

Multiobjective Optimization to Optimal Moroccan Diet Using Genetic Algorithm

Abdellah Hourag⁽¹⁾, Karim El Moutaouakil⁽²⁾, Mouna Chegour⁽³⁾, Saliha Chellak⁽³⁾, Hicham Baizri⁽³⁾

^(1*) Sidi Mohamed Ben Abdellah University, Technical Sciences Faculty, MOROCCO
e-mail: abdellahhourag01@gmail.com

⁽²⁾ Sidi Mohamed Ben Abdellah University, FPT of Taza, MOROCCO
e-mail: karim.elmoutaouakil@usmba.ac.ma

⁽³⁾ Cadi Ayyad University Faculty of Medicine and Pharmacy, Marrakech, MOROCCO
e-mails: sidmouna@gmail.com; chellak2000@yahoo.fr; baizri72@gmail.com

SUMMARY

Proper glucose control is designed to prevent or delay the complications of diabetes. Various contexts can lead to a fluctuation of the blood sugar level to a greater or lesser extent. It can be, for example, eating habits, treatment, intense physical activity, etc. The feeding problem interpolated by a minimum cost function is well-known in the literature. The main goal of this paper is to introduce a multiobjective programming model with constraints for the diet problem with two objective functions, the first of which is the total glycemic load of the diet while the second objective function is the cost of the diet. the MOGA (multiobjective Genetic Algorithm) algorithm was used to resolve the proposed model. The experimental results show that our system ([proposed model – MOGA]) is able to produce adequate diets that can settle glycemic load and cost while respecting the patient's requirements.

KEYWORDS: *Genetic algorithm; multiobjective optimization; optimal diet; nutrient; glycemic load.*

1. INTRODUCTION

Healthy eating is the most important factor in maintaining and improving the health of each individual throughout his or her lifetime. Due to the increasing number of patients suffering from lifestyle diseases, it is important to control and design a balanced diet as one of its aspects. Blood sugar also called "sugar level" or "glucose level" in the blood, can vary in a person with diabetes for several reasons, for example, dietary habits. Achieving glycemic balance is essential for a good day-to-day life with diabetes.

In this work, a constrained multiobjective programming model is introduced to determine diets with a delicate trade-off, whose first objective function is the glycemic load of the diet while the

second objective function is the cost of the diet.

The first author who introduced a linear program with the glycemic load as the objective function is Turkish Esra Bas (2014) [1]. He introduces a mixed integer programming model for the diet problem with the glycemic load values of foods as the parameters of the objective function. He assumes that the glycemic load values are subject to uncertainty. Feiferlick (1985) [2] suggested the concept of minimum-cost nutritious diets using mathematical models [2], and Darman et al. (2002) [3] optimization, also using linear programming as a method to design nutritionally adequate diets. Eghbali et al. [4], [5] (2011) performed the determination of the optimal diet plan for type 2 diabetic patients using a linear mathematical model.

Regarding multiobjective optimization of nutrition, P. Czyzak et al. (1991) [6] proposed the solution of a multiobjective optimization problem of diet under uncertainty. KD Rothley et al. (1997) [7] introduced a multiobjective programming approach to foraging to settle conflicting demands. A multiobjective mathematical model for diet optimization and the detailed design process of the diet optimization program based on the quantum genetic algorithm (QGA) were discussed by Youbo Lv (2009) [8]. Maryam Eghbali-Zarch et al. (2017) [9] developed a novel mixed integer multiobjective linear programming model under uncertainty to design appropriate, diverse, and cost-effective diets for diabetic patients. Similarly, SH Amin et al. (2019) [10] performed food selection for a diet problem using a multiobjective approach under uncertainty. A multiobjective model for daily diet planning used to optimize the location of new health facilities was introduced by Mohd Arif Khan et al. (2021) [11].

