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Fuzzy clustering-based modeling of surface interactions and emulsions of selected whey protein concentrate combined to ι-carrageenan and gum arabic solutions

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ABSTRACT

Gums and proteins are valuable ingredients with a wide spectrum of applications. Surface properties (surface tension, interfacial tension, emulsion activity index “EAI”, and emulsion stability index “ESI”) of 4% whey protein concentrate (WPC) in a combination with ι-carrageenan (0.05%, 0.1%, and 0.5%) or gum arabic (0.5%, 1%, and 5%) were investigated. The results showed that the addition of ι-carrageenan to 4% WPC significantly decreased interfacial tension, and improved the EAI, and ESI, but addition of gum arabic to 4% WPC significantly increased the interfacial tension, EAI, and ESI. In addition, a fuzzy-based clustering model was used to predict the surface properties. The fuzzy model achieved accuracies of (94%, 97%, 98%, and 94%) for predicting (EAI, ESI, surface tension, and interfacial tension), respectively.

1. Introduction

The food industry and academia have expressed an interest in gum–protein mixtures because of their contributions to stability and functionality. The interaction between proteins and polysaccharides in many food systems are responsible for structural, mechanical, and physicochemical properties of emulsions, foams, and gels (Igoe, 1982). The gum–protein interaction may play a more significant role in the food system compared to the single contribution of the individual polymer (Dickinson, 1997). Proteins improve the surface properties of food systems by forming a protective steric barrier around oil droplets, whereas gums improve the steric stabilizing properties through forming a thick secondary layer on the outside of protein (Dickinson, 1998). Thus, a fundamental understanding of behavior, mechanism and interaction between gums and proteins in beverage systems, are limited. Probably the most effective interaction between hydrocolloids and wheat protein is ionic. Electrostatic effects of the polysaccharides not explain all the interactions. The configuration of the molecules and the availability of charged groups also may be important. The carboxylate groups on the acidic heteropolysaccharides (e.g. xanthan) are mainly associated with α- amino, ε-amino group of the protein. The actual strength of interactions is related to the number and distribution of these sites as well as the overall charge of the protein. The hydrogen bonding also may play important role the hydrophilic and hydrophobic interactions may occur between the hydrocolloids and proteins. Thus, a fundamental understanding of behavior, mechanism and interaction between gums and proteins in beverage systems, are limited.

Soluble whey proteins can be used in beverage production as an alternative for casein and soy proteins (Kinsella, 1984; Dallgleish 1996; Singh and Ye, 2000). Whey protein concentrate (WPC) is used in the processing of different food products such as: in bakery, confectionery, beverages and in formulated meats due to the gelling, foaming and emulsifying properties (Blecker et al., 1997). The dairy industry has done little to promote the use of whey protein concentrate in beverages. Without research to promote the effectiveness of whey protein in beverages, the dairy industry will lose out.

The hydrocolloids (gums) have the ability to control both the rheology and texture throughout the stabilization of emulsions, suspensions, foams and starch gelatinization (Rosell et al., 2001). Whey protein–polysaccharide interactions should be well-known in order to formulate ingredients in a more accurate way. ι-Carrageenan (sulfated hydrocolloid) and gum arabic “amphiphilic

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polysaccharides" (formed from galactose, rhamnose, arabinopyronose, glucouronic acid, and 4-methyl glucouronic acid) are carbohydrates of relatively high molecular weight when compare with simple sugar. Gum arabic is the most commonly used biopolymer emulsifier in beverage production (Tan, 1998). The two types of macromolecules are both important in controlling the rheology and the stability of the food system. Interactions of these biopolymers with proteins in the food system determine structure–property relationships in foods. The decrease in surface tension by proteins and amphiphilic macromolecules is usually caused by the surface active entity of the macromolecules, adsorption and unfolding of the macromolecule at the interface, and the adsorbed segments rearrangement at the fluid interface (Dickinson, 2003).

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 surface properties of whey protein concentrate (WPC) in a combination with ι-carrageenan or gum arabic is 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 fuzzy logic technique.

The use of fuzzy logic-based techniques has been recently getting more importance in the field of food engineering. Davidson et al. (1999) developed a fuzzy control system for continuous, cross-flow peanut roasting. A combination feedforward–feedback scheme was implemented in application software developed by this research group for fuzzy rule-based control. The control system was tested on a pilot-scale roaster and it successfully maintained roasted peanut color within an acceptable range. Mohebbi et al. (2008) introduced a genetic fuzzy rule base system (GFRS) for modeling of viscosity in enzyme-modified cheese (EMC) is described based on experimental data. It is concluded that construction of an optimized fuzzy model for the evaluation of viscosity in EMC is a reliable procedure. Perrot et al. (1999) conducted a study on the estimation of food product quality using fuzzy sets through two specific examples: (i) prediction of the luminance of biscuits during a baking process and (ii) prediction of wet-milling quality of maize during a drying process. Two fuzzy approaches were validated: a black-box approach and a knowledge-based approach to modeling. The results were good and coherent in both cases and the models ere robust. Samhouri et al. (2007) found that the neuro-fuzzy modeling technique (i.e. ANFIS) can be used to achieve very satisfactory prediction accuracy (about 98%) in a model color mayonnaise system. Also, very satisfactory prediction accuracy (about 96%) was achieved by applying neuro-fuzzy modeling technique (i.e. ANFIS) in predicting the emulsion stability and viscosity of a gum–protein emulsifier in a model mayonnaise system (Abu Ghoush et al., 2008).

