International Journal of Food Engineering

Volume 3, *Issue* 4 | 2007 | *Article* 11

Fuzzy Identification and Modeling of a Gum-Protein Emulsifier in a Model Mayonnaise Color Development System

Murad Samhouri, *The Hashemite University*
Mahmoud Abughoush, *The Hashemite University*
Thomas Herald, *Kansas State University*

Recommended Citation:
Samhouri, Murad; Abughoush, Mahmoud; and Herald, Thomas (2007) "Fuzzy Identification and Modeling of a Gum-Protein Emulsifier in a Model Mayonnaise Color Development System," *International Journal of Food Engineering*: Vol. 3: Iss. 4, Article 11.
DOI: 10.2202/1556-3758.1255
Available at: http://www.bepress.com/ijfe/vol3/iss4/art11

Fuzzy Identification and Modeling of a Gum-Protein Emulsifier in a Model Mayonnaise Color Development System

Murad Samhouri, Mahmoud Abughoush, and Thomas Herald

Abstract

The aim of this study was to employ iota-carrageenan (IC) and wheat protein (WP) as an emulsifier alternative to egg yolk in a model mayonnaise system. A solution of 0.1% IC and 4% WP was prepared and used as an emulsifier in five different mayonnaise formulas. All mayonnaise treatments were evaluated and compared based on lightness and yellowness (i.e., L and b values respectively) at 4, 23, and 40°C. In addition, an adaptive neuro-fuzzy inference system (ANFIS) was used to model and identify the properties of the resulted mayonnaise, with the temperature and ratios. Experimental validation runs were conducted to compare the measured values and the predicted ones. The L value of the mayonnaise produced from different emulsifiers decreased at the lower storage temperature. The b-value was significantly the highest for mayonnaise formulated from 100% egg yolk. The comparison showed that the adoption of this neuro-fuzzy modeling technique (i.e., ANFIS) achieved a very satisfactory prediction accuracy of about 98%.

KEYWORDS: mayonnaise, color values, iota-carrageenan, wheat protein, Fuzzy Inference System

1. Introduction

Proteins and polysaccharides are present together in many food emulsion products. The presence of polysaccharides in protein stabilized emulsions can have variable effect on stability and rheological properties (Dickinson and Euston, 1991; Dickinson and Pawlowsky, 1996).

Hydrocolloids (polysaccharides) are added to increase the quality of the interfacial film separating the droplets that prevent coalescence. Subsequently, hydrocolloids control stability and viscosity of the emulsion (Rosell, Rojas, and Bendito de barber, 2001). Carrageenans are commonly used as stabilizers, thickeners and gelling agents in milk based products. They are sulphated polysaccharides have various forms which differ in the number and position of the sulphate groups on the polygalactose backbone (Enriquez and Flick, 1989). Kontogiorgos, , Biliaderis, Kiosseoglou, and Doxastakis, (2004) demonstrated that cereal β-glucans could be used as stabilizers in model salad dressings. Also, Worrasinchai, Suphantharika, Pinjai, and Jamnong (2006) used spent brewer's yeast β-glucan as a fat replacer in mayonnaise.

During the formation of an emulsion, oil droplets are dispersed into a continuous phase. Thus, the oil droplets tend to flocculate due to attractive forces. Therefore, one of the keys in preparing a stable mayonnaise is to form small oil droplets in a continuous water phase with sufficiently high viscosity to prevent coalescence of the oil droplets (Wendin, Aaby, Ellkejair, and Solheim,1997; Wendin, Ellkejair, and Solheim, 1999). At the same time, proteins improve the surface properties of an emulsion by forming a protective steric barrier around the oil droplets (Dickinson, 1997). Subsequently, several types of proteins are used as emulsifiers in foods since they have a high proportion of non polar group and surface active (Damodoran, 1996). Wheat protein can be an alternative and compete with other proteins in emulsion production as an alternative for casein and soy proteins due to its functional and dietary benefits.

Fuzzy logic and fuzzy inference system (FIS) is an effective technique for the identification and modeling of complex nonlinear systems. Fuzzy logic is particularly attractive due to its ability to solve problems in the absence of accurate mathematical models (Zadeh, 1965; Zadeh, 1973; Kasabov, 1998). The prediction of properties of the resulted mayonnaise (e.g., lightness, and yellowness) could be considered as a complex system, so using the conventional technology to model these properties results in significant discrepancies between simulation results and experimental data. Thus, this complex nonlinear system fits within the realm of neuro-fuzzy techniques (Jang and Sun, 1995; Kosko, 1992; Yamaguchi et al, 1991).

The application of a neuro-fuzzy inference system to prediction and modeling is a novel approach that overcomes limitations of a fuzzy inference system such as the dependency on the expert for fuzzy rule generation and design of the non-adaptive fuzzy set (Lin and Liu, 2001; Nauck et al, 1997; Takagi and Hayashi, 1991; Pedrycz, 1993).

Modeling and identification of food properties and processing has been the subject of many researchers in the food engineering field. Perrot, Me, Trystram, Trichard, and Deloux (2003) presented a hybrid approach based on fuzzy logic and genetic algorithms to control a crossflow microfiltration pilot plant. The results of simulations and pilot tests showed that it becomes possible to impose dynamics to the process that leads to maintain the state variable at a given reference. Tsourveloudis and Kiralakis (2002) applied a rotary drying process to olive stones. They described and modeled the process using fuzzy and neuro-fuzzy techniques based on available expertise and knowledge for a given, industrial size, rotary dryer. They also used ANFIS controller based on data taken from an empirical model of the dryer under study.

