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Single- and Multi-Objective Optimization of Low Fat Ice-Cream Formulation, Based on Genetic Algorithms

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ABSTRACT

Application of either protein or carbohydrate-based products as fat replacers in low fat ice-creams can improve the properties of these products. However, the type and level of fat and fat replacer utilized are affected by such different parameters as functional ones, namely: viscosity and overrun, hardness and melting rate, nutritional properties (calories) as well as the price of the final product. Throughout the present study, single- and multi-objective optimization method as based on the genetic algorithms (GAs) was applied to select the suitable fat-free as well as low-fat ice-cream formulations. The data related to single-objective optimization of selected parameters revealed that the ice-creams containing 3.5% Simplesse plus 1.72% fat, and 2.95% Maltodextrin plus 1.87% fat have ended up with the most desirable functional objectives. The application of multi-objective optimization led to a range of solutions of different fat and fat replacer contents out of which the producers can adopt the most suitable choice depending on the needs.

Keywords: Genetic algorithm, Low-fat ice-cream, single and multi objective optimization.

INTRODUCTION

Ice-cream is constituted of a complex multiphase system consisting of ice crystals, air cells and fat globules embedded in a high viscous freeze concentrated matrix phase (Goff *et al.,* 1999, Aime *et al.,* 2001). Ice-cream is characterized by such unique physical properties as hardness and melting traits, influenced by ingredients, air entrapment as well as ice content. Structure development in ice-cream is often attributed to the macromolecules present in the products' mix, milk fat as well as complex carbohydrates. Milk fat interacts with other ingredients to develop the texture, mouth feel, creaminess and the overall sensation of lubricity (Giese, 1996; Akoh, 1998).

During the freezing of the product, the whipping action along with ice crystallization destabilizes the fat emulsion in the mix. The destabilized fat acts as a cementing agent and provides support to the air bubbles primarily lined up by proteins. A combination of milk proteins and partially coalesced fat provides strength and structure to the product (Goff and Jordan, 1989; Marshall and Arbuckle, 1996). Thus, creating and stabilizing the desired structure in low-fat frozen dessert products is difficult, because the coalesced fat fraction is lowered, whereas the protein fraction may be on the increase. These structural changes can be detected by evaluating physical and sensory properties of the frozen dairy desserts (Adapa *et al*., 2000).

Typically, ice-cream contains 10 to 16% fat. In recent years, some ice-cream manufactures have attempted to lower the level of fat fraction due to health concerns

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and have replaced the fat with either carbohydrates or proteins (LaBarge, 1988; Giese, 1996).

However, replacing fat with protein or carbohydrates alters the physical properties. This is of particular concern in production of frozen dairy desserts. In such systems, the balance of fat and serum content of solids helps to in promoting stability during the mixing process and allows fat destabilization to occur during freezing. Thus replacing the fat alters the balance, and thereafter affects whipping as well as melting properties (Arbuckle, 1977; Thomas, 1981). Both carbohydrates and proteins may help stabilize emulsions through different mechanisms. Carbohydrates increase the viscosity of the continuous phase, whereas proteins act as the oil/water interphase and generally decrease the interfacial tension (Schmidt *et al*., 1993).

Carbohydrate- and protein-based fat replacers have been utilized in the preparation of ice-cream to reduce the fat levels (Aime *et al*., 2001; Specter and Sester, 1994; Schmidt *et al*., 1993; Roland *et al*., 1999; Adapa *et al*., 2000). Schmidt *et al*. (1993) found that ice-cream containing Simplesse D-100 was similar to full-fat ice-cream in terms of rheological properties in comparison with ice-cream containing a Maltodextrin-based fat replacer. Prindiville *et al.* (2000) suggested that Simplesse behaved more like fat in terms of flavor interactions than did carbohydrate-based fat replacers. Adapa *et al.* (2000) stated that carbohydrate- and protein-based fat replacers may be more helpful in increasing the viscous properties than the elastic properties in a dairy-based system.

A reduction of fat content affects the rheological properties as well as the consumer acceptance of the final product. Thus the primary objective of replacing fat with a fat replacer is to improve the texture of low-fat or fat-free ice-cream while retaining its palatable taste. To obtain the most acceptable formulation, fat and fat replacer contents should be optimized, based on the ideal rheological properties (viscosity, overrun, hardness as well as melting rate) of the low-calorie ice-cream.