The main motivation behind this work is that promote the effectiveness of using whey protein concentrate in combinations with ι-carrageenan and gum arabic in beverages production. Therefore, the main aims of this study were: (1) evaluate the effect of gums (ι-carrageenan and gum arabic) and proteins (whey protein), in combination, on the surface, and emulsions properties of a fluid food system and (2) model, identify, and predict the surface properties of whey protein–gum interactions using a fuzzy clustering model. The fuzzy prediction models for the surface properties of whey protein in biphasic system with ι-carrageenan and gum arabic solutions will open the opportunity for untapped beverage market. The benefits will reach the producers, consumers, processors, communities and agriculture. Also, fuzzy modeling will give the opportunity for the manufacturers to know the optimum conditions for formulating high quality stable products.

2. Materials and methods

Whey protein isolate (WPC) was obtained from Davisco Foods International (BIPRO, Le Sueur, MN). ι-Carrageenan (IC) and gum arabic (GA) were obtained from TIC Gums Inc., Belcamp, MD, USA.

2.1. Emulsions preparation and evaluation

2.1.1. Preparation of emulsions

ι-Carrageenan (0.05, 0.1) or gum arabic (0.5%, 1%, and 5%) were prepared in buffer by stirring the dispersions vigorously for 30 min at room temperature, while heating at 50 °C until the solution became clear. Whey protein concentrate (4%)/ι-carrageenan and gum arabic were made based on the process patented by Chen et al. (1989).

2.1.2. Emulsions evaluations

Emulsion activity index (EAI), and emulsion stability index (ESI) for all the above combinations were determined by using a turbidimetric method developed by Pearce and Kinsella (1978). The surface and interfacial tensions were determined by a fisher surface tensiometer (model 21). The force acting on the ring was measured as it was moved upward for an air-solution dispersion interface, and as it was moved downward for an oil-solution interface. The equilibrium time for steady state surface tension measurements was 30 min. All tests were carried out in triplicate.

2.2. Statistical analysis

A two-way factorial classification in complete randomized design (CRD) was used to design the experiments of this work. Data were analyzed using statistical analysis software (version 8.2, SAS Institute Inc., Cary, NC). Three batches of solutions 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), and treatment means were considered significant at $P < 0.05$.

2.3. Fuzzy-based clustering model

Clustering of numerical data forms the basis of many classification and system modeling algorithms. The purpose of clustering is to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior (Jang and Gulley, 2000). A cluster is a set of objects that are more similar to each other than to objects from other clusters. Various clustering algorithms have been developed recently. These include: fuzzy C-means algorithm (Bezdek, 1974), mountain clustering algorithms (Yager and Filev, 1994), and a more computationally efficient version of mountain clustering algorithm or subtractive clustering (Chiu, 1994).

Fuzzy subtractive clustering is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data (Chiu, 1994). Subtractive clustering is based on a measure of the density of data points in the feature space (Jang et al., 1997). The idea is to find regions in the feature space with the high densities of data points. The point with the highest number of neighbors is selected as center for a cluster. The data points within a pre-specified fuzzy radius are then removed (subtracted), and the algorithm looks for a new point with the highest number of neighbors. This continues until all the data points are examined.

The subtractive clustering algorithm starts by considering a collection of $\mathbf{K}$ data points specified by m-dimensional vectors $\boldsymbol{u_k}$, $\boldsymbol{k} = 1, 2, \ldots, \mathbf{K}$. Without loss of generality, the data points are assumed normalized. Since each data point is a candidate for a cluster center, a density measure at data point $\boldsymbol{u_k}$ is defined as

$$D_k = \sum_{j=1}^{K} \exp\left(-\frac{||\boldsymbol{u_k} - u_j||}{(r_a/2)^2}\right) \quad (1)$$

Hence, a data point will have a high density value if it has many neighboring data points. Only the fuzzy neighborhood within the radius r_a, contributes to the density measure.

After calculating the density measure for each data point, the point with the highest density is selected as the first cluster center.

