Available online at www.sciencedirect.com
ScienceDirect
Journal of Food Engineering 84 (2008) 348–357
JOURNAL OF FOOD ENGINEERING
www.elsevier.com/locate/jfoodeng

Formulation and fuzzy modeling of emulsion stability and viscosity of a gum–protein emulsifier in a model mayonnaise system

Mahmoud Abu Ghoush [a,*], Murad Samhouri [b], Murad Al-Holy [a], Thomas Herald [c]

[a] Department of Clinical Nutrition and Dietetics, Hashemite University, Zarka, Jordan
[b] Department of Industrial Engineering, Hashemite University, Zarka, Jordan
[c] Food Science Institute, Kansas State University, Manhattan, KS 66502, United States

Received 29 October 2006; received in revised form 10 May 2007; accepted 16 May 2007
Available online 26 May 2007

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 emulsion stability and viscosity 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 mayonnaise formulated with the 25:75 (E: CP) at 4 °C was the highest stable system. The maximum viscosity was observed in the 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 96%.

Keywords: Mayonnaise; Stability; Viscosity; Iota-carrageenan; Wheat protein; Emulsifier; Fuzzy

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 & Euston, 1991; Dickinson & Pawlowsky, 1996). Hydrocolloids are added to increase the stability of the interfacial film separating the droplets that prevent coalescence (Buffo, Reineccius, & Oehlert, 2001). Carrageenans are commonly used as stabilizers, thickners and gelling agents in milk based products. They are sulphated polysaccharides, and various forms of carrageenan mainly differ in the number and position of the sulphate groups on the polygalactose backbone (Enriquesz & Flick, 1989). Kontogiorgos, Biliaderis, Kiosseoglou, and Doxastakis (2004) demonstrated that cereal β-glucans could be used as stabilizers in model salad dressings. Worrasinchai, Suphantharika, Pinjai, and Jamnong (2006) used spent brewer's yeast β-glucan as a fat alternative in mayonnaise production.

During the formation of an emulsion, oil droplets are dispersed into a continuous phase. The oil droplets tend to flocculate due to attractive forces. 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, & Solheim, 1997, 1999). The wheat industry has done little to promote the use of wheat protein in emulsions productions. Proteins improve the surface properties of an emulsion by forming a protective steric barrier around the oil droplets (Dickinson, 1997; Prakash, Joseph, & Mangino, 1990). Several types of proteins are used as emulsifiers in foods since they have a high proportion of nonpolar group and surface active (Damodoran, 1996). Wheat protein can be an alternative and compete with other proteins

* Corresponding author. Fax: +962 5 3903350.
E-mail addresses: abulaith@hu.edu.jo (M.A. Ghoush), samhouri@hu.edu.jo (M. Samhouri).

0260-8774/$ - see front matter © 2007 Elsevier Ltd. All rights reserved.
doi:10.1016/j.jfoodeng.2007.05.025

in emulsion production such as 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. The prediction of properties of the resulted mayonnaise (e.g., viscosity, stability) 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.

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 nonadaptive fuzzy set.

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 properties using fuzzy modeling that 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 (Midsol WPI 2100 from Midwest Grain, Inc., DWP) mixture. A mayonnaise with a 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 Fig. 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)