GA (Genetic Algorithm) is a combinatorial optimization technique, searching for an optimal value of a complex objective function by simulation of the biological evolutionary process, based as in genetics, on crossover and mutation. An optimal value can be searched, in parallel, with a multi-point search procedure. GAs have been successfully employed in a wide variety of problem domains (Goldberg, 1989). The focus is on applications of GAs to the optimal control of agricultural production and food processing systems. Morimoto *et al*. (1997) applied GA to optimization of heat treatment for fruits during storage. Chtioui *et al.* (1998) reported seed selection while using GA in combination with artificial vision. The modeling and optimization of PHA (polyhydroxyalkanoates) production through fermentation of the industrial waste (ice cream residue) was studied by employing statistical experimental design methods (Lee and Gilmore, 2006). Koc *et al.* determined the optimal process conditions of whole milk powder, using neural networks and genetic algorithm optimization. Cogne *et al.* (2003) developed physical models that could predict the thermal properties of a standard overrun ice-cream based on its composition and on the intrinsic thermal properties of each major pure component.

The objectives in this study were: (i) to analyze the effects of fat and fat replacer content on the calorie content and on the rheological properties of ice-cream samples, namely: viscosity, overrun, melting rate as well as hardness, and (ii) applying GA technique to optimize the formulations of fat-free and content low-fat ice-creams.

MATERIALS AND METHODS

Sample Preparation

Liquid ingredients (skim milk and fresh cream) were placed into a mixing tank and warmed. Dry ingredients (NFDM, sugar, Maltodextrin DE= 5, Simplesse 100, stabilizer-emulsifier) were then added. The mixes were pasteurized for 30 minutes at 68°C. Following pasteurization, the mixes were homogenized in a double-stage homogenizer (Behsaz Machine, type OM) with homogenization pressure of 135 bar on the first stage and 35 bar at the second stage. The pasteurized homogenized mixes were then cooled and aged at 4 to 5°C for 24 hours. Prior to freezing, ice-cream mixes were flavored with vanilla, then frozen in an ice-cream freezer (Carpigiani, Bologna, Italy) to achieve maximum overrun. Samples were packed in 100 mL plastic cups and placed in a freezer at -20°C to be hardened.

Analyses

Viscosity

A viscometer (model DVII, spindle # 2, UK Viscometer, Ltd., Brookfield, Stoughton, MA) was employed to measure the viscosity of 600 mL of ice-cream mixes at 4±1°C and after 24 hours of aging.

Overrun

Following overnight refrigeration at 4±1°C, the mixes were thoroughly stirred and frozen in the ice cream freezer to -5°C with overrun values being estimated by comparing the weight of ice-cream mixes *vs.* ice-creams in a fixed volume container. Overrun (in %) was calculated as fallows (Arbuckle, 1977).

$$\%\ Overrun = \frac{\text{Weight of unit volume of mix} - \text{Weight of unit volume of ice cream}}{\text{Weight of unit volume of ice cream}} \times 100$$

Hardness

According to Bourne (1966), hardness can be estimated by measuring the degree of deformation under a known compression force. The plunger attachment of the Instron Universal Testing Machine (IUTM, model 1140) was applied to obtain an instrumental value for hardness of the frozen samples.

To control temperature, sample preparation for each firmness test followed a strict routine. For temperature control, samples were completely surrounded by crushed ice. Hardness measurements were made at room temperature, using a texture analyzer equipped with a 3.12 mm diameter stainless steel cylindrical probe. The penetration speed of the probe was 2 mm s^{-1} to a distance of 20 mm. Duplicate determinations were made for each sample.

Rate of Melt

The melting rate of ice-cream samples was analyzed at room temperature (25±2°C). Hardened ice-cream was cut into cylinders (6 cm diameter, 2.5 cm thickness), tempered at -15°C, and placed on a sieve (No. 10, 2 mm wide, square openings) suspended over a Petri dish. The quantity of ice-cream drained into the petri dish at 25±2°C was weighed every 5 minutes. Melting rate was based upon the weight of drip collected after 30 min at room temperature (Aime and Arntfield ,2001). Duplicate determinations were carried out on all samples.