Let $\boldsymbol{u_{c1}}$ be the point selected and $\boldsymbol{D_{c1}}$ its density measure. Next, the density measure for each data point $\boldsymbol{u_k}$ is revised by the formula

$$D'_k = D_k - \boldsymbol{D_{c1}} \exp\left(-\frac{||\boldsymbol{u_k} - \boldsymbol{u_{c1}}||}{(r_b/2)^2}\right) \quad (2)$$

Therefore, the data points near the first cluster center $\boldsymbol{u_{c1}}$ will have significantly reduced density measures, thereby making the points unlikely to be selected as the next cluster center. The constant r_b, defines a neighborhood to be reduced in density measure. It is normally larger than r_a to prevent closely spaced cluster centers, typically $r_b = 1.5r_a$.

After the density measure for each point is revised, the next cluster center $\boldsymbol{u_{c2}}$ is selected and the density measures are revised again. The process is repeated until a sufficient number of clusters are generated (Jantzen, 1998). When applying subtractive clustering to a set input/output data, each of the cluster centers represents a rule. To generate rules, the cluster centers are used as the centers for the premise sets in a singleton type of rule base.

An important advantage of using a subtractive method to find rules is that the resultant rules are more tailored to the input data than they are in a fuzzy inference system generated without clustering. This reduces the problem of combinatorial explosion of rules when the input data has a high dimension (the dreaded curse of dimensionality) (Jang and Gulley, 2000).

3. Results and discussion

3.1. Surface tension and interfacial tension of whey protein concentrate – gum solutions

The surface tension of 4% WPC was not significantly changed with addition of ι-carrageenan or gum arabic, except in case of 0.5% gum arabic (increased by 3.5%) (Fig. 1). That means there was no effect of the gums addition on the surface tension of the protein water phase. The effect of the polysaccharide in increasing the rate of surface tension by the protein is consistent with substantial net attractive interaction between GA and WPC. As shown in Fig. 2, the interfacial tension of 4% WPC decreased by addition of 0.05% and 0.1% ι-carrageenan by 34.1% and 41.6%, respectively. Whereas, the interfacial tension of 4% WPC decreased by addition of 0.5% gum arabic by 41.6% and increased by addition of 1% or 5% gum arabic by 15%. The increase or the decrease in the interfacial tension within each polysaccharide–protein combination was due to the effect of the net attractive interaction and the degree of the adsorption and unfolding at the interface. The decrease in surface tension by proteins and amphiphilic hydrocolloids is usually caused the surface active entity to diffuse from the bulk phase to the subsurface layer. This step is followed by the adsorption and unfolding of the macromolecule at the interface and finally the adsorbed segments rearrange at the fluid interface. In addition to lowering the interfacial tension, amphiphilic macromolecules can form continuous viscoelastic films at the interface via non-covalent intermolecular interactions (Dickinson, 2003; Singh et al., 2003).

3.2. Emulsion activity index (EAI) and emulsion stability Index (ESI) whey protein concentrate – gum solutions

Lower concentration of ι-carrageenan had significant increase EAI of 4% WPC than the higher concentration. Whereas, addition of 0.05% and 0.1% ι-carrageenan increased the EAI of 4% WPC by 228.2% and 59.2%, respectively. Addition of 0.5% and 1% gum arabic

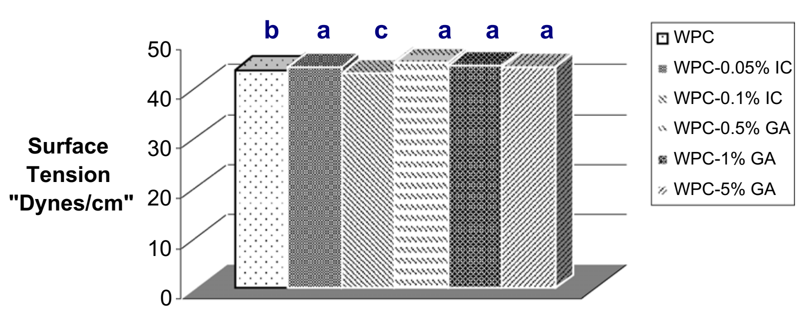

Fig. 1. Comparison between ι-carrageenan (IC) and gum arabic (GA) on surface tension of 4% whey protein concentrate (WPC). Bars with the same letters are not significantly different at $P < 0.5$.

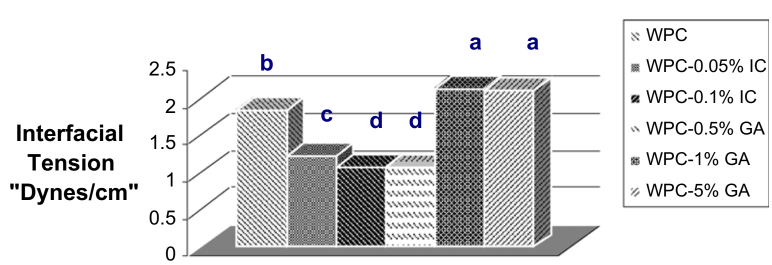

Fig. 2. Comparison between ι-carrageenan (IC) and gum arabic (GA) on the interfacial tension of 4% whey protein concentrate (WPC). Bars with the same letters are not significantly different at $P < 0.5$.

