error (MSE)* | 0.139 | 0.196 | 0.286 | 1.4936 |
| *Root mean squared error (RMSE)* | 0.373 | 0.443 | 0.535 | 1.2221 |
| *Mean relative percentage residual (MRPR %)* | -0.758 | -0.693 | -2.057 | -0.239 |
| *Mean absolute percentage residual (MAPR %)* | 5.359 | 5.962 | 7.506 | 17.919 |
| *Bias factor ($B_f$)* | 1.005 | 1.003 | 1.016 | 0.9609 |
| *Accuracy factor ($A_f$)* | 1.054 | 1.060 | 1.076 | 1.2121 |
| *Standard error of prediction (SEP %)* | 5.671 | 6.743 | 8.150 | 18.596 |

AFLS shares like AGFINN, the same defuzzifier output as well as the AGFINN's premise part, without however any clustering stage, while utilizing the classic Gaussian membership function. AFLS's optimal performance was achieved with a structure of 12 fuzzy rules. ANFIS performed very satisfactory, its performance however was achieved with a high computational cost, by utilizing two membership functions for each input variables and 128 fuzzy rules. An MLP network has been also implemented using the same FTIR dataset utilizing two hidden layers (with 12 and 6 nodes respectively). The PLS method is a linear multivariate regression method, used currently in many food microbiology applications, and in our case, the nonlinear iterative partial least squares algorithm (NIPALS) has been chosen as its appropriate learning scheme. Performances of all these models in predicting TVCs in beef samples in terms of statistical indices are presented in Table IV.

TABLE V. CLASSIFICATION PERFORMANCE OF AGFINN (CASE 2)

| True class | Predicted class | | | Row total | Sensitivity (%) |
|---|---|---|---|---|---|
| | Fresh | Semi-fresh | Spoiled | | |
| Fresh (7) | 7 | 0 | 0 | 7 | 100 |
| Semi-fresh(5) | 0 | 4 | 1 | 5 | 80 |
| Spoiled (7) | 0 | 0 | 7 | 7 | 100 |
| Column total | 7 | 4 | 8 | 19 | |
| Specificity (%) | 100 | 100 | 87.5 | | |
| Overall correct classification (accuracy): 94.73% | | | | | |

AGFINN model outperformed all models, indicating thus its efficiency in handling problems with nonlinear characteristics. Although AGFINN, AFLS and MLP share the same learning training algorithm, i.e. the gradient descent method, the different "philosophy" in building the proposed neurofuzzy architecture, allowed AGFINN model to achieve such superior performance.

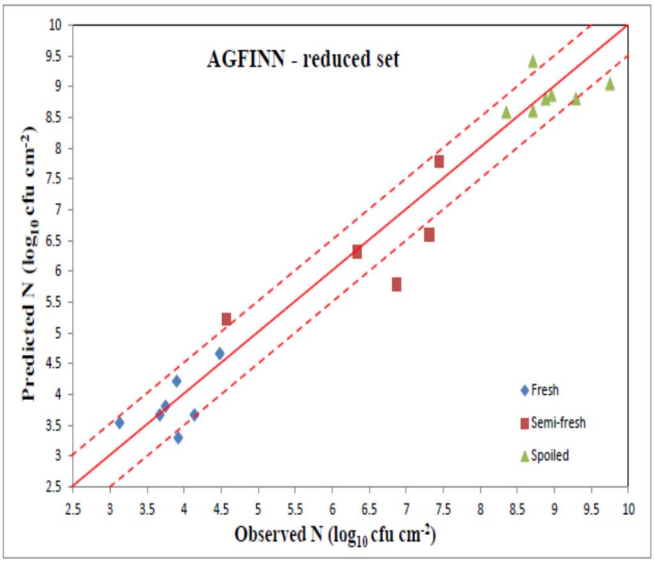


Fig. 7. AGFINN prediction model for TVC (Case 2)

In order to investigate further the capabilities of AGFINN model in this prediction problem, a second experiment was carried out, where the initial FTIR dataset was divided into a training subset with approx. 75% of the data, and a testing subset with the remaining 25% (i.e. 19 samples). Similarly to previous case, AFLS, ANFIS and MLP models have been also evaluated for comparison reasons, to associate the same spectral data from FTIR analysis with beef fillet spoilage during aerobic storage at different temperatures. For this particular case, after trials, it has been found that 10 rules were necessary for the proposed model to achieve an acceptable performance for this particular case/experiment. The training set consisted of 55 samples, while 19 (7 fresh, 5 semi-fresh and 7 spoiled) meat samples were included in the testing subset.