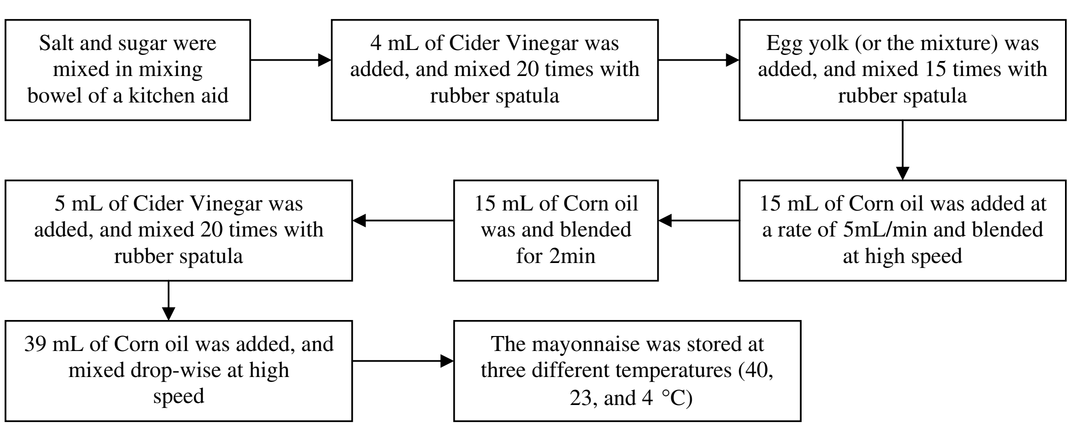

Fig. 1. Mayonnaise production steps.

2.2. Mayonnaise evaluation

Two main properties of the resulted mayonnaise (i.e., viscosity and stability) were measured and evaluated. The emulsion stability of the mayonnaise stored at different temperatures was evaluated every 24 h. Daily readings were taken until the emulsion broke (oil separation). All samples were assayed in triplicate. The emulsion viscosity was measured using a Bohlin VOR Rheometer (Bohlin instrument, USA) equipped with a cone plate geometry. Triplicate sample was taken from each mayonnaise type that is stored at different temperatures (4, 23, and 40 °C). The viscosity of the complex was determined at a frequency of 0.5 Hz within a shear rate range of 10–100 s^{-1}.

2.3. Statistical analysis

A factorial classification in complete randomized design (CRD) was adopted in this paper. Data were analyzed using statistical analysis software (version 8.2, SAS Institute Inc., Cary, NC). Three batches of mayonnaise were produced for each treatment. 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.

Figs. 2 and 3 illustrated that the prediction of properties of the resulted mayonnaise (i.e., viscosity, stability) 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

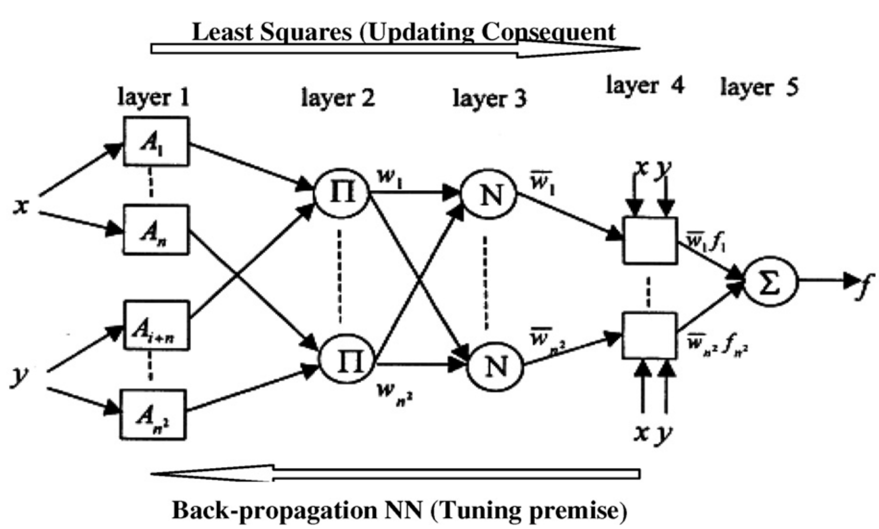

Fig. 2. General adaptive neuro-fuzzy interface system (ANFIS) architecture.