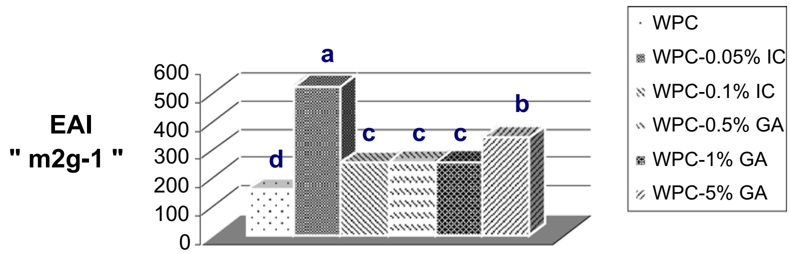

Fig. 3. Comparison between ι-carrageenan (IC) and gum arabic (GA) on the emulsion activity index "EAI" of 4% whey protein concentrate (WPC). Bars with the same letters are not significantly different at $P < 0.5$.

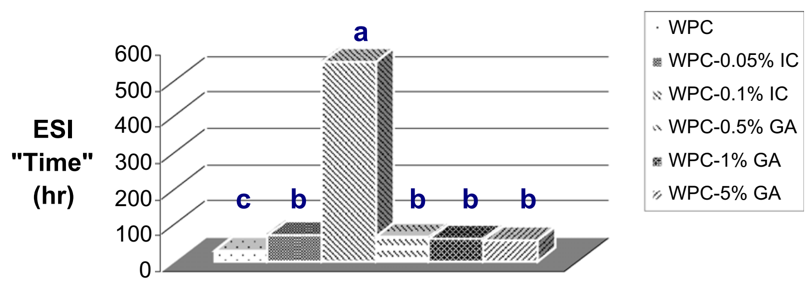

Fig. 4. Comparison between ι-carrageenan (IC) and gum arabic (GA) on the emulsion stability index "ESI" of 4% whey protein concentrate (WPC). Bars with the same letters are not significantly different at $P < 0.5$.

significantly increased the EAI of 4% WPC by 60%. Whereas, addition of 5% gum arabic increased the EAI of 4% WPC by 114.3% as illustrated in Fig. 3.

The ESI of 4% WPC was significantly increased by addition of 0.05% and 0.1% ι-carrageenan by 125.9% and 1654.8%, respectively. Whereas, ESI of 4% WPC was significantly decreased by addition of 0.5%, 1%, and 5% gum arabic by 118.8%, 102.7%, and 92.3%, respectively, as illustrated in Fig. 4. Interactions between the two polymers could be segregative or associative. For instance, for gum arabic at low concentrations solutions, the system is stable and proteins and polysaccharides are co-soluble. Upon increasing concentration, the system becomes unstable depending of the type of interaction. In this case, biopolymer mixtures tend to segregate (Grinberg and Tolstoguzov, 1997; Tolstoguzov, 1991). This trend is usually attributed to repulsive interactions between polymer segments. Segregation leads to a reduction of the local concentration of one of the polymer near the second one due to a decrease of conformational entropy of macromolecules at an interface. In case of ι-carrageenan, associative may be observed due to interaction between the two biopolymers. At high concentrations solutions, the system becomes stable. The polysaccharide molecules may adsorb onto protein and even bridging between several protein molecules. The gums additions increase the stability of emulsions by the formation of a polysaccharides network that prevents the fat globules from coalescence. This could be due to the formation of a matrix within fluid phase especially in the presence of protein that can form a second protective layer surround the fat globules (Prakash et al., 1990).

3.3. Fuzzy clustering-based prediction of surface properties of whey protein

3.3.1. Clustering data preparation

Generating a subtractive clustering-based fuzzy inference system (FIS) requires dividing the training data into two matrices: (a) an input matrix which contains all the input values to be used in training the fuzzy system. This input matrix should contain values for solution type and solution proportion %. Actually, 30 data points of these inputs were selected as given in Table 1. These points were then gathered into one matrix called "input matrix" and (b) an output matrix which contains all the output values to

Table 1
Training data matrix used to build the fuzzy model of surface properties using subtractive clustering