Kavdir and Guyer (2003) introduced an apple grading system using fuzzy logic model. Fuzzy logic was applied as a decision making support to grade apples. Grading results obtained from fuzzy logic showed 89% general agreement with results obtained from human expert, providing good flexibility in reflecting the expert's expectations and grading standards into the results.

In fact, there is no published data in the literature on application of iota-carrageenan (IC) and wheat protein (WP) to partially replace egg yolk in mayonnaise production. Therefore, the gum-protein interaction may play a role in the mayonnaise compared to the single contribution of the individual polymer.

The main motivation behind this work is that consumers have demanded that the use of egg yolks be reduced because of the inherent cholesterol. Therefore, the aim of this research was to take advantage of the gum-protein interaction, formulate a mayonnaise with similar characteristics as mayonnaise prepared with egg yolk, and construct a prediction model for the mayonnaise color using fuzzy modeling. This modeling can be used as an indicator of usefulness of fuzzy in such system which directly can be used as a tool by the food processors to produce a high quality mayonnaise product.

2. Materials and Methods

2.1 Mayonnaise production

Five mayonnaise formulations were prepared, and physical evaluations were performed. Four of the mayonnaise formulations contained an emulsifier prepared from 1% iota-carrageenan: 4% wheat protein mixture. A mayonnaise with a

DOI: 10.2202/1556-3758.1255

traditional egg yolk formulation was used as a control. The basic formulations included 9 mL Vinegar, 0. 94 g salt, 1.3 g sugar and 69 mL Corn oil and 10 g egg yolk or mixture as given in Figure 1. The following includes the different ratios of (egg yolk: gum-protein) mixtures that were used as emulsifiers in the mayonnaise formulations:

100: 0 egg yolk (E):1% iota-carrageenan+4% wheat protein (CP)
75:25 egg yolk (E):1% iota-carrageenan+4% wheat protein (CP)
50:50 egg yolk (E):1% iota-carrageenan+4% wheat protein (CP)
25:75 egg yolk (E):1% iota-carrageenan+4% wheat protein (CP)
0:100 egg yolk (E):1% iota-carrageenan+4% wheat protein (CP)

2.2 Mayonnaise Evaluation

Two main properties of the resulted mayonnaise (lightness and yellowness) were measured and evaluated to be used in fuzzy modeling. The mayonnaise color (Lightness (L), and yellowness (b)) was analyzed using Hunter lab spectrophotometer (Hunterlab MiniScan Spectrophotometer, Hunter Associates Laboratory, Inc, Reston, VA).

2.3 Statistical Analysis

A factorial classification in complete randomized design (CRD) was adopted to perform this experiment. Data were analyzed using statistical analysis software (version 8.2, SAS Institute Inc., Cary, NC). Three batches of mayonnaise were produced for each treatment. Triplicate sample was taken from each mayonnaise type that is stored at different temperatures (4, 23, and 40 ºC). All samples were assayed in triplicate. Analysis of variance (ANOVA) and means separations were calculated by the general linear model procedure (Proc GLM). Comparisons among treatments were analyzed using Fisher Least Significant Difference (LSD). Treatment means were considered significant at $P < 0.05$.

2.4 Fuzzy Modeling of Output Properties

One way to represent data and knowledge, closer to human-like thinking, is to use fuzzy rules instead of exact rules. Fuzzy systems are rule-based expert systems based on fuzzy rules and fuzzy inference. A fuzzy inference system can be viewed as a real-time expert system used to model and utilize a human operator's experience or process engineer's knowledge. A fuzzy inference system can be considered to be composed of five functional blocks described as follows:

1) A rule base containing the fuzzy if-then rules.
2) A database which defines the membership functions of the fuzzy sets used in the fuzzy rules.
3) A decision-making unit which performs the inference operations on the rules.
4) A fuzzification interface which transforms the numerical input variables into fuzzy variables with linguistic labels.
5) A defuzzification interface which transforms the fuzzy results of the knowledge base in combination with the results of the decision-making unit into a numerical output variables.

Figures 4 and 5 illustrated that the prediction of properties of the resulted mayonnaise (i.e., color) is a nonlinear and complex process. In fact, these properties could be nicely modeled as fuzzy properties. Fuzzy logic can model nonlinear functions of arbitrary complexity. It provides an alternative solution to nonlinear modeling because it is closer to the real world. Nonlinearity and complexity is handled by rules, membership functions, and the inference process which results in improved performance, simpler implementation, and reduced design costs.

Neuro-fuzzy is an associative memory system that consists of fuzzy nodes instead of simple input and output nodes. Neuro-fuzzy uses neural network learning functions to refine each part of the fuzzy knowledge separately. Learning in a separated network is faster than learning in a whole network.

One approach to the derivation of a fuzzy rule base is to use the self learning features of artificial neural networks, to define the membership function based on input-output data. A fuzzy inference system (consisting of rules, fuzzy set membership functions, and the defuzzification strategy) are mapped onto a neural network-like architecture.

Adaptive neuro-fuzzy inference system (ANFIS) is a fuzzy inference system implemented in the framework of an adaptive neural network. By using a hybrid learning procedure, ANFIS can construct an input-output mapping based on both human-knowledge as fuzzy. If-Then rules and stipulated input-output data pairs for neural networks training. ANFIS architecture is shown in Figure 2, where x and y are the inputs, f is the output, A_i and A^2_n are the input membership functions, w_i and w^2_n are the rules firing strengths. Five network layers are used by ANFIS to perform the following fuzzy inference steps: (i) input fuzzification, (ii) fuzzy set database construction, (iii) fuzzy rule base construction (iv) decision making, and (v) output defuzzification. This is a multi-layered neural network architecture where the first layer represents the antecedent fuzzy sets, while the consequent fuzzy sets are represented by the middle layers, and the defuzzification strategy by the output layer. The nodes which have 'square' shape are those containing

DOI: 10.2202/1556-3758.1255

adaptable parameters, whereas the 'circular' nodes are those with fixed parameters.