In this paper, a constrained multiobjective programming model is used to determine optimal diets. The first objective function represents the total glycemic load of the diet, the second objective function represents the total price of the diet, and the constraints traduce the experts' recommendations and response to the needs of the patients in terms of nutrients. Genetic algorithm based on appropriate genetic operators is used to solve the proposed mathematical model. The rest of the paper is organized as follows: the second section gives the multiobjective optimization model that represents the optimal diet problem; the third discusses the estimation of the parameters of the multiobjective model; the fourth presents several experimental results. At the end of our paper, some conclusions and perspectives are offered.

2. MULTIOBJECTIVE OPTIMIZATION FOR THE OPTIMAL DIET

2.1 KNOWLEDGE ABOUT DIET PROBLEM

The essential knowledge of the diet problem is to set the foods according to nutritional values such as glycemic load, vitamins, calcium, phosphorus, magnesium, etc. These components are divided into two groups:

- Positive nutrients: Calories (c), Protein (p), Carbohydrate (car), Potassium (po), Magnesium (mg), Dietary fibre (tdf), Calcium (ca), Iron (ir), Phosphorus (ph), Zinc (z), Vitamin b6 (Vb6), b12 (Vb12), C (Vc), A (Va), E (Ve).
- Negative nutrients: saturated fatty acids (sf), Sodium, Cholesterol, Fat (tf).

The daily positive nutrient requirements and the minimum tolerable negative nutrient requirement are subject to uncertainty, but a nominal estimate is used:

$$b_c = 2.000kcal, b_p = 91g, b_{car} = 271g, b_{po} = 4044mg, b_{mg} = 380mg, b_{tdf} = 31g, b_{ca} = 1316mg,$$

$b_{ir} = 18mg$, $b_{ph} = 1740mg$, $b_z = 14mg$, $b_{vb6} = 2.4mg$, $b_{vb12} = 8.3\mu g$, $b_{vc} = 155mg$, $b_{va} = 1052\mu g$,
 $b_{ve} = 9.5mg$, $f_{sf} = 17g$, $f_s = 1.779mg$, $f_{ch} = 230mg$, and $f_{tf} = 65g$.

These parameters were taken from the USDA food guide at the reference of 2000-calorie level [1] and [12].

From now on, the following symbols are adopted:

A : Matrix of the values of foods' positive nutrients; in our case, (number of positive nutrients, number of foods) = (4, 177);

E : Matrix of the values of foods' negative nutrients; in our case, (number of negative nutrients, number of foods) = (4, 177);

b : Minimum required positive nutrients (number of positive nutrients, 1);

f : Maximum tolerable negative nutrients (number of negative nutrients, 1);

A_c : Line vector corresponding to the calories coming from positive nutrient;

c_i : Vector of the calories coming from the nutrient i of {car, p, tf, sf};

r_i : Percentage of total calories of i nutrients from $r_p = 18\%$, $r_{car} = 55\%$, $r_{sf} = 7.8\%$ and $r_{tf} = 29\%$;

x_j : The quantity of food j adopted in our diet. Thus, the vector is defined $x = (x_j)_{1 \leq j \leq 177}$;

g : Vector of glycemic loads generated by each food.

$C = (C_1, C_2, \dots, C_{177})^T$: Is a vector whose components represent the cost of 100g of the 177 foods.

Problem: Given $A, E, b, f, A_c, c_i, g, C, r_i, r_p = 18\%$, $r_{car} = 55\%$, $r_{sf} = 7.8\%$, and $r_{tf} = 29\%$, the optimal diet problem looks for the optimal amount of foods $x = (x_j)_{1 \leq j \leq 177}$ that meet the daily requirements and minimize the glycemic load and minimize the total cost.

2.2 CONSTRAINTS

Constraints on positive nutrients: if the decision $x = (x_j)_{1 \leq j \leq 177}$ is adopted, Ax are the vectors of 15 rows each of which represents the total amount of each positive nutrient offered by our diet, then there is the following family of constraints $Ax \geq b$.

The total calories from carbohydrates must make up at least $r_{car} = 55\%$ off the calories from all positive diet nutrients; hence the constraint is $c_{car}^T x \geq 0.55(A_c^T x)$ [12].