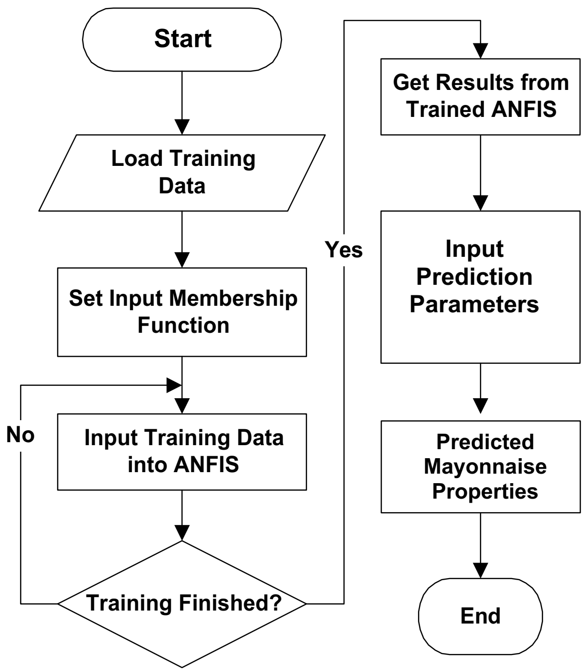

Fig. 3. Flowchart of ANFIS for mayonnaise system properties.

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 Fig. 2, where x and y are the inputs, f is the output, A_i and A_n^2 are the input membership functions, w_i and w_n^2 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 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). 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 Fig. 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) Layer 5: The single node in this layer is a fixed node that computes the overall output as the summation of all incoming signals.

From the ANFIS architecture, shown in Fig. 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. Table 1 summarized the activities and adaptive and fixed parameters in each pass.

ANFIS modeling and prediction of output properties of mayonnaise system starts by obtaining a data set (input–

Table 1
Two passes in the hybrid procedure for ANFIS

	ANFIS forward pass	ANFIS backward pass
Premise (antecedent) parameters (Fuzzy membership parameters) Fuzzy rule IF part	Fixed (Do not change during fuzzy output calculation)	Neural gradient descent (Errors are back propagated and used to adapt the premise parameters)
Consequent parameters (Defuzzification parameters fuzzy rule then par)t	Least squares estimate (Crisp output are evaluated by defuzzification process using least squares of linear combination of input variables)	Fixed (Do not change during error propagation)
Signals (Output values of the pass)	Node outputs (Fuzzy modeled values)	Error rates (Difference between modeled and actual outputs)

output data points) and dividing it into training and validating data sets. Table 2 gives the training data points (i.e., data base) used in this work to train ANFIS to identify or model the viscosity and stability properties of mayonnaise system. 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., on of the mayonnaise 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. Fig. 3 shows the ANFIS training and modeling process.

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

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

The full equation has ($5n^2$) terms, where n^2 is the number of input implications. In this model of mayonnaise properties of Eq. (1), (T, E, CP) are the input parameters (i.e., storage temperature, egg yolk, and solution), and $\overline{w_1}$–$\overline{w_{n^2}}$ are the normalized firing strengths of fuzzy rules. The consequent parameters of the fuzzy membership functions $\{P_1^1, \dots, P_0^{n2}$, are tuned off-line using linear least square method, and then updated on-line by a gradient descent back-propagation neural networks.

Table 2
ANFIS training data points for modeling mayonnaise properties

Temperature (C°)	Egg yolk concentration (%)	Solution concentration (%)	Viscosity (Pa s)	Stability (days)
40	100	0	1.95	2
23	100	0	2.8	2
4	100	0	8.9	9
40	75	25	2.21	4
23	75	25	2.5	4
4	75	25	4.18	17
40	50	50	2	3
23	50	50	2	6
4	50	50	6.6	10
40	25	75	1.9	5
23	25	75	2.085	5
4	25	75	8.9	25
40	0	100	1	0.042
23	0	100	1.21	0.042
4	0	100	1.1	0.042
40	100	0	1.9	2
23	100	0	2.83	2
4	100	0	8.6	8
40	75	25	2.1	4
40	75	25	2.305	4
23	75	25	2.6	4
4	75	25	4	18
40	50	50	1.9	3
40	50	50	1.895	3
23	50	50	2.15	5
4	50	50	7	9
40	25	75	1.95	4
23	25	75	2	5
4	75	25	9	24
40	0	100	1.05	0.042
23	0	100	1.1	0.042
4	0	100	1.2	0.042
40	100	0	2	2
4	100	0	8.5	9
23	100	0	2.76	2
40	100	0	1.95	2
23	100	0	2.8	2
4	100	0	8.9	9
40	75	25	2.21	4
23	75	25	2.5	4
4	75	25	4.18	17
40	50	50	2	3
23	50	50	2	6
4	50	50	6.6	10
40	25	75	1.9	5
23	25	75	2.085	5
4	25	75	8.9	25
40	0	100	1	0.042
23	0	100	1.21	0.042
4	0	100	1.1	0.042