ANFIS is more powerful than the simple fuzzy logic algorithm and neural networks, since it provides a method for fuzzy modeling to learn information about the data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data (Jang, 1993). ANFIS also employs sugeno-type fuzzy inference system, which is a natural and efficient modeling tool, and is suited for modeling non-linear system by interpolating between multiple linear models. In addition, ANFIS is more powerful than neural network system since it is better than all of them in convergence rates (running time), average training error, root mean square error, and the coefficient of correlation, and it has a built-in ability to validate the modeled system. On the other hand, ANFIS is much more complex than the fuzzy inference systems, and is not available for all of the fuzzy inference system options. It only has a single output, and no rule sharing. In addition, ANFIS cannot accept all the customization options that basic fuzzy inference allows. That is, no possibility to make our own membership functions and defuzzification functions; the ones provided by ANFIS must be used.

In the next section, the application of ANFIS to model and predict the output properties for the mayonnaise system is discussed.

2.5 ANFIS Modeling of Mayonnaise Properties

An adaptive neuro-fuzzy inference system (ANFIS) is an architecture which is functionally equivalent to a Sugeno-type fuzzy rule base. ANFIS is a method for tuning an existing rule base with a learning algorithm based on a collection of training data. This allows the rule base to adapt. Training data is used to teach the neuro-fuzzy system by adapting its parameters (which in essence are fuzzy set membership function parameters) and using a standard neural network algorithm which utilizes a gradient search, such that the mean square output error is minimized.

The architecture of ANFIS, illustrated in Figure 2, has five layers to accomplish the tuning process of the fuzzy modeling system. The five layers are:

1) Layer 1: Every node in this layer is an adaptive node with a node function (i.e., membership function). Parameters of membership functions are referred to as premise or antecedent parameters.
2) Layer 2: Every node in this layer is a fixed node, which multiplies the incoming signals and sends the product out. Each node represents the firing strength of a fuzzy rule.
3) Layer 3: Every node in this layer is a fixed node which calculates the ratio of the one firing strength to the sum of all rules' firing strengths. The

outputs of this layer are called normalized firing strengths.

4) Layer 4: Every node in this layer is an adaptive node with a node function (i.e., linear combination of input variables). Parameters in this layer are referred to as consequent parameters.
5) From the ANFIS architecture Layer 5: The single node in this layer is a fixed node that computes the overall output as the summation of all incoming signals, shown in Figure 2, it is observed that given the values of premise parameters, the overall output can be expressed as a linear combination of the consequent parameters.

ANFIS applies two techniques in updating parameters. For premise parameters that define membership functions, ANFIS employs gradient descent back-propagation neural networks to fine-tune them. For consequent parameters that define the coefficient of each output equation, ANFIS uses that least squares method to identify them. This approach is called the hybrid learning method. More specifically, in the forward pass of the hybrid learning method, functional signals go forward until layer 4 and the consequent parameters are identified by the least square estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent.

ANFIS modeling and prediction of output properties of mayonnaise system starts by obtaining a data set (input-output data points) and dividing it into training and validating data sets. Each input/output pair contains three inputs (i.e., storage temperature (T), egg yolk concentration (E), and solution concentration (CP)) and one output (i.e., mayonnaise color properties). The training data set is used to find the initial premise parameters for the membership functions by equally spacing each of the membership functions. A threshold value for error between the actual and desired output is determined. The consequent parameters are computed using the least squares method. Then, an error for each data pairs is found. If this error is larger than the threshold value, the premise parameters are updated using the back propagation neural networks. This process is terminated when the error becomes less than the threshold value. Then, the testing data points are used to compare the model with actual system for validating purposes. Figure 3 shows the ANFIS training and modeling process.

The overall property output (*f*) of ANFIS given in Figure 2, can be written as

$$Y = (\overline{w_1}\,T)\,P_1^1 + (\overline{w_1}\,E)\,P_2^1 + (\overline{w_1} CP) P_3^1 + (\overline{w_1})\,P_0^1 + \ldots + (\overline{w_{n^2}}\,T)\,P_1^{n^2} + (\overline{w_{n^2}}\,E)\,P_2^{n^2} + (\overline{w_{n^2}} CP) P_3^1 + (\overline{w_{n^2}})\,P_0^{n^2} \;\ldots\ldots\ldots\ldots(1)$$

The full equation has ($5n^2$) terms, where n^2 is the number of input implications. In this model of mayonnaise properties of equation (1), (*T, E, CP*) are the input parameters (i.e., storage temperature, egg yolk, and solution), and $\overline{w_1}$ to $\overline{w_{n^2}}$ are

DOI: 10.2202/1556-3758.1255

the normalized firing strengths of fuzzy rules. The consequent parameters of the fuzzy membership functions $\{P_1^1, \ldots\ldots, P_o^{n2}$, are tuned off-line using linear least square method, and then updated on-line by a gradient descent back-propagation neural networks

3. Results and Discussion

3.1 Mayonnaise Color

Lightness (L-value)
L- values of the five mayonnaise formulations at different storage temperatures is presented in Figure 4. For all formulations, the 40 °C treatments exhibited a significantly higher L-value. The 0:100 (egg yolk: 0.1% iota-carrageenan+ 4% wheat protein) had the highest L-value, whereas the 25:75 (egg yolk: 0.1% iota-carrageenan+ 4% wheat protein) had a lowest L-value. This result means that the degree of mayonnaise lightness decreased significantly as the percentage of egg yolk decreased.