The total calories from proteins must be at least $r_p = 18\%$ of the calories from all positive diet nutrients; hence the constraint is $c_p^T x \geq 0.18(A_c^T x)$ [12].

Constraints on negative nutrients: Ex is the vector of 4 rows each of which represents the total amount of each negative nutrient offered by diet. Since f represents the total maximum of each negative nutrient, there is the following family of constraints $Ex \leq f$. The total calories from total fat must be at most $r_{tf} = 29\%$ off the calories from all positive diet nutrients; hence the constraint is $c_{tf}^T x \leq 0.29(A_c^T x)$ [12].

The total calories from saturated fat must be at most $r_{sf} = 7.8\%$ of the calories from all positive diet nutrients; hence the constraint is $c_{sf}^T x \leq 0.078(A_c^T x)$ [12]. When evaluating a diet, three criteria are taken into consideration.

If the quantity x_j of food j is taken, the glycemic load associated with this quantity is g_j . Thus, the glycemic load generated by a decision x is $g^T x$; it is this quantity that must be minimized

(Objective function). This paper introduces a constrained multiobjective optimization model, to examine compromises between glycemic load and cost of the diet.

2.3 MULTIOBJECTIVE MODEL

The least expensive of mathematical models minimizing the total glycemic load and ensures the minimum necessary positive nutrients and limits the consumption of negative nutrients is given by:

$$(P) \left\{ \begin{array}{l} \min g^T x, \min C^T x \\ A \cdot x \geq b \\ E \cdot x \leq f \\ c_i^T x \geq r_i(A_c^T x) \quad i \in \{car, p\} \\ c_i^T x \leq r_i(A_c^T x) \quad i \in \{tf, sf\} \\ x \geq 0 \end{array} \right.$$

3. MATERIALS AND METHODS: ESTIMATION OF THE MULTIOBJECTIVE PROBLEM PARAMETERS

To calculate the different parameters (A, E, b, f, g, C) of the diet multiobjective model (P), the project team, collected almost 177 foods (available on the Moroccan market) while considering the nutrients with positive (respectively negative) effects on the human body; see Table 1 [1]. A survey was conducted in pertinent e-data bases including Pubmed, Google Scholar, HINARI, Cochrane Library, Popline, LILACS, CINAHL, EMBASE, etc., to establish the actual state-of-the-art of the topic investigated. Several nutrient ingredients (minerals, vitamins, other ingredients) data have been studied and the most interesting column is the value of the Glycemic Load (GL). This data was enough to fill the 177 rows of the table representing Food (fruits Vegetables, liquids, etc.) and 26 columns. Unfortunately, these tables are very large and difficult to integrate into our report, (all data are available in [13]).

First, it is noticed that this classification of nutrients into positive and negative is based on the following definition [1]: A nutrient is said to be positive if the excess consumption of this nutrient does not harm the human body (for example, potassium). On the contrary, a nutrient is said to be negative if an excess consumption of this nutrient harms the human body (for example, cholesterol). It should be noticed that even those listed as negative are necessary for life, but the goal of this study, especially the mathematical model, is to maximize their intake below certain limits extracted from DRI recommendations [1] and [12].

Table 1 Basic nutrient

Positive nutrients	Negative nutrients
<i>Calories, Protein, Carbohydrate</i>	<i>Saturated fat</i>
<i>Potassium, Phosphorus, Magnesium</i>	<i>Sodium</i>
<i>Calcium, Iron, Phosphorus, Zinc</i>	<i>Cholesterol</i>
<i>Vb6, Vb12, VC, VA, VE</i>	<i>Total fat</i>

For every 100g of each of the 177 foods, the level of each nutrient considered is assessed; for example, Figure 1 shows the content in 100g of apricot of the different nutrients (on the left positive nutrients, and on the right negative nutrients).