3. Results and discussion

3.1. Mayonnaise stability

Mayonnaise stability was determined by monitoring oil separation and texture attributes. The emulsion stability (i.e., shelf-life) of different mayonnaise formulations is presented in Fig. 4. The emulsion stability increased significantly (more than 2 folds) for the mayonnaise formulated

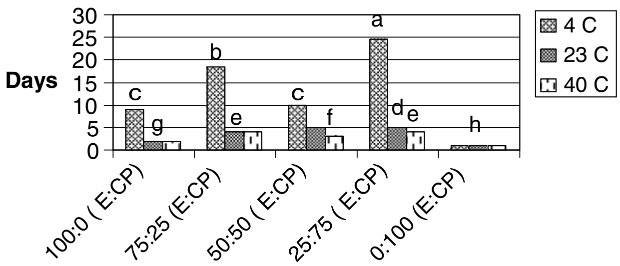

Fig. 4. Mayonnaise stability (shelf-life) of five mayonnaise formulations at three storage temperatures (4, 23, and 40 °C). (E: egg yolk, and CP: carrageenan and wheat protein combination). Bars with the same letters are not significantly different at $P < 0.5$.

with 25:75 (egg yolk: 0.1% iota-carrageenan + 4% wheat protein, E:CP) at 4 °C compared to the 100:0 (E:CP) treatment. This result suggests that this treatment may possess better polysaccharides–protein interaction in stabilizing mayonnaise formulation and can have variable effect on stability and rheological properties. Also, this result confirms the previous finding that addition of yeast β-glucan can efficiently stabilize the oil-in-water emulsion (Kontogiorgos et al., 2004). Thus, the oil droplets were kept apart by the particulate 0.1% iota-carrageenan + 4% wheat protein and coalescence became less likely than that of the 100% egg yolk during storage at various temperatures. Also, 75:25 and 50:50 (E:CP) treatments exhibited a better stability compared to 100:0 (E:CP) while 0:100 (E:CP) treatment exhibited a very poor emulsion stability.

The emulsion stability decreased significantly for the mayonnaise stored at higher temperatures. This could be due to the very rapid flocculation and/or coalescence of small droplets occurred with increasing storage temperatures.

3.2. Mayonnaise viscosity

The emulsion viscosity of different mayonnaise formulations is presented in Fig. 5. The viscosity significantly increased as temperature of storage decreased. A significantly higher mayonnaise viscosity was obtained from the 100:0 formulation. This result means that the highest viscosity was obtained for mayonnaise formulated from 100% egg yolk. At the same time, the viscosity decreased

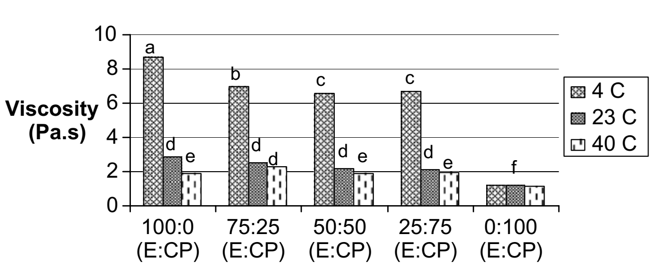

Fig. 5. Viscosity of five mayonnaise formulations at three storage temperatures (4, 23, and 40 °C). (E: egg yolk, and CP: carrageenan and wheat protein combination). Bars with the same letters are not significantly different at $P < 0.5$.