TABLE VI. PERFORMANCE OF AGFINN MODEL FOR TVC (CASE 2)

| Statistical index - (19 test) | Fresh | Semi-fresh | Spoiled | Overall AGFINN |
|---|---|---|---|---|
| *Mean squared error (MSE)* | 0.1314 | 0.4459 | 0.1875 | 0.2348 |
| *Root mean squared error (RMSE)* | 0.3625 | 0.6677 | 0.4330 | 0.4846 |
| *Mean relative percentage residual (MRPR %)* | 0.1052 | 1.4208 | 0.7227 | 0.6789 |
| *Mean absolute percentage residual (MAPR %)* | 7.7555 | 8.9653 | 3.8137 | 6.6216 |
| *Bias factor ($B_f$)* | 0.9942 | 0.9801 | 0.9917 | 0.9896 |
| *Accuracy factor ($A_f$)* | 1.0821 | 1.0957 | 1.0390 | 1.0695 |
| *Standard error of prediction (SEP %)* | 9.4017 | 10.2635 | 4.8376 | 7.5362 |

Table V illustrates these testing results. It has to be mentioned, that only one semi-fresh meat sample, was identified as spoiled one. In addition, AGFINN's second output modelled successfully the TVCs, as illustrated in Fig. 7. In this case, the plot of the predicted vs. the observed TVC for the testing dataset, have shown reasonably good distribution around the line of equity without any particular trend, with the majority of data (ca. 78.95%) included within the ± 0.5 log unit area. The performance of the AGFINN model to predict TVCs in beef samples for this second simulation, in terms of statistical indices is presented in Table VI. Based on the calculated values of the bias factor $B_f$ , it can be assumed that the neurofuzzy network under-estimated TVCs in semi-fresh and overall samples ( $B_f$ <1), whereas for the remaining cases was almost optimal (ca. 0.99). However, a closer comparison of AGFINN performance from these two simulation case studies reveals a problem with the limited number of samples for training. The SEP index is much worse in this second case, and this reflects an open problem in learning-based systems, i.e. the need to have as large as possible training datasets.

TABLE VII. PERFORMANCE OF COMPARABLE MODELS (CASE 2)

| Statistical index - (19 test) | Overall AFLS | Overall ANFIS | Overall MLP |
|---|---|---|---|
| *Mean squared error (MSE)* | 0.286 | 0.4998 | 0.6697 |
| *`Root mean squared error (RMSE)* | 0.534 | 0.7070 | 0.8183 |
| *Mean relative percentage residual (MRPR %)* | -1.298 | 7.5060 | -0.7773 |
| *Mean absolute percentage residual (MAPR %)* | 7.282 | 10.3494 | 9.7201 |
| *Bias factor ($B_f$)* | 1.007 | 0.9081 | 0.9964 |
| *Accuracy factor ($A_f$)* | 1.075 | 1.1313 | 1.1019 |
| *Standard error of prediction (SEP %)* | 8.311 | 10.9953 | 12.7269 |

Similarly to the previous case study, AFLS, ANFIS and MLP models have been developed to predict TVCs for this reduced dataset. Results are illustrated in Table VII. AFLS system utilizing 15 fuzzy rules managed to provide a rather satisfactory response compared to AGFINN, whereas both ANFIS and MLP revealed some modelling difficulties to tackle adequately datasets with small number of samples. Overall results revealed that prediction accuracies of the AGINN model were better compared with the performances of other models, in the characterization of meat samples for this reduced number of samples, indicating again the superiority of this proposed neurofuzzy approach in tackling complex, nonlinear problems such as the meat spoilage.

## V. CONCLUSIONS

In conclusion, this simulation study demonstrated the effectiveness of the detection approach based on FTIR spectroscopy which in combination with an appropriate learning-based modelling scheme could become an effective tool for monitoring meat spoilage during aerobic storage at various temperatures. The collected spectra could be considered as biochemical "signatures" 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 novel neurofuzzy model which incorporates an asymmetric Gaussian membership functions as well as a clustering component ant for defining the fuzzy rules. Overall prediction for TVCs has been considered as very satisfactory, although lower performance was observed especially for the fresh samples. Prediction performances of MLP and PLS schemes revealed the deficiencies of such systems which have been utilized widely in the area of Food Microbiology, while in the same time the performance of neurofuzzy systems justified the hypothesis of using this type of hybrid architectures in the area of Food science.