Yellowness (b-value)
The positive b-value refers to the degree of yellowness. There was a significant difference in the b-value among the different treatments as shown in Figure 5. The mayonnaise formulated from the 100% egg yolk produced the highest b-value among the treatments stored at the three different temperature followed by the 75: 25 treatment. A general comparison of L and b values of two mayonnaise formulations stored for 3 days at 23 °C can be seen in Figures 6 and 7.

3.2 ANFIS Modeling Results

The fuzzy logic toolbox of Matlab 6.1 was used to obtain the results. A total of 27 nodes and 8 fuzzy rules were used to build the fuzzy systems for modeling the mayonnaise properties.

A Model for Lightness
Figure 8 shows the training curve for building a fuzzy model for lightness. Fifteen neural nets learning epochs were used to get a low error of training (i.e., RMSE = 0.927 or 3 percent of the training data range = *Maximum – Minimum* = 30.9). A comparison between the actual and ANFIS predicted lightness after training is shown in Figure 9, which shows that the system is well-trained to model the actual lightness.

Five data points, which are different from the training data, were used to validate the system. The final fuzzy model of lightness is shown in Figure 10.

This surface plot illustrates that the relationship between inputs variables (E, CP) and the lightness has a nonlinear nature. A two (Gaussian) type membership functions for each input resulted in high accurate prediction results.

A Model for Yellowness

Fifteen neural nets epochs were required to train on the data of yellowness in order to build a high accurate model. The training root mean square error was found to be 0.249 (i.e., about 2 percent of the training data range = *Maximum* – *Minimum* = 12.45). Six points, which are different from the training data, were used to validate the system. The final yellowness model, generated by ANFIS, is shown in Figure 11 as a surface plot of yellowness as a function of input variables. A two (Gaussian) type membership functions for the input variables resulted in high accurate prediction results.

3.3 Models Validation

The ANFIS prediction models for mayonnaise properties were validated by selecting a certain number of data points, different from the other 50 points used for ANFIS training. Each validation data point (i.e., T, E, and CP) was fed into the system, and then the predicted properties (i.e., V, S, L, and Y) were plotted with the actual values of these properties. The average percent errors in the modeling of properties were as follows: 0.5% for lightness, and 2.5% for yellowness. Figures 12 and 13 show the diagrams of the actual and predicted properties values. These figures show that the ANFIS predicted values are a close match of the actual ones.

4. Conclusions

In this paper, a mayonnaise with similar characteristics as mayonnaise prepared with egg yolk, was formulated. In addition, an ANFIS fuzzy models for predicting the output properties of mayonnaise system, was constructed. The following conclusions can be drawn from the above analysis:

(1) A shelf stable mayonnaise can be formulated with a gum-protein egg substitute although the gum-protein substitute alone did not produce a mayonnaise with the same yellow colour as the 100% egg yolk

(2) The L value of the mayonnaise produced from different emulsifiers decreased at the lower storage temperature. The b-value was significantly higher for mayonnaise formulated from 100:0 and 75:25 treatments.

(3) ANFIS models achieved an average prediction error of output properties of only 4%. The present study shows that ANFIS is a technique that can be used

DOI: 10.2202/1556-3758.1255

efficiently to predict the food properties. It is believed that this approach can be applied to predict many other parameters and properties in food industry.