Name of foods	Vitamin A mg /100g	Vitamin C mg /100g	Vitamin E mg /100g	Vitamin B6 mg /100g	Vitamin B12 mg /100g	Calcium mg /100g	Phosphor mg /100g	Magnesium mg /100g	Potassium mg /100g	Iron mg /100g	Zinc mg /100g	Calorie mg /100g	Protein mg /100g	Carbs mg /100g	Sodium mg /100g	Lipids mg /100g	Cholesterol (SFAs) mg/100g	
Apricot	0	5.5	0.6	0.1	0	15.6	16.6	8.7	237	0.3	0.1	49	0.9	1	0.39	0.1	18	0.027

Fig. 1 The content in 100g of apricot of the different nutrients

For illustrative purposes, parts of the table of 177 items are presented in Figure 2 and Figure 3.

Name of foods	Vitamin A mg /100g	Vitamin C mg /100g	Vitamin E mg /100g	Vitamin B6 mg /100g	Vitamin B12 mg /100g	Calcium mg /100g	Phosphor mg /100g	Magnesium mg /100g	Potassium mg /100g	Iron mg /100g	Zinc mg /100g	Calorie mg /100g	Protein mg /100g	Carbs mg /100g	Sodium mg /100g	Lipids mg /100g	Cholesterol (SFAs) mg/100g	
Apricot	0	5.5	0.6	0.1	0	15.6	16.6	8.7	237	0.3	0.1	49	0.9	1	0.39	0.1	18	0.027
Dried apricot	0	1	4	0.2	0	61.2	68.3	36.5	1090	4.3	0.3	271	3.1	53	10	0.51	0.195	0.017
Garlic	0	17	0	1.2	0	17.7	161	20.7	555	1.3	0.8	131	7.9	21.5	17	0.5	0	0.089
Pineapple	0	12	0.1	0.1	0	20.3	11	19.8	170	0.2	0.7	53	0.4	11	1	0.12	1	0.009
Canned pineapple	0	5.5	0.6	0.1	0	15.6	16.6	8.7	237	0.3	0.1	49	0.9	1	0.39	0.1	18	0.027

Fig. 2 The content in 100g of aliments of the different nutrients

Name of foods	Vitamin A mg /100g	Vitamin C mg /100g	Vitamin E mg /100g	Vitamin B6 mg /100g	Vitamin B12 mg /100g	Calcium mg /100g	Phosphor mg /100g	Magnesium mg /100g	Potassium mg /100g	Iron mg /100g	Zinc mg /100g	Calorie mg /100g	Protein mg /100g	Carbs mg /100g	Sodium mg /100g	Lipids mg /100g	Cholesterol (SFAs) mg/100g	
Passion fruit	0	30	0	0.1	0	10.4	67.1	26.7	348	1.6	0.1	84	2.2	9.5	0.1	0.7	0	0.1
Gnouchi	0	5	0.9	0.1	0.0002	5.1	39	18.8	184	0.7	0.5	179	5	34.3	402	2.1	129	0.3
Guava	0	0	0	0.1	0	0	0	0	0	0	0	88	0.4	19.4	0.1	0.9	0	0.3
Sesame	0	0	0	0.8	0	962	604	324	468	14.6	5.7	9.3	17.7	9.3	0.1	49.7	0	7
Sunflower seeds	0	0.5	31.9	1.2	0	94.3	477	364	622	4.9	3.8	642	20.2	15	4.7	51.46	0	0.1
Artichoke	0	8.1	0.6	0.2	0	4.3	18	7.5	262	0.3	0.4	71	1.1	17	0.1	1.2	0	0.1
Artichoke	0	29.5	1	0	0	25.5	25.9	9	187	0.3	0.1	40	0.9	4.8	0.1	0.6	0	0.1

Fig. 3 The content in 100g of aliments of the different nutrients

In addition, several sites and documents were consulted to estimate positive daily nutrition needs [14], [15], [16], [17], [18], and [19]. Table 2 gives estimations of positive daily nutrition requirements of Calories, Protein, Carbohydrate, Potassium, Magnesium, Calcium, Iron, Phosphorus, Zinc, VB6, VB12, VC, VA, and VE(AT).