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

Fig. 6. Comparison of emulsion stability, and viscosity of two mayonnaise formulations at day zero. (E: egg yolk, and CP: carrageenan and wheat protein combination).

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

Fig. 7. Comparison of emulsion stability and viscosity of two mayonnaise formulations stored for three days at 23 °C. (E: egg yolk, and CP: carrageenan and wheat protein combination).

significantly as the percentage of egg yolk decreased by 25%. There was no significant difference in mayonnaise viscosity between 50:50 or 25:75 at each storage temperature. The emulsion viscosity decreased significantly for the mayonnaise stored at higher temperatures. This could be due to the very rapid flocculation and/or coalescence of small droplets occurred with increasing storage temperatures. Proteins and gums interactions affect both the stability and the viscosity of mayonnaise by forming a protective steric barrier around the oil droplets (Dickinson, 1997). A general comparison of emulsion stability, and viscosity of two mayonnaise formulations stored for 3 days at 23 °C can be seen in Figs. 6 and 7.

3.3. 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.

3.3.1. A model for viscosity

The neural network training for building a fuzzy model for viscosity used 50 training data points, given in Table 2, and 50 learning epochs. Fig. 8 shows the training curve of ANFIS with root mean square error (RMSE) of 0.345 (i.e., almost 4%). A comparison between the actual and ANFIS predicted viscosity after training is shown in Fig. 9, which shows that the system is well-trained to model the actual viscosity.

Ten points, which are different from the training data, were used to validate the system. These validation data points are given in Table 3. The ANFIS-predicted viscosity (i.e., the viscosity model) is shown in Fig. 10 as a surface plot of viscosity as a function of the egg yolk and solution concentrations. This surface plot shows that the relationships between the (E, CP) inputs and the viscosity of the resulted mayonnaise has a complex and nonlinear nature, and this is the main reason of using the adaptive neuro-fuzzy system to model this property. Given any two values for the inputs (i.e., egg yolk and solution concentrations) in their training ranges, a value for the viscosity can be computed from the model or surface plot of Fig. 10. The complexity of this relationship could be also observed in Fig. 5. The viscosity cannot be modeled or predicted by using traditional methods when the concentrations change. This nonlinearity gets even worse when the third variable (i.e., the temperature) changes. Therefore, the model of Fig. 10 is necessary to predict the viscosity for changing concentrations and temperature.

Table 3
Validation data points

Temperature (C°)	Egg yolk concentration (%)	Solution concentration (%)	Viscosity (Pa s)	Stability (days)
40	100	0	1.95	2
23	100	0	2.9	2
4	100	0	8.7	9
40	75	25	2.4	4
23	75	25	2.4	4
4	75	25	4.26	17.5
4	50	50	6.7	10
40	25	75	2	4
4	25	75	8.85	24.5
23	0	100	1.1	0.042

Different types of membership functions (MF) of the inputs and output were tested to train the ANFIS prediction system. A two (Bell-shaped) type MF for each input resulted in high accurate modeling results and minimum training and validation errors. The final (MF) were tuned and updated by the ANFIS model to achieve a good mapping of the input variables to the viscosity output. The shape of MF is considered a key parameter in tuning the ANFIS. The (MF) shape determines the location of MF parameters, and in turn determines the degree of membership for the input values (i.e., fuzzified inputs), and referring to th previous discussion in Section 2.5, the fuzzy

