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A Multiobjective Diet Planning Model for Diabetic Patients in the Moroccan Health Context Using Particle Swarm Intelligence

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Abstract Recommended diets have a central role to play in creating a healthy dietary environment that enables populations to adopt and maintain health-promoting dietary practices. It's well known that foods with a low glycemic load (GL) help release a concentration of glucose in the blood, These can contribute to the prevention of various glycemia-related health problems. We aim to address an optimization model for diets in the Moroccan context that controls both glycemic load and total meal costs. The application of a multiple objective particle swarm method which aggregates the problem's restrictions with optimized objectives functions helps maintain dietary diversity and facilitates the search for trade-offs between objectives and problem-specific requirements.

Keywords Multiobjective Optimal diet, Particle swarm intelligence, Glycemic load, Diabetic patients, Cost of alimentation

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1. Introduction

Diabetic diets are a combination of foods, naturally rich in nutrients and low in fat and calories. In 1971, a report was published by the American Diabetes Society's dietary guidelines [1], Which presents recommendations concerning the impact of adopting recommended diets for the protection of patients with diabetes mellitus. During the same period, studies proposing high-carbohydrate, high-fiber diets for men with diabetes suggest the importance of plant fiber in dietary management and that a low-carbohydrate diet is necessary for diabetes control [2, 3]. One study (1985) involved data on 25,698 people in California, aged between 30 and 89; Asserts the hypothesis that a vegetarian diet (a diet characterized by whole plant foods) can reduce the risk of developing diabetes. Death certificates and diabetes in self-administered questionnaires show that death certificates as well as mortality rates are lower in vegetarians[4]. In addition, since the introduction of the concepts of GI and GL of carbohydrates (the early 1980s), several studies have indicated the importance of choosing bass (IG) and (GL) diets, rather than conventional or high (GI) and (GL) diets [5, 7]. in the treatment of diabetes, as well as in the prevention of other chronic illnesses such as obesity, cancer at cardiovascular sickness [8, 9]. Although diets play a major role in the control and treatment of diabetes, food prices can influence food choice, and these costs can limit the best dietary habits. Our work consists of solving a dietary problem for diabetic patients recently presented in the form of a multi-objective programming model using a multiobjective particle swarm method (MOPSO). Particle Swarm

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Optimization (PSO) is a recently proposed swarm intelligence heuristic algorithm and one of several widely used techniques for dealing with constrained and unconstrained optimization problems[10, 11]. In 1995, Kennedy and Eberhart wrote a research paper in which they introduced The Particle Swarm Optimization (PSO) algorithm which is based on the social behavior of organisms such as birds and bees [12]. They stated that sharing information within the group increases the survival advantage. to achieve a given goal in a common search space where each particle has a certain ability to remember and process information.
In 1998 a new parameter, called inertia weight, was added by Y. Shi et al.[13] to modify the particle swarm optimizer, which has an impact on improving the performance of (PSO). The first attempt to extend the PSO method into a multi-objective problem (MOO) was introduced in [14]. Subsequently, in 2002 Coello et al[15] proposed a multi-objective PSO (MOPSO) as an efficient algorithm for solving multi-objective problems (MOO), which use an external archive in which each particle will deposit its flight experiences after each flight cycle to preserve diversity. A state-of-the-art survey of the different MOPSOs mentioned in the literature, with a classification of each approach according to their main characteristics, is presented in [16]. The procedure of the method (MOPSO) will be discussed in detail in the next section.
The main objective of this work is to treat the multi-objective optimization model for diets that incorporates the glycemic load and the total costs of food combinations recently presented in [17], The use of the glycemic load in menu planning is an advanced method that is extremely useful for people who need to reduce their intake of carbohydrates, particularly sugar, such as diabetics.
The aggregation of constraints with objectives in the (MOPSO) used enables the search for solutions that satisfy both optimization objectives and constraints, as well as the search for trade-offs between objectives and constraints. The resolution of our model enables us to obtain healthy dietary choices that help prevent glycemia-related diseases, and that remain affordable for consumers in the Moroccan context. The rest of our paper is organized as follows: the third section presents the formulation of our diet problem as well as the set of data and constraints and all the symbols adopted in the modeling of our problem, section 4 presents the set of diets provided by our model and a discussion of the numerical results found, and the last section constitutes a conclusion that summarizes the results brought by this work.