Table 2 The positive nutrient requirements

Favorable nutrient	Minimum required
Calories	2000 kcal
Protein	91g
Carbohydrate	271g
Potassium	4044mg
Magnesium	380mg
Calcium	1316 mg
Iron	18mg
Phosphorus	1740mg
Zinc	14mg
Vb6	2.4mg
Vb12	8.3µg
VC	155mg
VA	1052µg
VE(AT)	9.5mg

The maximum tolerable daily negative nutrients [20] and [1], Table 3.

Table 3 The negative nutrient requirements

<i>Nutrient negatives</i>	<i>Maximum tolerable</i>
<i>Saturated fat</i>	<i>17 g</i>
<i>Sodium</i>	<i>1779mg</i>
<i>Cholesterol</i>	<i>230mg</i>
<i>Total fat</i>	<i>65 g</i>

The first objective function of the optimal food problem consists of the glycemic vector g . The following formula is used to estimate the range containing the Glycemic Load (GL) content in 100g of each of the 177 foods:

$$GL = \frac{IG \times mass_{carb}(g)}{100}$$

Where IG is the glycemic index of the considered food and $mass_{carb}$ is the mass of carbohydrates in 100g of this food [1].

The notion of GI was developed to categorize dietary carbohydrates relative to their total impact on the level of blood glucose postprandially versus a baseline carbohydrate, typically neat sugar [21]. The GI is meant to reflect the relative suitability of carbohydrate-containing food. Foods whose carbohydrates are easily absorbed and metabolized are high GI ($GI \geq 70$ on the glucose scale), whereas low GI foods ($GI \leq 55$) are slowly assimilated carbohydrates eliciting a lower postprandial glycemic response. Medium GI foods fall between 56 and 69, being equivalent classification to (Low GL: <10 ; Medium GL 11-19; High: $GL >20$) [22].

The values measured for GI and GL are likewise open to fluctuation for many factors including fuzzy measurement of the GI involving the utilization of two benchmark foods and the volatility of GI values according to factors like cooking manner, processing procedure, kind of starch, fiber, sugar, fat and acidity [23].

For example, Table 4 gives the glycemic load contents in 100g of apricot, apricot Dry, Garlic, pineapple, bananas conserve, Artichaut, Asparagus, Eggplant, Veal brain, Chestnut, Shrimp chips, Cabbage White, and Sauerkraut.

Table 4 The content in 100g of foods in glycemic load

<i>Name of the food</i>	<i>Glycemic</i>		
	<i>Min. Value</i>	<i>Med. Value</i>	<i>Max. Value</i>
<i>Apricot</i>	<i>5.13</i>	<i>5.13</i>	<i>5.13</i>
<i>Apricot Dry</i>	<i>15.9</i>	<i>18.55</i>	<i>21.2</i>
<i>Garlic</i>	<i>3.225</i>	<i>3.225</i>	<i>3.225</i>
<i>Pineapple</i>	<i>3.57</i>	<i>3.753</i>	<i>3.936</i>
<i>Pineapple conserve</i>	<i>0</i>	<i>0.313</i>	<i>0.626</i>
<i>Artichoke</i>	<i>0.735</i>	<i>0.735</i>	<i>0.735</i>
<i>Asparagus</i>	<i>0.48</i>	<i>0.48</i>	<i>0.48</i>
<i>Eggplant</i>	<i>0.945</i>	<i>0.945</i>	<i>0.945</i>
<i>Cherry</i>	<i>29.88</i>	<i>29.88</i>	<i>29.88</i>
<i>Veal brain</i>	<i>0</i>	<i>0</i>	<i>0</i>
<i>Chestnut</i>	<i>28.68</i>	<i>28.68</i>	<i>28.68</i>
<i>Shrimp chips</i>	<i>0</i>	<i>0</i>	<i>0</i>
<i>Cabbage white</i>	<i>0.72</i>	<i>0.72</i>	<i>0.72</i>
<i>Cabbage red</i>	<i>0.75</i>	<i>0.75</i>	<i>0.75</i>
<i>Sauerkraut</i>	<i>0.24</i>	<i>0.24</i>	<i>0.24</i>

Concerning the second objective function, the information was gathered from the different Moroccan market; Table 5 shows the price range for 15 foods.