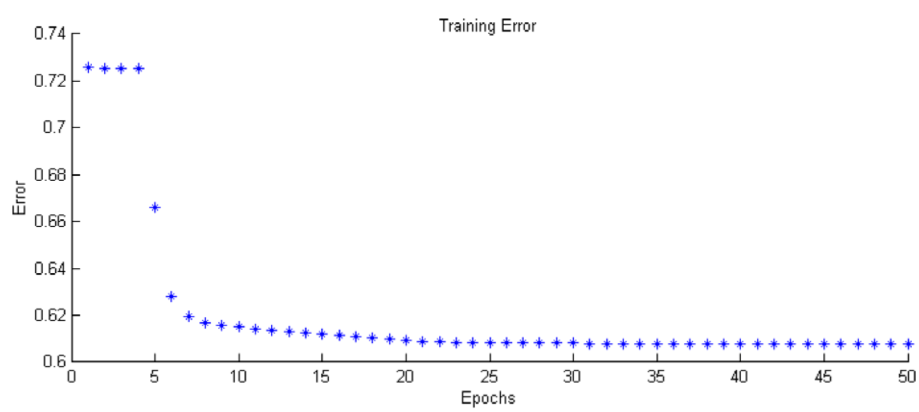

Fig. 8. ANFIS training curve for the viscosity model.

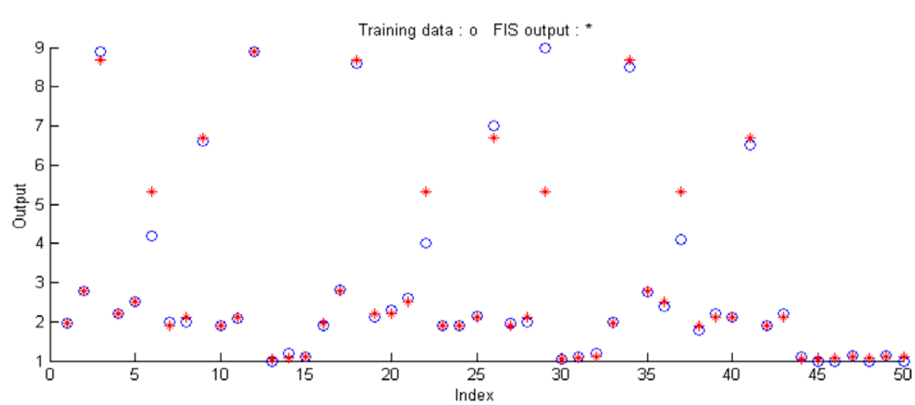

Fig. 9. Actual and ANFIS-predicted values of viscosity.

rules premise and antecedent parameters are directly affected by the (MF) shape and parameters. Consequently, the effect of changing the (MF) shape will propagate to reach all the ANFIS layers, and will have a considerable effect on the final output of the ANFIS network. More details about how ANFIS works could be found in (Jang, 1993).

3.3.2. A model for stability

Fuzzy modeling for stability using neural networks used 50 training data, given in Table 2, and 150 training epochs with (RMSE) of 0.513 (i.e., almost 2%). Ten data points, given in Table 3, which are different from the training data, were used to validate the system. The ANFIS-predicted stability is shown in Fig. 11 as a surface plot as a function of the egg yolk and solution concentrations. This plot is considered a nonlinear model of the relationship between (E, CP) and the stability.

A two (Bell-shaped) type membership functions (MF) for each input resulted in high accurate prediction results and minimum training and validation errors.

3.4. 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*), given in Table 3, 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: 5% for viscosity, 8% for stability. Figs. 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.