Solution type	Solution proportion (%)	EAI	ESI	Surface tension	Interfacial tension
(a) Inputs		*(b) Outputs*			
10	0	160.74	31	51	1.9
10	0	160.2	31.3	50	1.9
10	0	160.2	31.7	48.5	1.8
10	0	160.2	31.3	48	1.8
10	0	160.77	31.4	48.5	1.8
10	0.05	522.2	69.9	47.7	1.3
10	0.05	531.8	69.8	57	1
10	0.05	536.6	70.8	53.3	1.4
10	0.05	510.2	71.2	49.8	1.3
10	0.05	534.2	73.3	49.7	1.2
10	0.1	235.2	535	52.3	1.1
10	0.1	262.1	549	47.5	1.4
10	0.1	261.6	548	47.9	1.3
10	0.1	255.3	569	47.4	1
10	0.1	240.5	560	47.9	1
20	0.5	250.9	67.7	52.8	1.2
20	0.5	252.3	68.1	53.6	1
20	0.5	229	66.6	49.6	1
20	0.5	229.6	72.2	50	1.1
20	0.5	238	65.8	50	1.2
20	1	189.5	65.8	50.2	2.2
20	1	186.8	66.4	50.9	2
20	1	203.1	62.9	49.8	2.2
20	1	209.7	62.5	50	2.1
20	1	196	60.9	50.1	2.1
20	5	157.1	58.9	50	2
20	5	151.5	58.6	50	2.1
20	5	156.1	59.8	50	2.4
20	5	148.6	60.6	49.6	2.4
20	5	126.9	71.4	40.2	2

be used in training the fuzzy system. This output matrix should contain values for EAI, ESI, surface tension, and interfacial tension. Thirty output data points, corresponding to the selected input points, are given in Table 1, and gathered into one matrix called "output matrix". The remaining 6 input/output data points, which are different from the training data, were used for validation purpose as given in Table 2 (validation table).

3.3.2. Generating fuzzy inference system for surface properties

The subtractive clustering algorithm estimates the cluster centers in a set of data. It assumes each data point is a potential cluster center and calculates a measure of the likelihood that each data point would define the cluster center, based on the density of surrounding data points. The algorithm:

- Selects the data point with the highest potential to be the first cluster center.
- Removes all data points in the vicinity of the first cluster center (as determined by radii), in order to determine the next cluster and its center location.
- Iterates on this process until all of the data is within radii of a cluster center.

The radii variable is a vector of entries between 0 and 1 that specifies a cluster center's range of influence in each of the data dimensions, assuming the data falls within a unit hyperbox. Small radii values generally result in finding a few large clusters. Good values for radii are usually between 0.2 and 0.5. In this paper, a value of 0.8 for all the radii was chosen. This resulted in same accuracy and speed with less numbers of membership functions.

A special Matlab function, built-in the Fuzzy logic toolbox, was used to generate the FIS. This function extracts a set of rules that model the data behavior. This rule extraction method first uses the subtractive clustering centers and clusters to determine the number of rules and antecedent membership functions and then uses linear least squares estimation to determine each rule's consequent equations. This Matlab function returned an FIS structure that contains a set of fuzzy rules to cover the feature space.

The least squares method of this function works on the consequent part of FIS, especially on the generated fuzzy rules. This function minimizes the number of inference rules, but it uses large numbers of membership functions. This complicates the fuzzification process only, but it simplifies the inference and defuzzification process, which has more impact on the computational time. The fuzzy inference system, generated depending on the subtractive clustering, has a Sugeno-type inference, with a weighted-average defuzzification method. Eight bell-shaped membership functions (MF) for all inputs were used, some of them are coincident, were shown for each the two inputs (solution type and solution proportion %) in Fig. 5.

Table 2
Validation table of the predicting fuzzy clustering-based model for surface properties of whey protein

Solution type	Solution proportion (%)	EAI act.	EAI prediction	EAI error (%)	ESI act.	ESI prediction	ESI error (%)	Surface tension act.	Surface tension prediction	Surface tension error (%)	Interfacial tension act.	Interfacial tension prediction	Interfacial tension error (%)
10	0	162	160	1.23	31	31.3	0.97	49	49.2	0.41	1.9	1.84	3.16
10	0.05	491	527	7.33	70	71	1.42	50	51.5	3	1.2	1.24	3.33
10	0.1	233	251	7.72	509	552	8.44	50	48.6	2.8	1	1.16	16
20	0.5	230	240	4.34	72	68.1	5.41	50	51.2	2.4	1.1	1.1	0
20	1	198	197	0.50	63	63.7	1.11	50	50.2	0.4	2.2	2.12	3.63
20	5	129	148	14.7	62	61.9	0.16	50	48	4	2	2.18	9
Average percent error				**6**			**3**			**2**			**6**