2. Multiobjective particle swarm optimizers

In particle swarm optimized, the entire set S of solution candidates to the optimization problem is represented as a particle swarm (each particle refers to a candidate solution) particles carrying information on decision variables or model parameters take up their position in an objective functional space. Then, throughout generations (iterations), each particle keeps its trajectory (personal best solution), which is determined by its best performance and that of its neighbors (self-learning and social learning), Similarly, it tries to change its position using information about its current position, its speed, the distance between the current position and the personal optimum, and the current position and the swarm optimum. The formula for updating the particle velocity and position at each iteration, assuming the particle swarm size is n and the dimension of the search space is d is as follows:

$$V_i^{(k+1)} = \omega V_i^{(k)} + c_1\gamma_1 \times \left(pbest_i^{(k)} - x_i^{(k)}\right) + c_2\gamma_2 \times \left(gbest^{(k)} - x_i^{(k)}\right). \quad (1)$$

where,

$$x_i^{(k+1)} = x_i^{(k)} + V_i^{(k+1)}. \quad (2)$$

The procedure for moving a particle in the (PSO) method is described in the following figure:

i : the i-th individual particle, $i \in [|1, n|]$.
k: is the number of the current iteration.
$x_i^{(k)}$: The particle i's location at step k.
$V_i^{(k)}$: the value of the speed of a given particle i at step k.

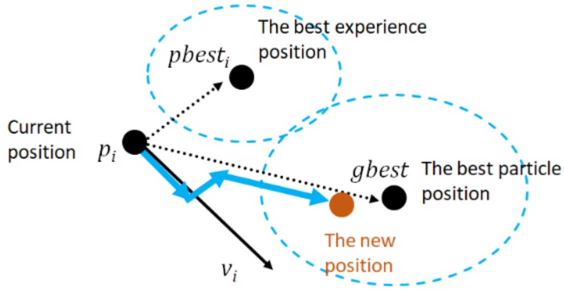

Figure 1. Particle movement in the (PSO) method

$pbest_i^{(k)}$: is the current best location of the particle i in the history of operation k.
$gbest^{(k)}$: referred to as the cluster swarm guide, is the location of the single particle with the best ability value at step k.

ω : the weight of inertia forced on the speed vector, computed for each iteration k as follows:

$$\omega = \omega_{max} - k \times \frac{(\omega_{max} - \omega_{min})}{k_{max}} \tag{3}$$

$\omega_{max}, \omega_{min}$ are the highest and minimum values of the weight of inertia. In most cases, the value is set at 0.9 and 0.4 [4], and k_{max} is the total number of iterations. c_1, c_2 : are the local and global (cognitive and social) learning constants.
γ_1, γ_2 : are random numbers between 0 and 1.
If one particle position updated by a new velocity vector has a fitness value better than its previous best, the new position is assigned as $pbest$.
If one of the particles has the best fitness value than the others, it is assigned as $gbest$. These processes are repeated in a balance between exploration and exploitation until maximum iterations or mini-mum error criteria are not satisfied.

(MOPSO) is an extension of the (PSO) algorithm and is, therefore, a modification of the original (PSO) to be compatible with conflicting multi-objective optimization problems, it's an algorithm that must reach the global Pareto-optimal front and maintain the diversity in the Pareto-optimal front. A summary and discussion of the main changes required for this extension are presented in [16, 18].
The (MOPSO) algorithm uses the same principle as (PSO) such that the velocity and position update equations and all the parameters declared for (PSO) are also identical. The main difference is in the objective function, which contains multiple objectives and there is no single definition or "best" particle in the swarm, Thus, Multi-Particle Swarm Optimization uses the principle of Pareto dominant to assess the effectiveness of swarm optimization. a particle's direction of flight[15] To deal with multi-objective optimization problems, the (MOPSO) algorithm [15] maintains two archives, one to store the globally non-dominant solutions, the other to store the best individual solutions, then a Pareto archived evolution strategy presented in [19] used for diversity maintenance.