Optimization Method

Optimization methods can be classified into conventional ones, which are deterministic and gradient based *vs.* stochastic methods such as simulated annealing *vs.* genetic algorithms. Conventional gradient-based optimization methods have been widely tested on exact analytical test functions, but don't perform precisely if there are such random errors, in the objective function, as the use of numerical models. Such stochastic evolutionary algorithms as Genetic Algorithms (GA), do not yield under these drawbacks and hence have definite advantages in the optimization of engineering processes.

The basic principles of GA invented in 1960s are well-documented in several papers and texts (Goldberg, 1989; Holland, 1992; Michalewicz, 1994; Fogel, 1994). GA takes its inspiration from biological reproduction and evolution. Instead of starting from a single point as in conventional method, GA uses a population of solutions as demonstrated by the following typical pseudo code:

-Initialize random population of solutions

-Loop

- Rank all individuals in population in term of fitness and diversity
- Select parents based on ranking
- Create children and form new population

-Until maximum number of generation is reached

- At some generation, local search is employed to create members for new population

The present study was designed to use Genetic Algorithm to solve the problem of selecting the best fat and fat replacer contents to produce low fat ice-creams with preferred rheological properties and as well lowered/reduced calories.

Ranking and Sharing

All the solutions in a population are ranked according firstly to their fitness, and secondly to a diversity index, i.e. whether they are close to other solutions (Coello, 1999). Initially, all the non-dominated solutions are given an arbitrary "dummy fitness" value. Next, the dummy fitness values of close neighbors (similar solutions) are decreased or "shared" according to a certain formula. The minimum dummy fitness value is recorded. Then all the non-dominated values are removed from consideration and a new group of non-dominated solutions is formed from the remainder. Each of these is given a dummy fitness value, which must be smaller than the minimum, recorded earlier. Sharing is applied again.

Then these solutions are also removed from consideration and the whole cycle is repeated until every solution has been assigned a dummy fitness value, and thus the whole population ranked.

Selection

Two individuals selected at random from current population are compared in terms of dummy fitness. The individual with a higher dummy fitness is selected and makes more effect on producing children. This selection ensures that non dominated solutions benefit from a higher chance to reproduce than the rest of the population. Moreover, selection based on dummy fitness helps in maintaining the diversity of the population, in case two parents of same rank are selected.

Reproduction

Crossover and mutation are the most popular operators. Recently, other reproduction operators have been developed and it has been shown that they are very useful in searching and maintaining the characteristics of good feasible solutions. In this paper, besides mutation and crossover, interpolation as well as extrapolation (Pham,1997) are also employed.

A real-coded GA was used in this work, ie. each solution is represented by a real vector $\boldsymbol{u}$ (eg. u_1 could be Simplesse percent and u_2 could be Maltodextrin percent).

- Mutation causes a random, possibly large change in one element u_i of an existing solution, i.e. the new temperature regime is the same as the old one except for a random change.
- Crossover of two existing solutions A and B generates a new member having the following values:

$$u_i^{New} = \begin{cases} u_i^{A} & i \leq k \\ u_i^{B} & i > k \end{cases} \qquad (1)$$

Where, k is a random integer, i.e. temperature regime A is followed up to time k then switched to temperature regime B.

- Interpolation operator is the average of two parents:

$$u_i^{New} = (1-\alpha)u_i^A + u_i^B \quad i = 1 \text{ to } N \qquad (2)$$

where N is number of variable, α is positive number and α<1), i.e. temperatures in the new regime is always intermediate between those of two old regimes at all times.

- Extrapolation operator extrapolates past the better parent:

$$u_i^{New} = (1-\beta)u_i^A + u_i^B \quad i = 1 \text{ to } N \qquad (3)$$

Where β is a positive number and $\beta>1$. If regime A is better than regime B, we extrapolate past A in the hope that it will be better still. If regime A fits better than regime B, then extrapolation past A is performed with the hope that it will fit better still.

After children are produced, they are compared with the parents. If they dominate the parents, they are introduced into the new population. If they are dominated by a one parent, then they are rejected. The parents are introduced into the new population provided they are not already there.