Table 5 The price range of 16 foods

Name of the food	Price		
	Minimum price	Medium price	Maximum price
Apricot	0.9	1.1	1.3
Apricot dried	8.4	2	10
Garlic	4	6	8
Almond	6.9	20.4	33.9
Pineapple	3	3.4	3.8
Pineapple, canned	5.16	7.905	10.77
Artichoke	0.8	1	1.2
Asparagus	0.5	0.64	0.78
Aubergine	0.2	0.5	0.8
Avocado	5	6.5	8
Baguette	0.26	0.67	1.08
Banana	1	1.25	1.5
Beetroot	0.3	0.55	0.8
Egg white (cooked)	0.1	0.11	0.12
Broccoli (cooked)	1.8	2.15	2.5

4. NUMERICAL RESULTS AND ANALYSIS

In this section, multiobjective genetic algorithms MOGA [24, 25] is used to solve the optimal diet problem presented via our model (P). In this context, different models are developed using multiobjective techniques. Using the data, each model was solved with MATLAB software, resulting in different feasible diets that meet the nutritional requirements. In this context, Table 6 presents the values adopted for different parameters of the multiple-objective genetic algorithm used.

Table 6 The features adopted by the genetic algorithm

Characteristics	Values
Intersection	Selection function
Cross-over percentage	0.8
Initialization	Arbitrary
Number of iterations	100 × number of foods
Mutation	Gaussian
Population size	200
Selection function	stochastic uniform

As the glycemic load and the prices of different foods are presented by three values (min, mean, max), nine multiobjective models are considered. In the case of *Model 1*, low glycemic loads and low costs are considered corresponding to the lower bounds of the ranges of glycemic loads of 177 foods and the lower bounds of the food costs. For example, the glycemic load of the dried apricot considered in this case is 15.9 and the considered price of this food, in this case, is 6.8. Table 7 gives the considered models.

Table 7 Nine multiobjective models considered

		Cost		
		Minimum price	Medium price	Maximum price
Glycemic	Min value	Model 1	Model 4	Model 7
	Medium value	Model 2	Model 5	Model 8
	Max value	Model 3	Model 6	Model 9

Figure 4 illustrates the Pareto front of the models proposed by MOGA for low glycemic loads and low costs. Within this framework, it is possible to exploit this non-dominance to diversify the Patient meals over the course of the month. Table 8 gives MOGA’s estimated diet, glycemic load, and cost in *DH*. The main foods in these diets are eggplant, zucchini (cooked), soy milk, lentils, chickpeas, and tea in large quantities. The glycemic load of this diet is 82.91, which is acceptable, while the cost of this diet is 47.17*DH*, which is a reasonable price considering the standard of living of most Moroccans.

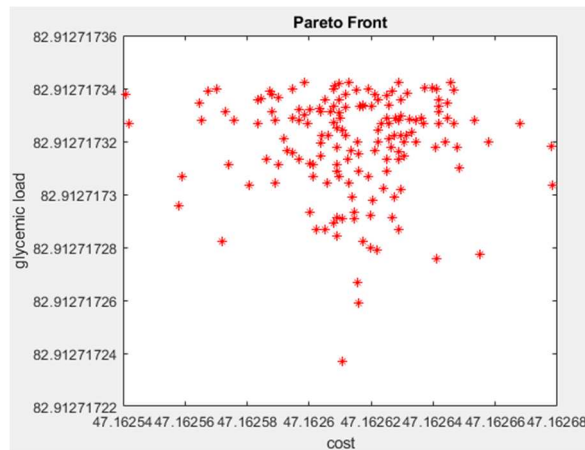


Fig. 4 Pareto front of model glycemic minimum and minimum cost regime

Table 8 Glycemic minimum and minimum cost regime

Name of the food	Regim
Eggplant	5.048E+00
Cooked egg white	1.006E-01
Sauerkraut	1.867E-01
Zucchini	6.000E+00
Soy milk	6.000E+00
Lentil	6.000E+00
Chickpea	4.218E+00
Salsify	2.120E+00
Tea	4.986E+00
Lemon zest	7.926E-01
Glycemic load of diet	82.9127
Cost of diet	47.1626