3. Formulation of the multiobjective model for ideal meal planning

3.1. About the data set of the diet problem

Diets are the combination of foods consumed over time. The key to understanding the dietary problem is to define foods in terms of their nutritional values, such as glycemic load, vitamins, calcium, phosphorus, magnesium and so on. each food provides the body with beneficial nutrients (Positive nutrients) (e.g. Calories(c), Protein(p),

Algorithm 1 The (PSO) method

for individual i particles in a swarm **do**
    Initialize x_i randomly within $[x_{min}, x_{max}]$
    Initialize V_i with zero
    Assign x_i to $pbest_i$
end for
repeat
for each particle in a swarm **do**
    Assessing an object value function $f(x_i)$
    if $f(x_i) < f(pbest_i)$ **then**
        Assign x_i to $pbest_i$
    end if
end for
Assign particle having best fitness value as the g_{best}
for every (i) particle in a swarm **do**
    Set V_i based on (Eq. 1)
    Set x_i based on (Eq. 2)
end for
Repeat the same procedure toward the maximum number of iterations

Algorithm 2 (MOPSO) algorithm

for each particle i in an swarm **do**
    Initialize x_i randomly within $[x_{min}, x_{max}]$
    Initialize V_i with zero
    Assign x_i to $pbest_i$
end for
repeat
for each particle in a swarm **do**
    Evaluate an objective function $f(x_i)$
    if $f(x_i) < f(pbest_i)$ **then**
        Assign x_i to $pbest_i$
    end if
end for
Initialize non-dominated particles in an external archive
Select a leader
repeat
for each particle i in an swarm **do**
    Set V_i based on (Eq. 1)
    Set x_i based on (Eq. 2)
    Increase diversity
    Evaluate an objective function $f(x_i)$
    if $f\,(x_i < f(pbest_i)$ **then**
        Assign x_i to $pbest_i$
    end if
end for
Maintain non-dominated particles in an external archive
Select a leader
Repeat the same procedure toward the maximum number of iterations

Carbohydrate(car), Potassium (po), Magnesium (mg), Dietary fiber (tdf), Calcium (ca), Iron (ir), Phosphorus (ph), Zinc (z), Vitamin b6 (vb6), Vitamin b12 (vb12), Vitamin C (vc), Vitamin A (va), Vitamin E (ve)), and potentially harmful elements (Negative nutrients) (e.g. saturated fatty acids (sf), Sodium (s), Cholesterol (ch), Total fat (tf)). The daily nutrient requirements of the plant foods available are given in the tables 2 and 1 . The parameters of the model (P) are computed from 177 aliments collected by the team project cited in the acknowledgments section. $x = (x_j)_{j=1,\dots,177}$, is, therefore, the portion vector representing the proportion of food j in the optimal diet, where 177 is the total number of foods available in the diet and from which the nutrient contents of the foods have been derived for 100 g portions. We aim to propose a qualitative and quantitative food composition (an ideal diet x) to achieve a minimal cost and glycemic load, which meets the needs of patients recommended by experts [20, 21], The symbols used to evaluate a diet are described below:
$C^T x$: Total cost of diet where $C = (C_j)_{j=1,\dots,177}$ denotes the vector of prices per unit of 100g of the foodstuffs considered.
$g^T x$: Glycemic load generated by foods composed of the diet.
A: Favorable nutrients matrix; in our case, the dimension of A is (Number of positive nutrients, Number of foods available)= $(16, 177)$;
E: Unfavorable nutrients matrix; in our case, the dimension of E is (Number of negative nutrients (4), Number of foods available (177));
b: The minimum amount of beneficial nutrients required.
f: Maximum acceptable levels of potentially harmful elements
A_c:The number of calories that come from foods that are considered beneficial to health;
c_n and τ_n are respectively the quantities and percentages of calories from the nutrients n in the following set $\{car, p, tf, sf\}$; $\tau_p = 0.18, \tau_{car} = 0; 55, \tau_{sf} = 0.078 \; and \; \tau_{tf} = 0.29$;

3.2. *Mathematical mapping of requirements*

Mapping the body's preferable nutriment requirements.
The total beneficial nutrients for an x food choice is Ax and the requirements are registered in b ; so we have $Ax \geq b$.
The ratio of calories generated by carbohydrates is delimited by the inequality $c_{car}^T x \geq 0.55 \left(A_c^T x\right)$.
The calories from Protein must verify the inequality $c_p^T x \geq 0.18 \left(A_c^T x\right)$.
Unfavorable nutrients needs mapping:
The vector of the total in unfavorable nutrients from the diet x is Ex and the requirements are enregistred in f; so we have $Ex \leq f$.
The total calories from saturated fat are controlled by the inequality $c_{tf}^T x \leq 0.29 \left(A_c^T x\right)$.
The total calories from total fat are controlled by the inequality $c_{sf}^T x \leq 0.078 \left(A_c^T x\right)$.