Ice-cream Characterization Model

Firstly, ice-cream formulations were prepared according to a factorial experimental design (2×3×4), with 2 types of fat replacers (Simplesse and Maltodextrin), 3 different contents of fat replacer (1.5, 2.5 and 3.5%) and 4 different contents of fat (0, 0.5, 2.5 and 5%). Secondly, their determined characteristics (viscosity, hardness, overrun, and melting rate), were analyzed employing SAS program. Finally, to model the evolution of ice-cream characteristics as a function of fat and fat replacer contents (%), the polynomial equations as follows were applied.

$$P = aF^2 + bF - c \qquad (1)$$

Where, P stands for the ice-cream characteristics, F represents the fat content of the ice-cream formulations (0, 0.5, 2.5 or 5%) while a, b and c stand for coefficients.

To account for the effect of replacer contents, the coefficients of model (a, b and c) were interpreted as functions of fat replacer (R) through polynomial relations as follows:

$$a = a_1R^2 + a_2R - a_3 \qquad (2)$$

$$b = b_1R^2 + b_2R - b_3 \qquad (3)$$

$$c = c_1R^2 + c_2R - a_3 \qquad (4)$$

Thus, there appeared 9 parameters (a_1, a_2, a_3, b_1, b_2, b_3, c_1, c_2 and c_3) to be identified. The constants of equations were estimated through Levenberg–Marquardt method by fitting the experimental data to the equations. Table 1 gives the optimal values of these coefficients.

The energy content of the different ice-cream formulations as a function of fat and fat replacer contents can finally be estimated through the following equation:

$$Energy = \frac{100 * [187.09 - (10 - F) * 8.79 + R * 1.5]}{(90 + F + R)} \qquad (5)$$

RESULTS AND DISCUSSION

Modelling of Ice-cream Properties Evolution

Figures 1 and 2 show the effect of fat and fat replacer contents (Maltodextrin and Simplesse, respectively) on viscosity, hardness and overrun properties. As can be seen, hardness of the ice-cream increased while its viscosity and overrun decreased with reference to the fat content. Figure 3 presents the comparative results between the experimental and the predictive functional properties (viscosity and hardness) obtained by the model as a function of fat content at the different fat replacer contents. As can be seen, there is a good agreement between experimental and predictive data.

Table 1. Data related to final factors of the provided model for two fat replacers.

c 3	c 2	c 1	b 3	b 2	b 1	a 3	a 2	a 1	Objective
Fat replacer									
Simplesse									
6.996E+01	- 1.758E+01	8.737	- 4.7039	2.036E+01	-4.104	8.560E-01	- 1.1898	2.556E-01	Viscosity
1.332E+02	- 2.415E+01	2.866	- 2.130	7.697	-9.492E-01	2.351	- 1.008	1.276E-01	Overrun
1.182E+02	- 4.174	-3.568E-01	- 1.328E+01	6.107E-01	-3.502E-01	8.359E-01	- 1.447E-01	9.663E-02	Hardness
3.435E+01	2.932	-8.793E-01	1.350	2.740	-1.366	- 5.753E-01	- 8.203E-01	3.279E-01	Melting Rate
Maltodextrin									
6.782E+01	- 1.365E+01	4.349	- 4.285	2.187	3.014E-01	3.006	- 1.034	1.41E-01	Viscosity
2.027E+02	- 5.844E+01	9.216	- 3.431E+01	8.940	1.488	1.488	7.129E-01	-1.329E-01	Overrun
9.300E+01	- 7.911	6.694E-01	- 1.290E+01	5.624	-9.115E-01	1.851	- 1.060	1.751E-01	Hardness
4.301E+01	- 1.072	-1.367E-01	+ 3.817	- 3.735	5.425E-01	- 1.413	6.175E-01	-8.407E-02	Melting rate