Figure 5 shows MOGA's Pareto front for low glycemic loads and average costs. Table 9 presents the estimated MOGA diet, glycemic load, and cost in DH. The main foods in these diets are eggplant, Cooked egg white, zucchini, shrimp, Turkey roast, Cooked lamb liver, Plain goat cheese, Soy milk, lentil, Chickpeas, Salasifis, Tea, and Lemon zest in large quantities. The glycemic load of this diet is 82.9127, which is acceptable, while the cost of this diet is 64.5631DH, which is a reasonable price considering the standard of living of most Moroccans.

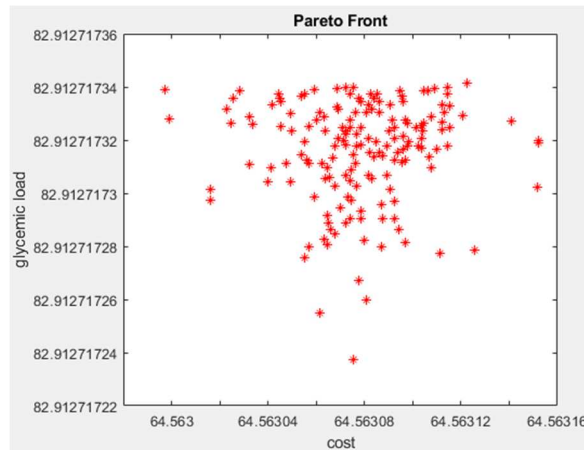


Fig. 5 Pareto front of model glycemic minimum and medium cost regime

Table 9 Glycemic minimum and medium cost regime

Name of the food	Regime
Eggplant	5.04830626
Cooked egg white	0.10063508
Zucchini	6
Shrimp	0.04766646
Turkey roast	0.03809841
Cooked lamb liver	0.07260813
Plain goat cheese	0.02343094
Soy milk	5.99981531
Lentil	6
Chickpeas	4.21812987
Salsifies	2.12013752
Tea	4.98627927
Lemon zest	0.79259588
Glycemic load of diet	82.9127
Cost of diet	64.5631

Figure 6 shows the Pareto front offered by MOGA in the case of low glycemic loads and maximum costs which offers an important diversity. Table 10 gives MOGA's estimated diet, glycemic load, and cost in DH. The main foods in these diets are eggplant, Cooked egg white, shrimp chips, Sauerkraut, zucchini, Salsify, Tea, and Lemon zest in large quantities. The glycemic load of this diet is 82.9127, which is acceptable, While the cost of this diet is 81.9635 DH, which is a reasonable price given the standard of living of most Moroccan people.