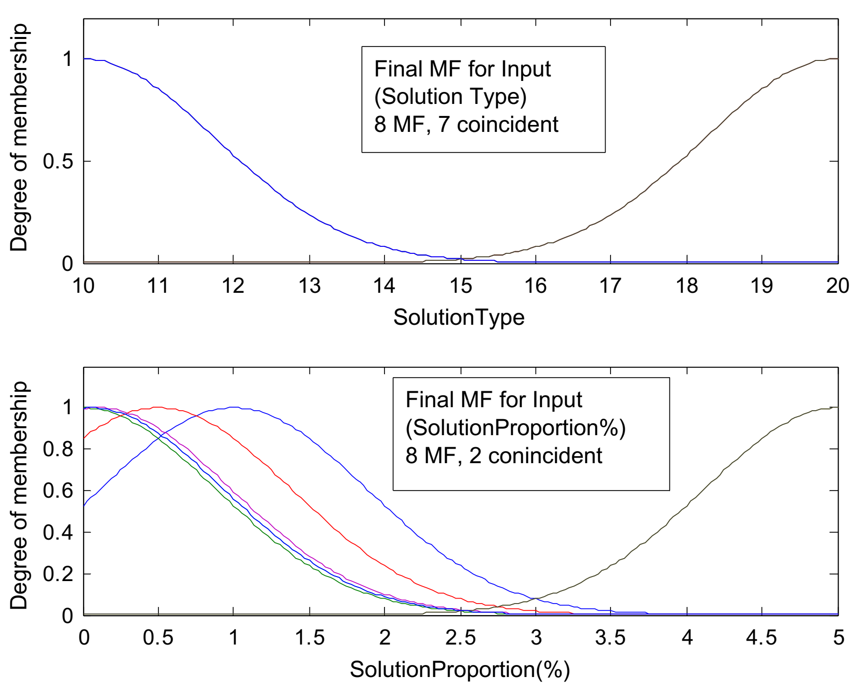

Fig. 5. Final MF of inputs for the surface properties prediction model using subtractive clustering-based algorithm.

Only 8 rules were found by the optimization algorithm to be necessary to generate a high efficient FIS that predicts the surface properties without any loss of accuracy, and with much less computational time. The final FIS structure is shown in Fig. 6. The final fuzzy models for predicting the surface properties of whey protein are given as surface plots of the outputs (i.e. EAI, ESI, surface tension, and interfacial tension) against the inputs (i.e. solution type and solution proportion %) as illustrated in Figs. 7–10, respectively.

3.3.3. Models validation

The fuzzy prediction models for surface properties of whey protein were validated by selecting a certain number of data points (6 points), different and independent from the other 30 points used for fuzzy model training. The test data points (i.e. 6 points) were selected randomly from the original experimental data points and removed from the total data points to leave the rest of the original data (i.e. 24 points) for training purposes. Upon completion of the training process on the training data, each validation data point (i.e. solution type and solution proportion %), given in Table 2, was fed into the system, and then the predicted surface properties (i.e. EAI, ESI, surface tension, and interfacial tension) were compared to the actual values of these properties. The average absolute percent error in each validation point was calculated by dividing the absolute difference between the actual and predicted values by the actual value, and then these ratios are taken as percentage values to find the average percent error in the prediction process. The average percent errors in the modeling of surface properties are given

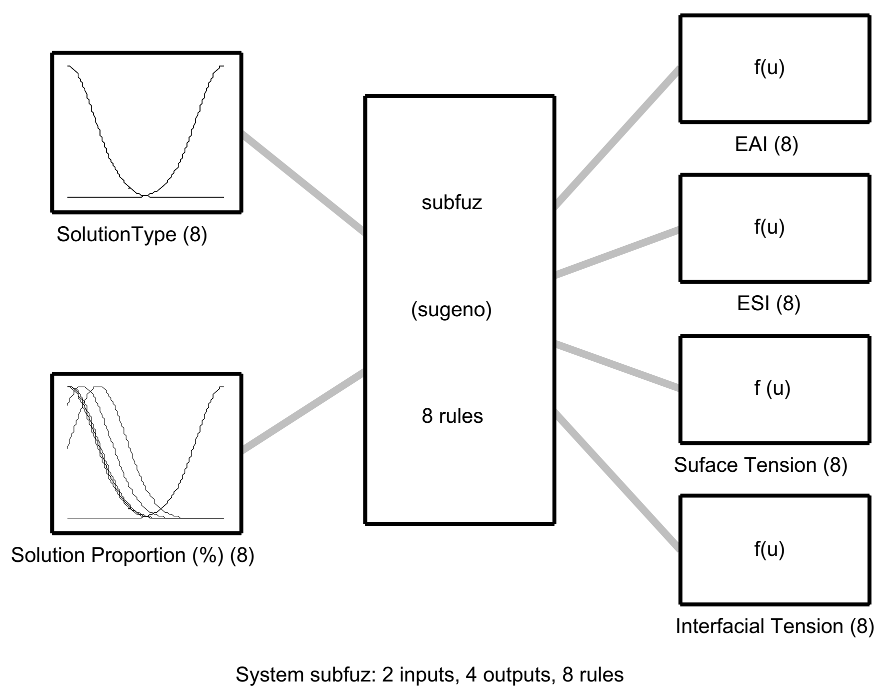

Fig. 6. Fuzzy inference system FIS for surface properties prediction using subtractive clustering-based optimization algorithm.