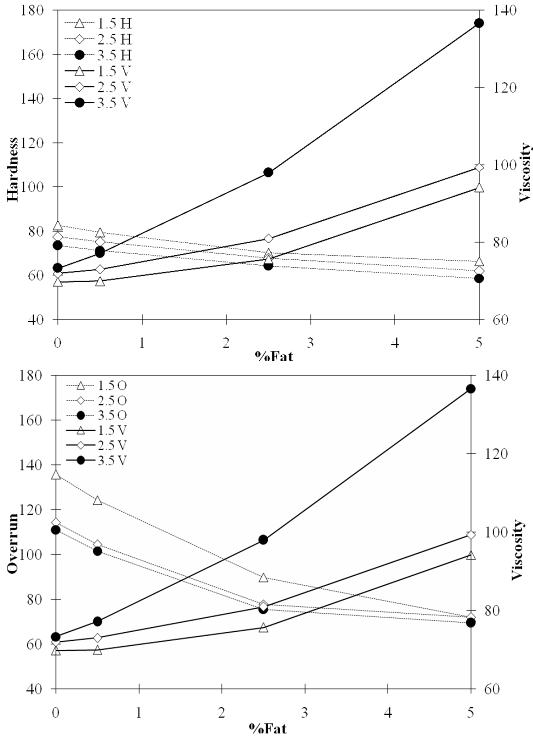


Figure1. Effect of using Fat+Maltodextrin (%) on viscosity, hardness and overrun values of ice-cream. (O: Overrun, V: Viscosity).

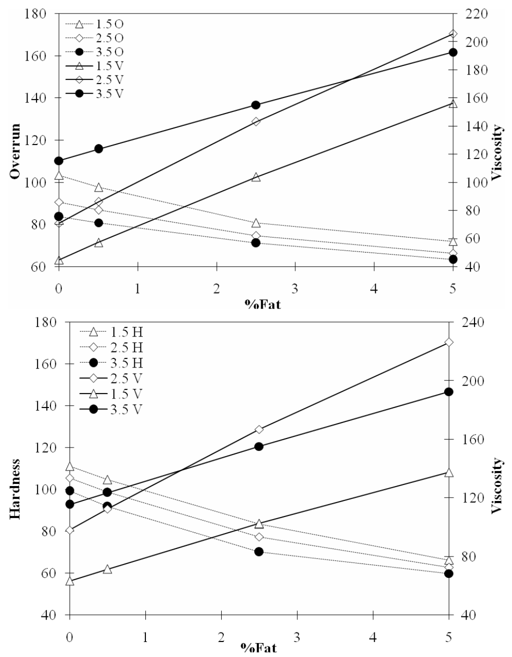
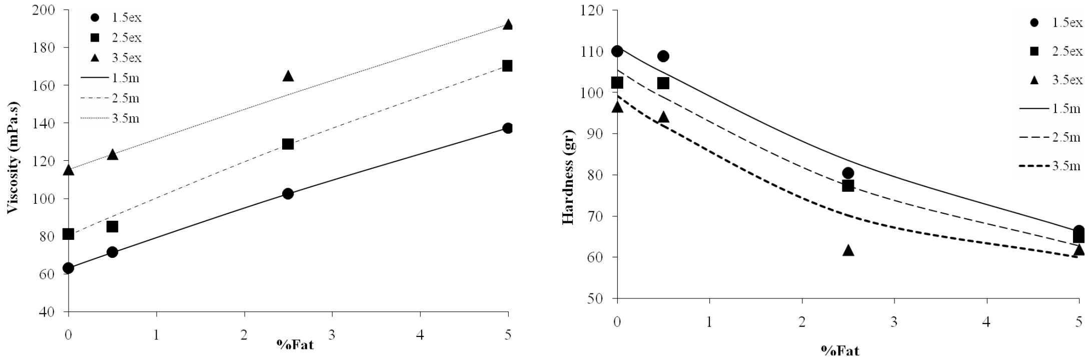
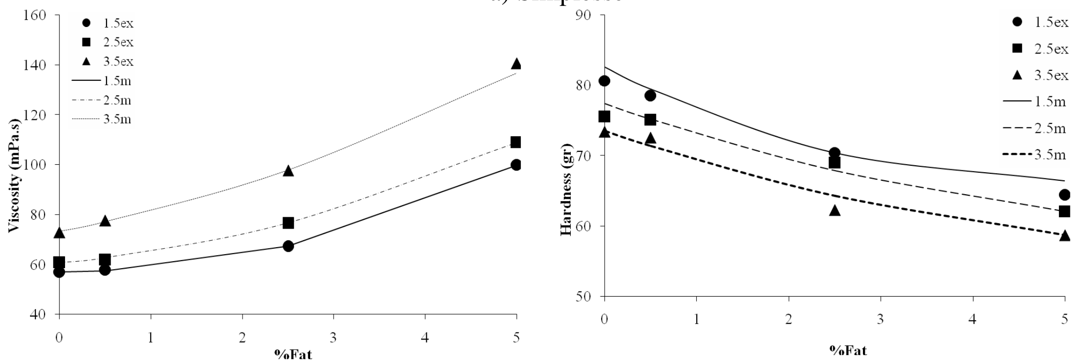


Figure 2. Effect of using Fat+Simplesse (%) on viscosity, hardness and overrun values of ice-cream.



a) Simplesse



b) Maltodextrin

Figure 3. A comparison of the experimental and the predictive functional properties (viscosity and hardness) obtained by the model as a function of fat content and at different fat replacer contents.