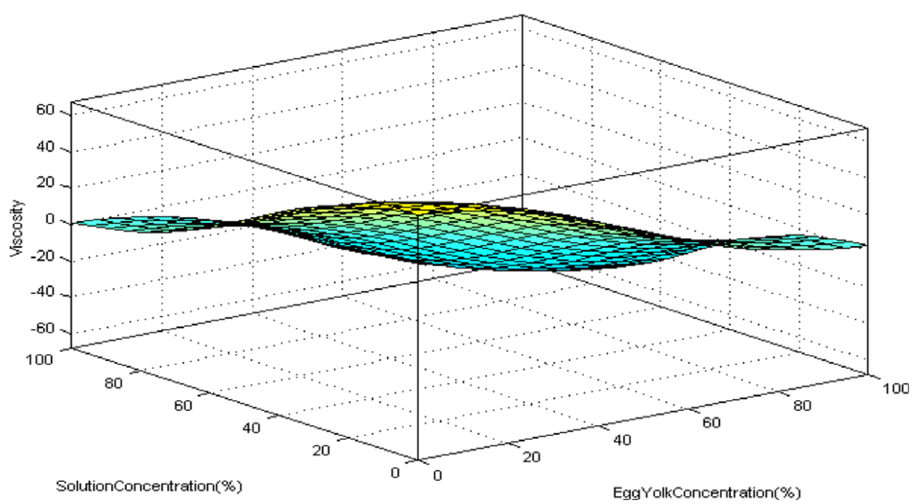

Fig. 10. A surface plot (fuzzy model) of viscosity versus egg yolk and solution concentrations.

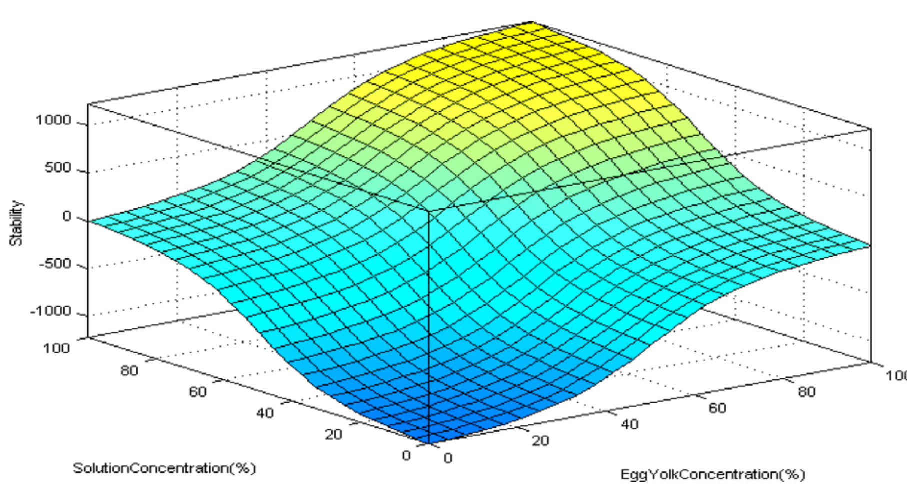

Fig. 11. A surface plot (fuzzy model) of stability versus egg yolk and solution concentrations.

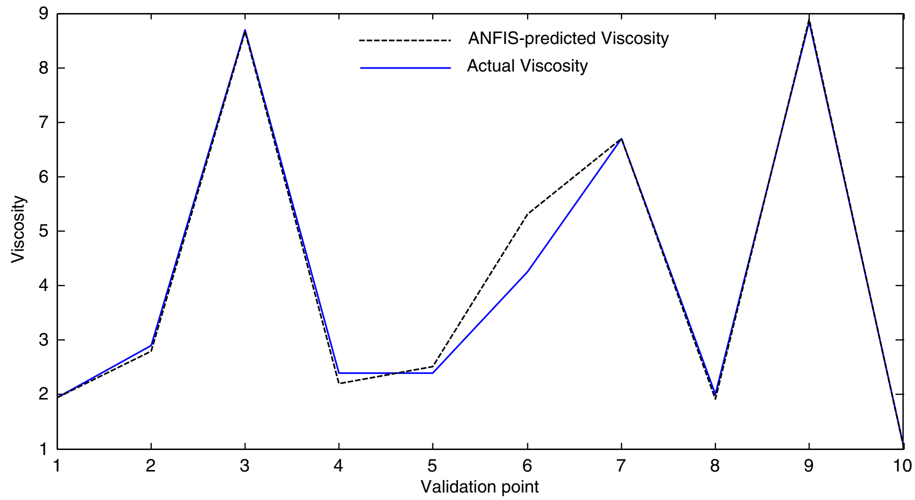

Fig. 12. Validation diagram of ANFIS-based viscosity model.