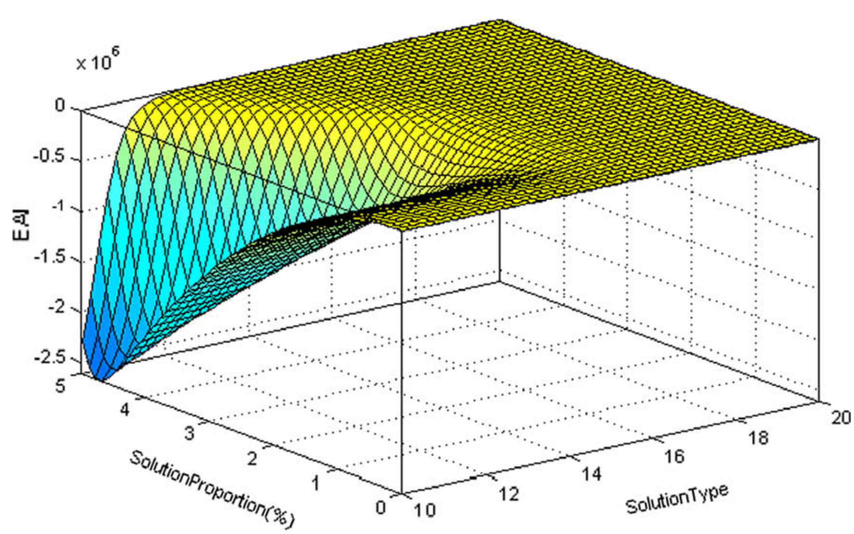

Fig. 7. A fuzzy model of EAI as function of inputs.

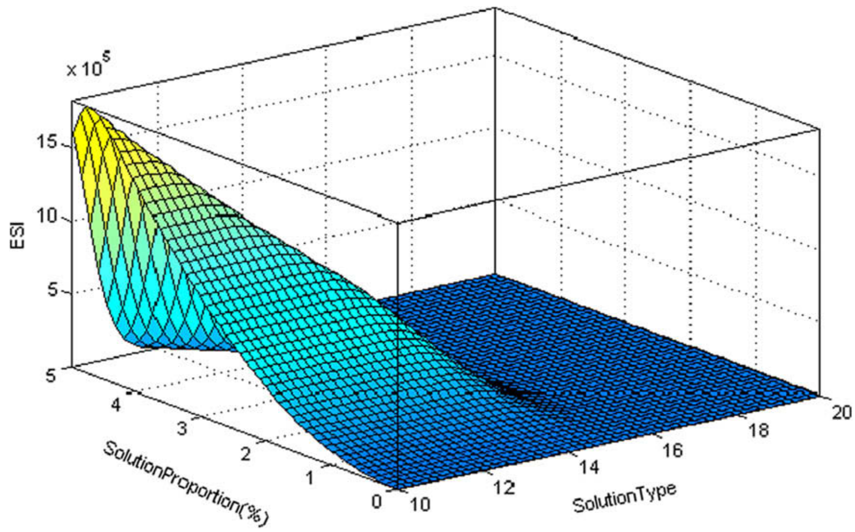

Fig. 8. A fuzzy model of ESI as function of inputs.

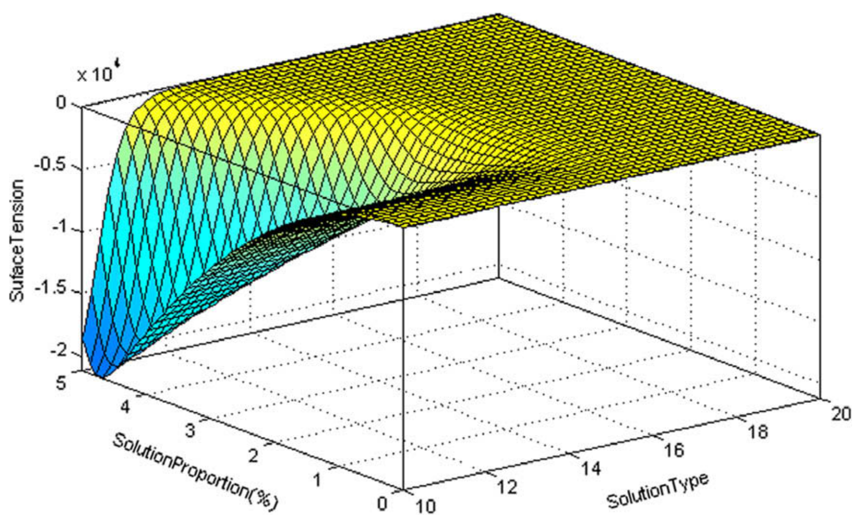

Fig. 9. A fuzzy model of surface tension as function of inputs.