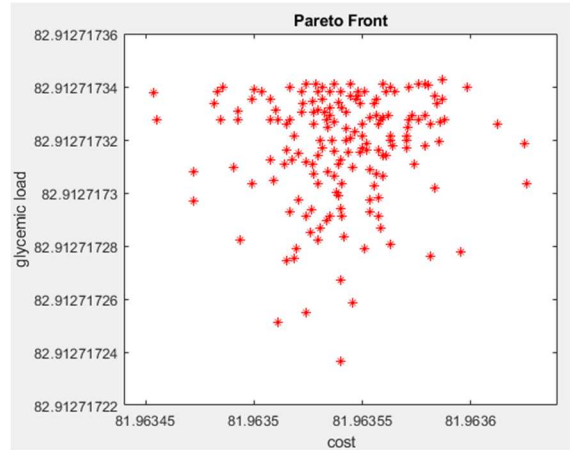


Fig. 6 Pareto front of the minimum glycemic model and maximum cost regime

Table 10 Min glycemic diet and max cost

<i>Name of the food</i>	<i>Regime</i>
<i>Eggplant</i>	<i>5.04830626</i>
<i>Cooked egg white</i>	<i>0.100635081</i>
<i>Shrimp chips</i>	<i>0.010586854</i>
<i>Sauerkraut</i>	<i>0.186717309</i>
<i>Zucchini</i>	<i>6</i>
<i>Salsify</i>	<i>2.120137524</i>
<i>Tea</i>	<i>4.986279271</i>
<i>Lemon zest</i>	<i>7.92595884</i>
<i>Glycemic load of diet</i>	<i>82.9127</i>
<i>Cost of diet</i>	<i>81.9635</i>

Figure 7 shows the Pareto curve of plans offered by MOGA in the case of medium glycemic loads and medium costs offering an important diversity. Table 11 gives MOGA’s estimated diet, glycemic load, and cost in *DH*. The main foods in these diets are eggplant, Cooked egg white, Shrimp, Turkey roast, Raw lamb liver, Lobster, Virgin olive oil, Avocado oil, Soy milk, Lentil, Chickpeas, and Tea in large quantities. The glycemic load of this diet is *83.7798*, which is acceptable, while the cost of this diet is *68.8284DH*, which is a reasonable price considering the standard of living of most Moroccans.

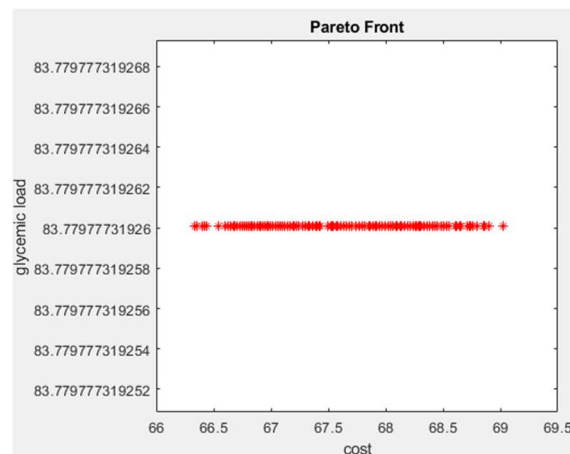


Fig. 7 Pareto front of model medium glycemic and medium cost of the diet

Table 11 *Medium glycemic and medium cost of the diet*

<i>Name of the food</i>	<i>Regime</i>
<i>Eggplant</i>	6
<i>Cooked egg white</i>	0.191101639
<i>Shrimp</i>	0.050002013
<i>Turkey roast</i>	0.323012391
<i>Raw lamb liver</i>	0.033221889
<i>Lobster</i>	0.072608126
<i>Virgin olive oil</i>	0.100191878
<i>Avocado oil</i>	0.027828534
<i>Soy milk</i>	0.09564942
<i>Lentil</i>	6
<i>Chickpeas</i>	6
<i>Salsify</i>	4.220041389
<i>Tea</i>	2.120137524
<i>Lemon zest</i>	4.986279271
<i>Glycemic load of diet</i>	83.7798
<i>Cost of diet</i>	68.8284

The estimated diets are almost equivalent. Indeed, some foods are always present (eggplant, soya milk, lentils, chickpeas, and tea), and rare foods are absent, such as cooked zucchini.

5. CONCLUSION

This paper introduces an original multiobjective programming model with constraints to present the diet problem based on two objective functions: the total glycemic load of the diet and the second one is the cost of the diet. Multiobjective Genetic Algorithm was used (MOGA) to solve the proposed model. In this sense, adequate genetic operators were adopted, particularly mutation, crossbreeding, and breeding strategy. Different food nutrient values were gathered from a recent scientific research paper and from professional and official websites.

Nine models based on different values of the glycemic load and the prices of different foods were examined. The experimental results showed that our system ([proposed Model-MOGA]) produced a balanced regime that makes a compromise between glycemic load and cost while respecting the patient's requirements. In the future, our model will be extended to take into account the stochastic aspect of food prices, glycemic load, and requirements [26] and [27].

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