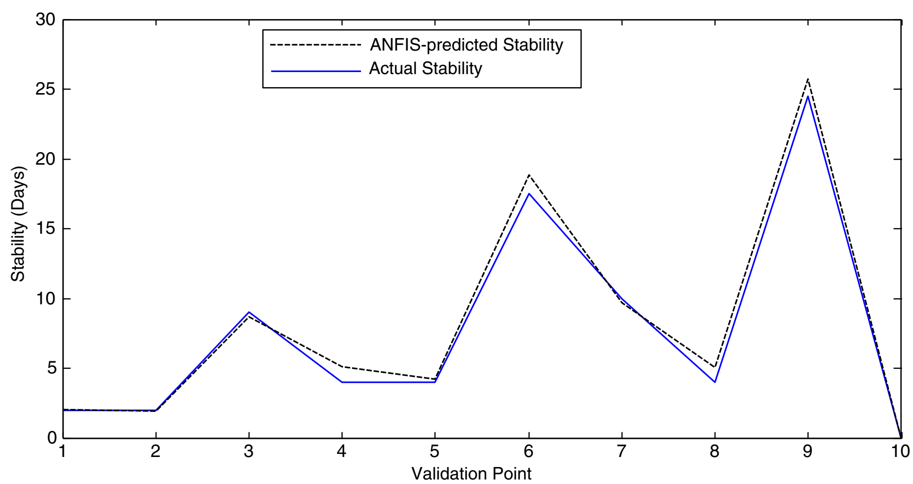

Fig. 13. Validation diagram of ANFIS-based stability model.

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 high viscosity as 100% egg yolk.
(2) The mayonnaise formulated with the 75:25 and 25:75 at 4 °C were stable for 18 and 25 days, respectively. As temperature was increased, the emulsion stability was significantly decreased.
(3) The maximum viscosity was observed in the 100:0 (egg yolk: gum–protein). This treatment exhibited the highest viscosity (8.8 Pa at 4 °C and 14.7–1 s).
(4) 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 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.

References

Buffo, R. A., Reineccius, G. A., & Oehlert, G. W. (2001). Factors affecting the emulsifying and rheological properties of gum acacia in beverage emulsions. *Food Hydrocolloids, 15*, 53–66.

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

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

Dickinson, E., & Euston, S. R. (1991). Stability of food emulsions containing both protein and polysaccharide. In E. Dickinson (Ed.), *Food polymers, gels and colloids* (pp. 132–146). Cambridge, UK: Royal society of Chemistry.

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, & D. J. Wedlock (Eds.). *Gums and stabilizers for the food industry* (Vol. 8, pp. 181–191). Oxford, UK: Oxford University press.

Enriquesz, L. G., & Flick, G. J. (1989). Marine colloids. In G. Charalambous & G. Doxastakis (Eds.), *Food emulsifiers: chemistry, technologhy, functional properties and applications* (pp. 235–334). Amestrdam: Elsevier.

Jang, J. S. R. (1993). ANFIS: adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man and Cybernetics, 23*(3), 665–685.

Kavdir, I., & Guyer, D. (2003). Apple grading using fuzzy logic. *Turk Journal Agriculture, 27*, 375–382.

Kontogiorgos, V., Biliaderis, C. G., Kiosseoglou, V., & 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.

Perrot, N., Me, L., Trystram, G., Trichard, J., & 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.

Prakash, A., Joseph, M., & Mangino, M. E. (1990). The effect of added proteins on the functionality of gum Arabic in soft drink emulsion system. *Food Hydrocolloids, 4*(3), 177–184.

Tsourveloudis, N., & 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., & Solheim, R. (1997). Low-fat mayonnaise influences of fat content, aroma compounds and thickners. *Food Hydrocolloids, 11*, 87–99.

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

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