Optimization of Ice-cream Formulation

There are a large number of parameters that affect the performance of the optimization method, some of such parameters being: the size of population, the number of generations, the parameters of reproduction operators, and the number of local searches. The optimal values for these parameters can only be found by trial and error. In order to ensure the efficacy of the suggested algorithm and parameter values, the method was tested for 6 test problems and while applying multi-objective optimization.

In case of the above problem, the algorithm was run for 60 generations using a population figure of 15, a crossover probability of 0.2, a probability of mutation equal to 0.01, a probability of extrapolation of 0.6 and finally an interpolation probability of 0.3.

The convergence of the solutions can be observed by plotting Pareto fronts in the objective function space at generations 20, 30, 40, 50 and 60 (the final generation) as in Figure 4.

From generation 30 onwards, the Pareto fronts get close to each other. As for generations 50 and 60, the Pareto fronts are identical indicating that the algorithm has converged to the optimal solution front.

The results of single-objective optimization indicated that the formulations containing 3.5% Simplesse plus 1.72% fat and 2.95% Maltodextrin plus 1.87% fat are of the highest functional objectives (Table 2).

The application of multi-objective optimization produced a range of solutions with different fat and fat replacer rations, of which the producer can select the most appropriate according to his own views, and depending on the importance that he attaches to each objective (Tables 3 and 4). Viscosity is one of the physical properties

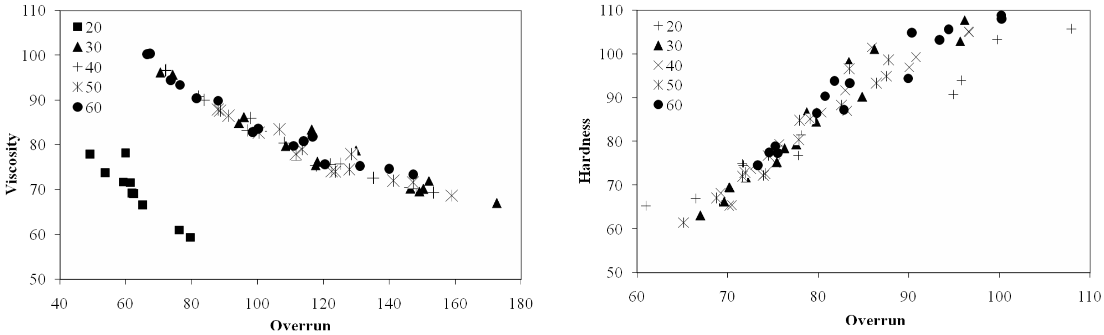


Figure 4. The convergence of the solutions by plotting Pareto fronts in the objective function space at generations 20, 30, 40, 50 and 60 (the final generation).

Table 2. Some results of single-objective optimization.

Parameter	Result	% Fat	% Simplesse	Result	% Fat	% Maltodextrin
B1,B2,B3,B4,B5[a]	1.6226	1.7196	3.5	1.2048	1.8764	2.9531
B1,B2,B3,B4	0.9209	5	1.5	0.5671	4.3139	2.5606
B1,B2,B3,B5	0.8034	0	2.2659	0.9736	1.069	2.7916
B1,B2,B4,B5	0.3167	0	1.5	0.7092	0	2.9871
B2,B3,B4,B5	1.4555	0.4363	2.7906	0.9796	1.3599	2.8912
B1,B3,B4,B5	0.9055	3.1497	3.5	0.94983	2.988	3.5
B1,B2,B3	0.761	5	1.5	0.4531	4.014	2.2628
B2,B3,B4	0.8541	5	1.5	0.4626	3.591	2.5035
B2,B4,B5	1.072	0	1.7382	0.4177	0	2.7042
B2,B3,B5	0.5431	0	2.1984	0.7093	0.5858	2.7465
B3,B4,B5	0.8421	2.699	3.5	0.7905	2.206	3.5
B1,B3,B5	0.5098	0	3.5	0.8275	1.9822	3.3218
B1,B2	1.0258	5	3.5	0.3177	1.3108	1.8645
B2,B3	0.9743	2	3.5	0.3134	3.1801	2.2862
B3,B4	0.014	5	3.5	0.074	4.8536	3.5
B2,B4	0.7544	4.8741	1.5	0.3209	2.4716	1.7218
B1,B3	0.006	5	3.5	0.0694	5	3.5