## REFERENCES


[1] M. Gagaoua, B. Picard, "Current Advances in Meat Nutritional, Sensory and Physical Quality Improvement", *Foods, vol.* 9, No. 3, 2020, pp. 321.

[2] G. ElMasry, D.W. Sun, "Meat Quality Assessment Using a Hyperspectral Imaging System", in Hyperspectral Imaging for Food Quality Analysis and Control, 2010, pp. 273 -294

[3] I.H., Cho, K. Seockmo, "Current Technical Approaches for the Early Detection of Foodborne Pathogens: Challenges and Opportunities", Int. Journal of molecular sciences, vol. 18, No.10, 2017, pp. 2078.

[4] D. Alexandrakis, N. Brunton, G. Downey, A. Scannell, "Identification of Spoilage Marker Metabolites in Irish Chicken Breast Muscle Using HPLC, GC–MS Coupled with SPME and Traditional Chemical Techniques", Food and Bioprocess Technology, Vol. 5, No. 5, 2011, pp. 1917-1923

[5] D.J.M. Mouwen, A. Hörman, H. Korkeala, A. Alvarez-Ordóñez, M. Prieto, "Applying Fourier-transform infrared spectroscopy and chemometrics to the characterization and identification of lactic acid bacteria", Vibr. Spectroscopy, vol. 56, No. 2, 2011, pp. 193-201.

[6] S. Meisel, S. Stöckel, P. Rösch, J. Popp, "Identification of meat-associated pathogens via Raman microspectroscopy", Food Microbiology, Vol. 38, 2014, pp. 36-43

[7] F. Tao, Y. Peng, "A method for non-destructive prediction of pork meat quality and safety attributes by hyperspectral imaging technique", J Food Eng. Vol. 126, 2014, pp. 98–106

[8] V.S. Kodogiannis, "Application of an Electronic Nose Coupled with Fuzzy-Wavelet Network for the Detection of Meat Spoilage", Food Bioprocess Technol., vol. 10, 2017, pp. 730–749.

[9] N. Nicolaou, R. Goodacre, "Rapid and quantitative detection of the microbial spoilage in milk using Fourier transform infrared spectroscopy and chemometrics", Analyst, Vol. 133, No. 10, 2008, pp. 1424-1431.

[10] M.S.Ammor, A. Argyri, G.-J.E. Nychas, "Rapid monitoring of the spoilage of minced beef stored under conventionally and active packaging conditions using Fourier transform infrared spectroscopy in tandem with chemometrics", Meat Science, vol. 81, No. 3, 2009, pp. 507-514.

[11] D.I. Ellis, D. Broadhurst, D.B. Kell, J.J. Rowland, R. Goodacre, "Rapid and quantitative detection of the microbial spoilage of meat by Fourier transform infrared spectroscopy and machine learning", Appl. Environ. Microbiol, vol. 68, 2002, pp. 2822–2828

[12] A.A. Argyri, E.Z. Panagou, P.A. Tarantilis, M. Polysiou, G.-J. E. Nychas, "Rapid qualitative and quantitative detection of beef fillets spoilage based on Fourier transform infrared spectroscopy data and artificial neural networks", Sensors and Actuators B, vol. 145, 2010, pp. 146-154

[13] V.S. Kodogiannis, A. Alshejari, "An Adaptive Neuro-Fuzzy Identification Model for the Detection of Meat Spoilage", Applied Soft Computing, Vol. 23, 2014, pp. 483-497

[14] V.S. Kodogiannis, I. Petrounias, E. Kontogianni, "Identification of meat spoilage by FTIR spectroscopy and neural networks", 2014 International Joint Conference on Neural Networks (IJCNN), Beijing, China, 2014, pp. 1644-1651.

[15] I. Rojas, H. Pomares, F.J. Fernandez, "A new methodology to obtain fuzzy systems autonomously from training data", IEEE conf. Fuzzy System 1999, Vol. 1, pp. 527–532.

[16] P. Jahankhani, V.S. Kodogiannis, J.N. Lygouras, I.P. Petrounias, "A Decision Support System for EEG signals based on Adaptive Inference Neural Networks", Journal of Computational Methods in Sciences and Engineering (JCMSE), Vol. 11, No. 4, 2011, pp. 209-225.

[17] A. Alshejari, "Neuro-fuzzy based intelligent approaches to nonlinear system identification and forecasting", PhD Thesis University of Westminster, 2018