3.3. *Multiobjectives optimization diet model*

The multi-objective mathematical representation of the diet that minimizes both glycemic loads and cost on the one hand, and meets patients' dietary needs on the other is given by: If a given food i is expensive (i.e. $C^T x$ is very large), then its negative nutrients are low (i.e. $x^t E^t E x$ is low), its positive nutrients are high (i.e. $x^t A^t A x$ is hight), its glycemic load is low (i.e. $g^T x$ is low). Thus $C^T x + K_1 \|Ax - b\|^2$ is contradictory with $g^T x + K_2 \|Ex - b\|^2$. Then, we have the following reduced multiobjective optimization problem:

$$(P) : \begin{cases} Min \; C^T x + K_1 \|Ax - b\|^2, Min \; g^T x + K_2 \|Ex - f\|^2 \\ \quad Subject \; to : \\ \qquad c_i^T x \geq \tau_i \left(A_c^T x\right) \qquad i \in \{car, p\} \\ \qquad c_i^T x \leq \tau_i \left(A_c^T x\right) \qquad i \in \{tf, sf\} \\ \qquad x \geq 0 \end{cases} \tag{4}$$

The constants K_1 and K_2 are chosen to make compromise between $C^T x$ and $\|Ax - b\|$ and between $g^T x$ and $\|Ex - f\|$, respectively.
It is important to note that mathematical programming models of feeding problems do not take into account the variability of nutrients in foods. Recall artificial intelligence techniques [22, 23, 24, 25, 26, 27] in particular fuzzy logic [28, 29, 30, 31] are being used to deal with the uncertainty associated with the parameters of the diet problem. Our problem was first presented in [20] in which the objectives are robust and presented separately as two single-objective robust optimization problems. The fact of the uncertain glycemic load in this problem was modeled in another way using quadratic and integral fuzzy methods [32, 33]. subsequently, we have previously treated this regime model as a multi-objective programming model in [17] and solved using multi-objective genetic algorithms (MOGA), which is destined by the use of genetic operators which is also efficient to converge to optimal schemes for this problem.

4. Model resolution and results

4.1. Computation of the proposed multiobjective model parameters

To evaluate a diet, we estimated the parameters of our model (P) based on 177 foods available in the Moroccan food environment, the nutrient content of each 100 g of these foods is described as 14 positive nutrients, and 4 negative nutrients, in this sense, the imprecision of the quantity of these nutrients have been taken into account, as an illustration, figure2 presents the nutrient contents considered for a 100 g portion of fruit (apricot). Other

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 mg/100g	(SFAs)
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

Figure 2. The amount of nutrients per 100g of apricot

examples are given in figures 3 and 4(dried apricot, garlic, pineapple and glazed pineapple).
Daily dietary requirements for positive nutrient minimums and tolerable maximums for potentially harmful

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 mg/100g	(SFAs)
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

Figure 3. The amount of nutrients per 100g of dried apricot, garlic, pineapple and glazed pineapple.

nutrients are estimated on the basis of U.S. Department of Agriculture guidelines and recommendations [20, 34], i.e. recommended daily allowances sufficient to meet nutritional needs.

The main objective of the optimal diet problem was the g glycemic load vectors. Glycemic load is a very useful indicator for classifying carbohydrate-containing foods, by measuring their impact on the body and blood sugar levels. In particular, how it is stored: as fat or glycogen reserves. According to researchers at the University of Sydney, who were among the first to study the glycemic load, a GL can be calculated using the following formula [21]:

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 mg/100g	(SFAs)
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

Figure 4. The number of nutrients per 100g of passion fruit, gnocchi, guava, sunflower seeds, sesame, and artichoke.

Table 1. The negative nutrient requirements

Potentially harmful elements	Maximum tolerable
Saturated fat (sf)	17 g
Sodium (s)	1.779mg
Cholesterol (ch)	230mg
Total fat (tf)	65g

Table 2. Nutrient requirements for beneficial nutrients

Nutriments favorables	Minimum requirements
Calories (c)	2000 kcal
Protein (p)	91 g
Carbohydrate (car)	271g
Potassium (po)	4044 mg
Magnesium (mg)	380 mg
Calcium (ca)	1316 mg
Iron (ir)	18mg
Phosphorus (ph)	1740 mg
Zinc (z)	14 mg
Vitamin b6 (Vb6)	2.4 mg
Vitamin b12 (vb12)	8.3 μg
Vitamin C (vc)	155 mg
Vitamin A (va)	1052 μg
Vitamin E (ve)	9.5 AT