[a] B1, B2, B3, B4, B5 denote melting rate, viscosity, overrun, hardness and calorie, respectively.

Table 3. Some results of multi-objective optimization for formulations containing Maltodextrin as fat replacer.

B1[a]	B2[b]	B3[c]	B4[d]	B5[e]	%Fat	% Maltodextrin
0.3097	0.0139	0.7913	0.4132	0.0284	0.1115	1.9576
0.0289	0.3725	0.0981	0.0861	1.0001	4.998	2.3977
0.3026	0.0227	0.7081	0.3855	0.046	0.185	2.1772
0.0335	0.4552	0.0664	0.0476	0.9482	4.7218	3.0905
0.097	0.3392	0.0598	0.0897	0.7806	3.8377	2.9988
0.3159	0.0094	0.8559	0.4239	0.0817	0.3866	1.5372
0.2327	0.1598	0.3345	0.2227	0.2751	1.2586	3.2055
0.0275	0.5501	0.0515	0.0227	0.9455	4.7062	3.4993
0.2736	0.1265	0.6371	0.2962	0.0286	0.0371	3.4853
0.2973	0.0229	0.6444	0.364	0.129	0.5933	1.986
0.2607	0.1459	0.5422	0.2672	0.1013	0.3907	3.4863
0.166	0.1709	0.1558	0.1729	0.7081	3.4772	1.866
0.2135	0.1144	0.247	0.2097	0.5847	2.8517	1.7235
0.218	0.1159	0.2675	0.2118	0.6069	2.9684	1.5254
0.2862	0.0535	0.5819	0.3346	0.0798	0.3258	2.6345

[a] Melting rate; [b] Viscosity; [c] Overrun; [d] Hardness, [e] Calorie.

Table 4. Some results of multi-objective optimization for formulations containing Simplesse as fat replacer.

B1[a]	B2[b]	B3[c]	B4[d]	B5[e]	% Fat	% Simplesse
0.2672	0.1874	0.3602	0.8263	0.1199	0.5459	2.0676
0.1673	0.4926	0.1262	0.2743	0.7984	3.9459	1.5053
0.2313	0.4224	0.1929	0.5016	0.3949	1.8833	2.3593
0.2671	0.2777	0.2856	0.664	0.2776	1.3168	1.9695
0.2433	0.3508	0.2399	0.6147	0.2753	1.289	2.4138
0.1697	0.4887	0.1277	0.2781	0.7932	3.919	1.5006
0.249	0.3636	0.2069	0.4706	0.5266	2.5629	1.5868
0.2302	0.4434	0.1737	0.4443	0.4865	2.3473	2.1436
0.2743	0.1022	0.4748	0.9213	0.0861	0.4093	1.5007
0.2636	0.0855	0.4648	0.983	0.0048	0.0038	1.8696
0.0403	0.8737	0.019	0.0817	0.7857	3.8593	3.4958
0.1472	0.6197	0.0839	0.2273	0.7878	3.8853	2.0834
0.2557	0.1818	0.3606	0.9121	0.0121	0.0065	2.5054
0.2557	0.1811	0.3611	0.9133	0.0112	0.002	2.5052
0.087	0.792	0.0362	0.1383	0.779	3.8295	3.0063

[a] Melting rate; [b] Viscosity; [c] Overrun; [d] Hardness, [e] Calorie.

that lays a major impact on the sensory quality and as well on the texture of the ice-cream. In general, formulations with higher fat and fat replacer contents were of higher viscosity values than those containing lower rations.