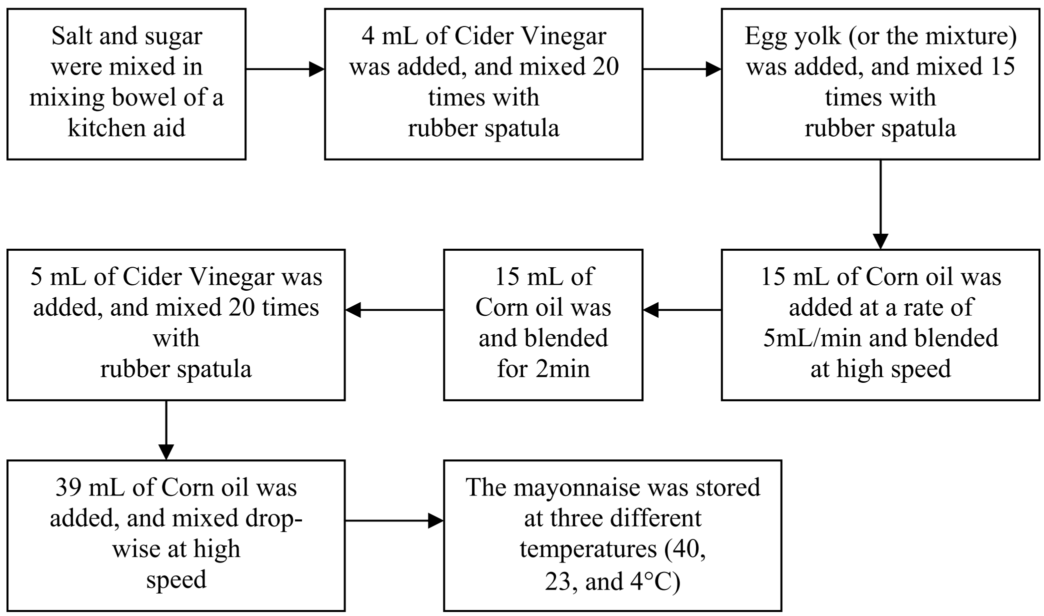

Figure 1

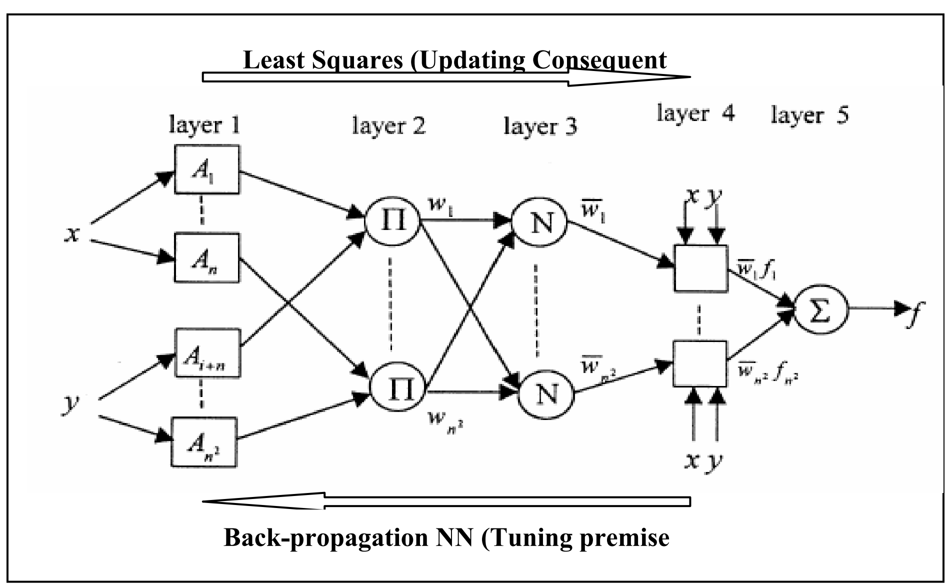

Figure 2

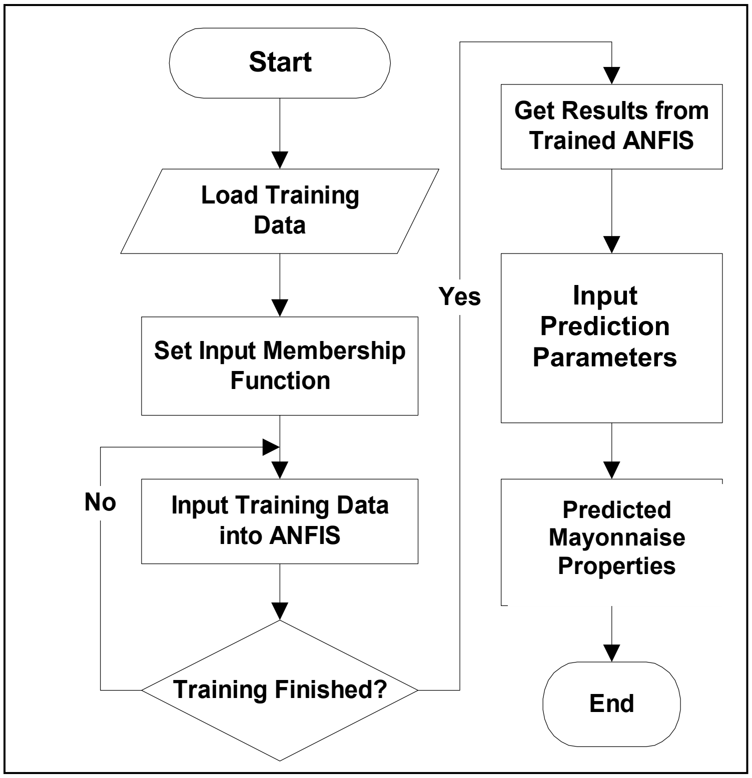

Figure 3

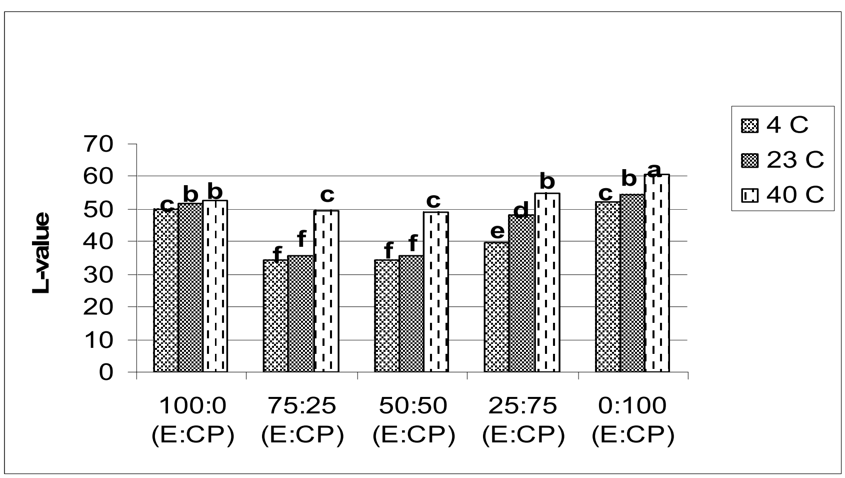

Figure 4

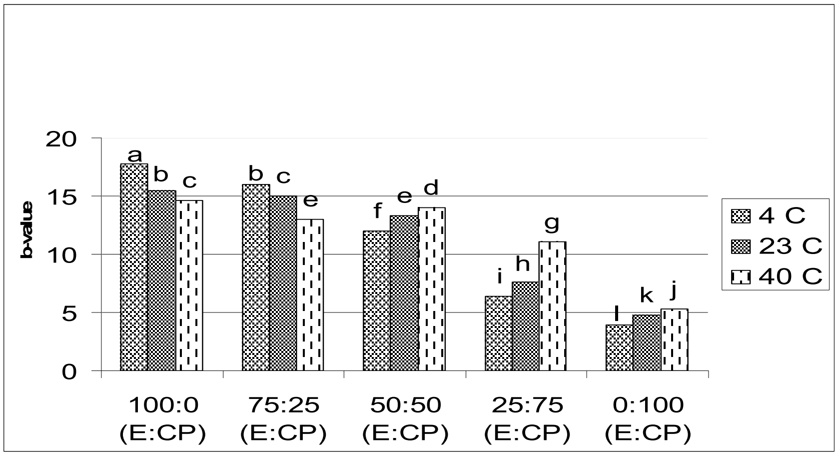

Figure 5

25:75 (E:CP) at 0 day **100:0 (E:CP) at 0 day**

Figure 6

25:75 (E:CP) at 3 day **100:0 (E:CP) at 3day**

Figure 7

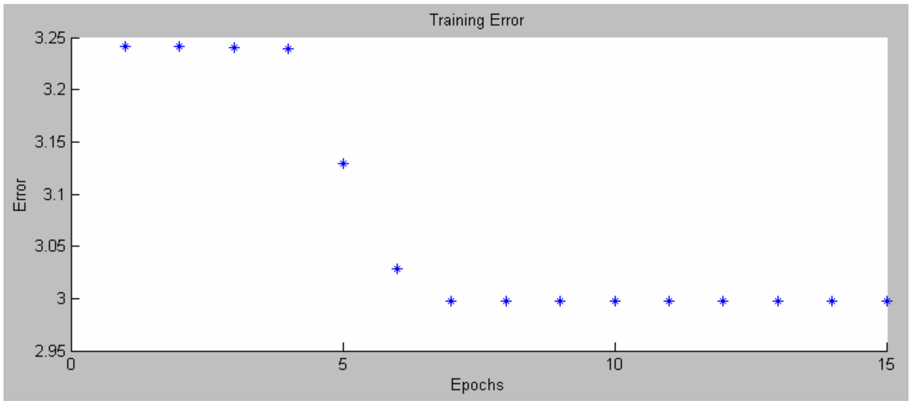

Figure 8

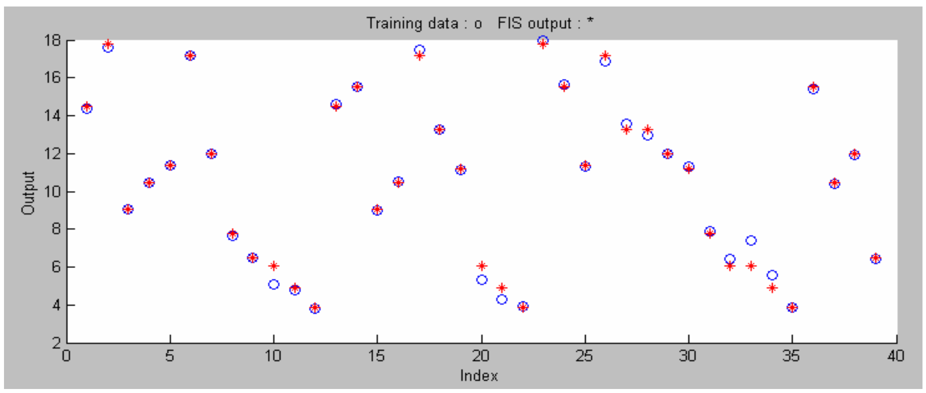