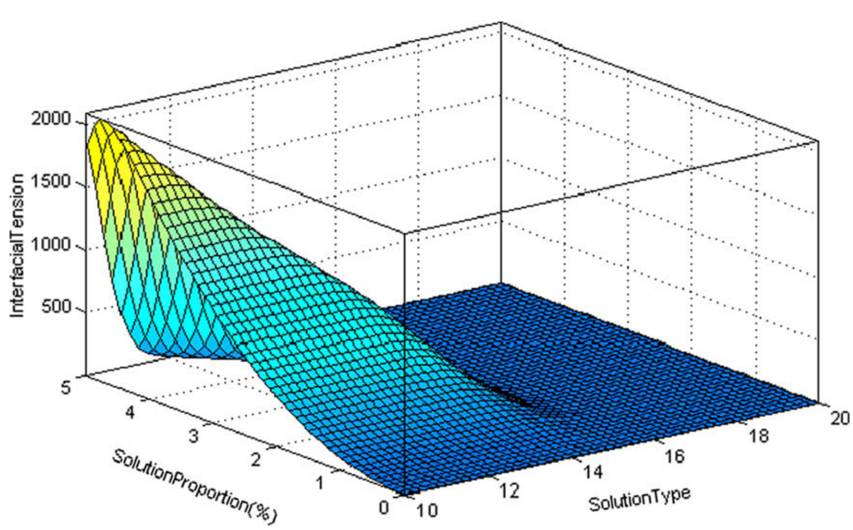

Fig. 10. A fuzzy model of interfacial tension as function of inputs.

in Table 2, and are as follows: 6% for EAI, 3% for ESI, 2% for surface tension, and 6% for interfacial tension.

The prediction accuracies achieved in this work are considered satisfactory when compared to previous work in this field. A classification of wheat by visible and near-infrared reflectance from single kernel was introduced by (Delwiche and Massie, 1996). Their classification model accuracy ranged from 65% for SRW wheat to 92% for SWH.Welch et al. (2003) presented a genetic neural network model of flowering time control in Arabidopsis thaliana. Their results included tracking a novel, temperature-dependent exchange in transition order exhibited by two mutants whose duplication is not possible by usual crop simulation methods. An artificial neural network prediction of amino acid levels in feed ingredients was introduced by Roush and Cravener (1997). Two types of neural networks and linear regression were evaluated for predicting amino acid levels in corn, wheat, soy bean meal, meat, bone meal, and fish meal. Samhouri et al. (2007) found that the neuro-fuzzy modeling technique (i.e. ANFIS) can be used to achieve very satisfactory prediction accuracy (about 98%) in a model color mayonnaise system. Also, very satisfactory prediction accuracy (about 96%) was achieved by applying neuro-fuzzy modeling technique (i.e. ANFIS) in predicting the emulsion stability and viscosity of a gum–protein emulsifier in a model mayonnaise system (Abu Ghoush et al., 2008).

4. Conclusions

In this paper, surface properties (surface tension, interfacial tension, emulsion activity index (EAI), and emulsion stability index (ESI)) of whey protein (WPC) in a combination with ι-carrageenan or gum arabic, were investigated. In addition, a subtractive clustering-based fuzzy models for predicting the surface properties of whey protein, was constructed. The following conclusions can be drawn from the above analysis:

(1) There was no significant effect of the gums addition on the surface tension of the 4% WPC water phase. While, the interfacial tension of 4% WPC decreased by addition of different concentration of ι-carrageenan. Also, the interfacial tension of 4% WPC decreased by addition of low concentration (0.5%) gum arabic and increased at high concentrations (1% or 5%) gum arabic. This trend is usually attributed to interactions between polymer segments. These interactions could be segregative or associative.
(2) ι-Carrageenan addition at lower concentration increased the EAI of 4% WPC than at higher concentration. Whereas, gum arabic addition significantly increased the EAI of 4% WPC at different concentrations. At the same time, the ESI of 4% WPC was significantly increased by increasing ι-carrageenan addition. Whereas, ESI of 4% WPC was significantly decreased by addition of gum arabic at various concentrations.
(3) Fuzzy subtractive clustering-based models achieved an average prediction error of whey protein surface properties of 4%. The prediction accuracies are considered satisfactory when compared to previous work, and the fuzzy model was capable of modeling the surface properties efficiently. The present study shows that fuzzy clustering is a technique that can be used efficiently to predict the food properties. The capability of the fuzzy predictions models for the surface properties permitted identification and quantification of EAI, ESI, surface tension, and interfacial tension to be studies in all types of emulsions (e.g. milk products, beverages). Computer vision shows promise for online prediction of surface properties in biphasic system.

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