With an increase in fat and fat replacer concentrations, total solids and thus viscosity increased while overrun decreased. In general, overrun decreased with increase fat and fat replacer contents. As for the Simplesse mixes such low overrun values are expected due to chemical properties of the fat replacer which might have negative impact on the incorporation of air into the mix. It has been stated that highly viscous systems do not favour foaming capacity but do favour foam stability (Adapa *et al.,* 2000). Marshal and Arbuckle (1996) also stated that ice-cram mixes of high viscosities show limited whipping traits.

Hardness of ice-cream is related to its texture. Air in ice-cream provides a light texture and influences the physical properties particularly hardness (Sofjan *et al.,* 2004) and according to Muse *et al.* (2004) hardness decreases when overrun values of ice-cream samples increase. Similar findings were observed in the current study. The texture of ice-creams in which the levels of fat and total solids have been lowered has been reported to be firmer than samples of higher fat and total solids. This is due to the higher levels of ice and hence the lower levels of crystallized milk fat, which is a softer component than ice (Aime *et al.,* 2001). It could be said that utilizing Simplesse and Maltodextrin as fat replacers can overcome the problem of increased ice crystal formation in reduced-fat ice-cream and provide a product of hardness values equivalent to those of ordinary-fat containing ice-cream. The observation of a slower melting phenomenon of ice-creams of higher fat and fat replacer contents has earlier been stated by Hyvonen *et al*. (2003).

Proteins, due to their amphoteric nature, are much more functional in emulsions than are carbohydrates (Schmidt *et al.,* 1993). In general, the ability of protein based fat replacers to mimic the physical properties of milk fat will be determined by the colloidal properties of the proteins involved and as well by their impact on mouth feel. Simplesse with tiny, individual gel particles, less than 5 μ in diameter, could confer lubricating effects, enhance viscosity and creaminess, while decreasing the perception of hardness. Maltodextrin as a hydrophilic colloid can increase the viscosity of the continuous phase in the unfrozen mix. Thus subsequent foam formation and stability would be improved, large crystal growth during freezing restricted and hardness decreased. Cottrell *et al.* (1980) also indicated that polysaccharides restricted ice crystal growth during storage and increased the viscosity of the mix.

CONCLUSIONS

Using protein or carbohydrate-based products as fat replacers in low-fat ice-creams influence the properties (viscosity, hardness, overrun, melting rate, calorie reduction, etc) of the final product. Single- and multi-objective optimization method based on the genetic algorithm were applied to select the appropriate fat free as well as low-fat ice-cream formulations. The results of single-objective optimization revealed that ice-creams containing 3.5% Simplesse and 1.72% fat *vs.* 2.95% Maltodextrin and 1.87% fat presented some best compatible solutions for the considered objectives. Multi-objective optimization presented solutions for the low-fat ice-cream formulations of different fat and fat replacer contents. Although only five objectives were considered in this paper, the findings show that the technique can be applied to a vast number of other problems that are presently at question.

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بهینه سازی فرمولاسیون بستنی کم چرب با استفاده از الگوریتم ژنتیکی

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چکیده

کاربرد ترکیباتی بر پایه پروتئین یا کربوهیدرات به عنوان جانشین های چربی در بستنی های کم چربی می تواند خواص این محصولات را بهبود بخشد. به هرحال نوع و مقدار چربی و جانشینهای چربی تابع پارامترهای متفاوتی همانند ویژگیهای عملکردی (ویسکوزیته و اورران بالا، سرعت ذوب شدن و سفتی کم)، ویژگیهای تغذیه ای (مقدار کالری پایین) و قیمت تمام شده پائین محصول است. الگوریتم ژنتیکی به دو روش Single-Objective و Multi-Objective جهت انتخاب فرمولاسیون‌های مناسب بستنی کم چربی و بدون چربی بکار گرفته شد. نتایج بهینه سازی پارامترهای انتخابی بر مبنای Single-Objective نشان داد که فرمولاسیون‌های حاوی ۳/۵ ٪ سیمپلس با ۱/۷۲٪ چربی و ۲/۹۵٪ مالتودکسترین با ۱/۸۷٪ چربی دارای بهترین مجموعهٔ ویژگی‌های در نظر گرفته شده می باشند. کاربرد Multi-Objective منجر به تولید مجموعه ای از ترکیب میزان چربی– جانشین چربی گردید که تولید کنندگان میتوانند از بین آنها مناسبترین ترکیب را بسته به اهمیت هر یک از ویژگیهای کیفی مذکور از نقطه نظر خود انتخاب نماید.