Figure 9

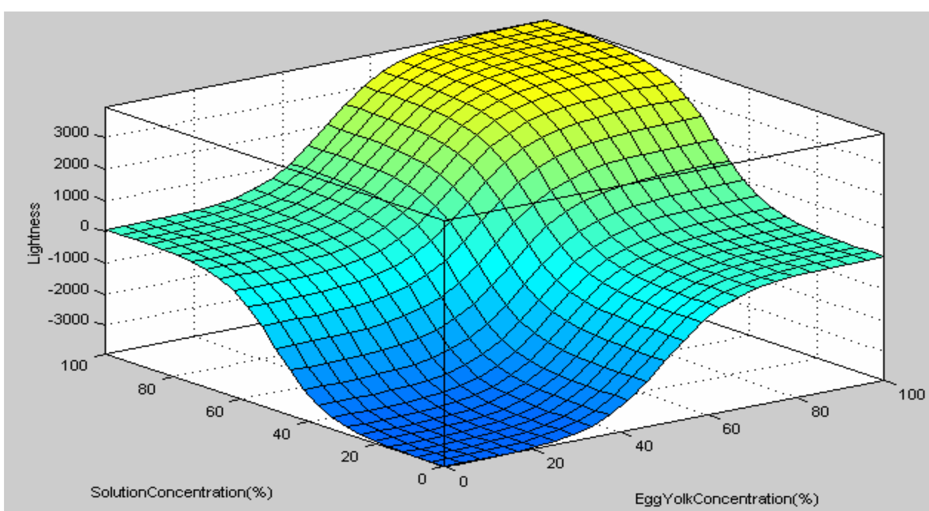

Figure 10

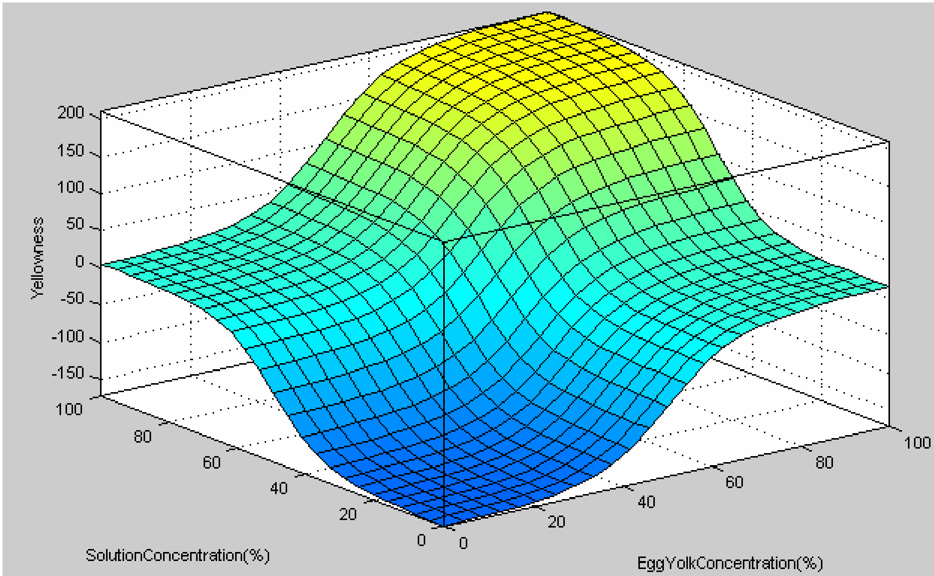

Figure 11

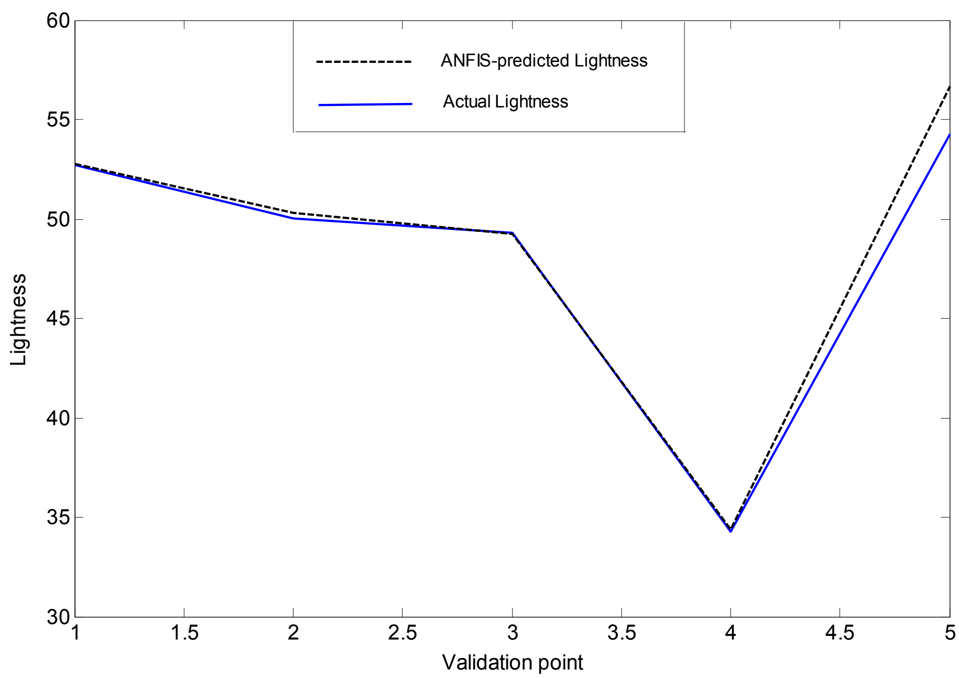

Figure 12

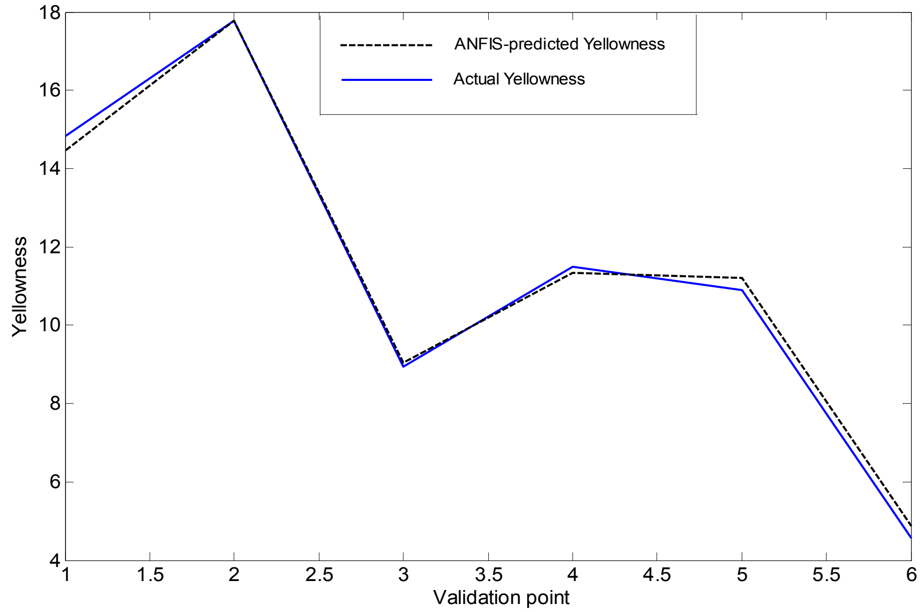

Figure 13

Legend for figures

Figure 1. Mayonnaise production steps

Figure 2: General Adaptive Neuro-Fuzzy Interface System (ANFIS) Architecture

Figure 3: Flowchart of ANFIS for Mayonnaise System Properties

Figure 4 L- values of five mayonnaise formulations at three storage temperatures (4, 23, and 40 ºC). (E: Egg yolk, and CP: carrageenan and wheat protein combination). The different letters within each beverage property suggest a significant difference at p‹ 0.05.

Figure 5: b- values of five mayonnaise formulations at three storage temperatures (4, 23, and 40 ºC). (E: Egg yolk, and CP: carrageenan and wheat protein combination). The different letters within each beverage property suggest a significant difference at p‹ 0.05.

Figure 6: Comparison of lightness and yellowness of two mayonnaise formulations at day zero. (E: Egg yolk, and CP: carrageenan and wheat protein combination).

Figure 7: Comparison of lightness and yellowness of two mayonnaise formulations stored for 3 days at 23 °C. (E: Egg yolk, and CP: carrageenan and wheat protein combination).

Figure 8: ANFIS training curve for the lightness model

DOI: 10.2202/1556-3758.1255

Figure 9: Actual and ANFIS-predicted values of lightness

Figure 10: A surface plot (fuzzy model) of lightness versus egg yolk and solution concentrations

Figure 11: A surface plot (fuzzy model) of yellowness versus egg yolk and solution concentrations

Figure 12: Validation diagram of ANFIS-based lightness model

Figure 13: Validation diagram of ANFIS-based yellowness model

References

Damodoran, S. (1996). Amino acids, peptides and proteins. In O. R. Fennema, *Food Chemistry* (3rd ed) (pp. 321- 3430). Marcel Dekker, NY.

Dickinson, E**.** (1997). Properties of emulsions stabilized with milk proteins: Overview of some recent development. *Journal of Dairy Science*, 80: 2607-2619.

Dickinson, E., and Euston, S. R. (1991). Stability of food emulsions containing both protein and polysaccharide. In E. Dickinson, *Food Polymers, Gels and Colloids* (pp. 132-146). Royal society of Chemistry: Cambridge, U.K.

Dickinson, E.; Pawlowsky, K. (1996). Rheology as a probe for protein-polysaccharide interactions in oil- in- water emulsions. In G. O. Phillips, P. A. Williams, and D. J. Wedlock. *Gums and Stabilizers for the Food Industry* (Vol.8) (pp. 181-191) Oxford University press: Oxford, U.K.

Enriquesz, L. G., and Flick, G. J. (1989). Marine colloids. In G. Charalambous and G. Doxastakis. *Food Emulsifiers: Chemistry, Technologhy, Functional properties and Applications* (pp. 235-334). Amestrdam.

Jang J.S.R. (1993) "ANFIS: Adaptive-Network-Based Fuzzy Inference System". In Man and Cybernetics*, IEEE Transactions on Systems* (Vol. 23)(pp. 665-685).

Jang, J. and Sun, C., (1995). Neuro-fuzzy Modeling and Control. *Proceedings of IEEE*, 83: 378-407.

Kasabov, N., (1998). Foundations of Neural Networks, Fuzzy Systems and Knowledge Engineering. The MIT Press, Cambridge, Massachusetts.

Kavdir, I., and Guyer, D. (2003) "Apple Grading Using Fuzzy Logic", *Turk Journal Agric*, 27: 375-382.

Kontogiorgos, V., Biliaderis, C.G., Kiosseoglou, V., and Doxastakis, G. (2004). Stability and rheology of egg-yolk-stabilized concentrated emulsions containing cereal β-glucans of varying molecular size. *Food Hydrocolloids,* 18: 987–998.

Kosko, B., (1992). Neural Networks and Fuzzy systems: A Dynamical Systems Approach to Machine Intelligence. Prentice-Hall, Englewood Cliffs, NJ.

Lin, Z. and C. Liu, (2001). Application of an Adaptive Neuro-Fuzzy Inference System for the Optimal Analysis of Chemical-Mechanical Polishing Process Parameters. *International Journal of Advanced Manufacturing Technology*, 18: 20-28.

Nauck, D., Klawonn, F. and Kruse, R., (1997). Foundations of Neuro-fuzzy Systems. John Wiley & Sons, Chichester, U.K.

Pedrycz, W., (1993). Neuro-Computations in Relational Systems. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 13: 289-296.

Perrot, N., Me, L., Trystram, G., Trichard, J., and Deloux, M. (2003) "An Hybrid Approach Based On Fuzzy Logic and Genetic Algorithms To Control A Crossflow Microfiltration Pilot Plant", Department of Food Engineering, *ENSIA-INRA*, 91305.

Rosell, C. M., Rojas, J. A. and Bendito de barber, C. (2001). Influence of hydrocolloids on dough and bread quality. Food Hydrocolloids, 15: 75-81.

Takagi, H. and Hayashi, H.,(1991). NN-driven fuzzy Reasoning. International Journal of Approximate Reasoning, 5, No. 3:191-212

Tsourveloudis, N., and Kiralakis, L. (2002) "Rotary Drying of Olive Stones: Fuzzy Modeling and Control", Department of Production Engineering and Management, Technical University of Crete, BA3015.

Wendin, K., Aaby, K., Ellkejair, R., and Solheim, R. (1997). Low-fat mayonnaise influences of fat content, aroma compounds and thickners. Food Hydrocolloids. 11: 87-99.

Wendin, K., Ellkejair, R., and Solheim, R. (1999). Fat content and homogenization effects on flavor and texture of mayonnaise with added aroma. Lebensm Wiss. U. Tech., 32: 377-383.

DOI: 10.2202/1556-3758.1255

Worrasinchai, S., Suphantharika, M., Pinjai, S., and Jamnong, P. (2006). β-Glucan prepared from spent brewer's yeast as a fat replacer in mayonnaise. Food Hydrocolloids, 20: 68-78.

Yamaguchi, T. Takagi, T. and MITA, T., (1991). Self-Organizing Control Using Fuzzy Neural Networks. Technical Report, Laboratory for International Fuzzy Engineering Research, Yokohama-shi, Japan, 337-361.

Zadeh, L., (1965). Fuzzy Sets. Information and Control, 8: 338-353.

Zadeh, L., (1973). Outline of a New Approach to Analysis of Complex Systems and Decision Process. IEEE Transactions on Systems, Man, and Cybernetics, 28-44.