$GL = (GI\times$ the amount of carbohydrate) divided by one hundred such as (GI) is the glycemic index of the food, a table of glycemic index values for different foods can be found in [35]. A Glycemic Load below 10 units is considered low, while above 20 units it is considered high. We used the ranking equation described above to estimate the values (minimum, average, maximum) of the glycemic load, part of these values are given in the table 3. Concerning feed costs, a study of the various regions of Morocco has enabled us to determine the price margins

Table 3. The level of glycemic load contained in any 100g portion of certain foods

Aliments	the quantity in GL		
	low	***medium***	***high***
Apricot	5.13	5.13	5.13
apricot Dry	15.9	18.55	21.2
Garlic	3.225	3.225	3.225
ppineaple	3.57	3.753	3.936
ananas conserve	0	0.313	0.626
Artichaut	0.735	0.735	0.735
Asparagus	0.48	0.48	0.48
Eggplant	0.945	0.945	0.945
Cherry	29.88	29.88	29.88
Veal brain	0	0	0
Chestnut	28.68	28.68	28.68
Shrimp chips	0	0	0
Cabbage white	0.72	0.72	0.72
Cabbage red	0.75	0.75	0.75
Sauerkraut	0.24	0.24	0.24

for each feed, some of these prices are shown in the following table. 4

Table 4. Costs of some adopted foods

	Cost		
	low	***medium***	***high***
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

4.2. Numerical results

In this section, we have used the multiobjective particle swarm optimizer (MOPSO) to solve the multiobjective regime problem model proposed in Section 3. The (MOPSO) method is applied by aggregating the constraints and the two objective functions using the following penalty parameters: Penalization parameters (GLp) for glycemic load, (Cstp) for diet cost, Favp for the favorable nutrient gap, and (Unfavp) for the unfavorable nutritional gap. These parameters have been varied in the interval [0.2 1] with a step of 0.2 thus we have solved 625 multi-objective problems.

The parameters of the adopted particle swarm optimizer are given by : Swarm Size=100, MaxIterations=500, pswcreation='uniform density', Inertia Range interval= [0.1,1.1], Minimum Neighbors Fraction= 0.25, Self Adjustment Weight= 1.49, Social Adjustment Weight= 1.49.
The following figure 5 shows the Pareto Front (non-dominated solution) obtained for our diet problem (P), in which 6 diets (optimal solution) were established taking into account the compromise between glycemic loads and total diet cost and respecting problem constraints. The objective values of the solutions found, along with the gaps in

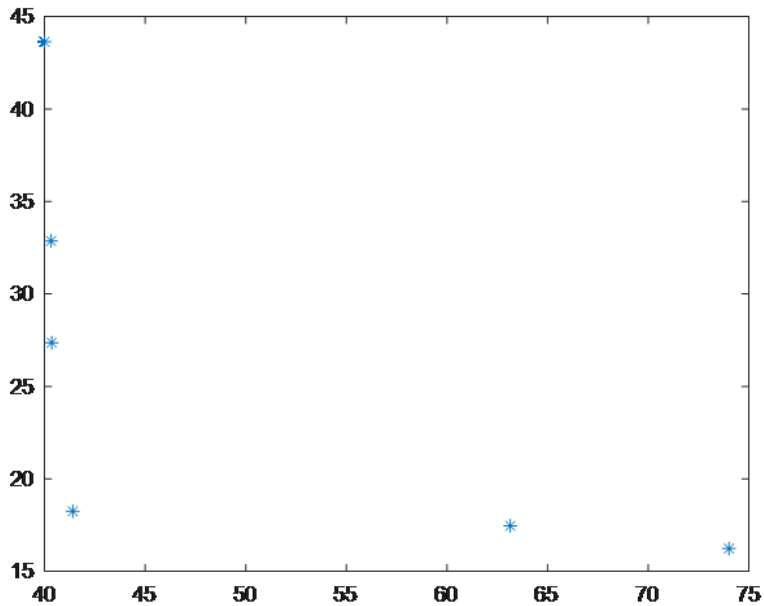

Figure 5. Pareto curve basing on 625 simulations

nutritional requirements and the weight of each diet, are shown in the table 5

Table 5. Objective values for the 6 food combinations identified by our model

Diet	Total glycemic load	Diet price (MD)	Favorable nutrients gap (mg)	Unfavorable nutrients gap (mg)	Weight of the diet g
1	40.36	27.37	1762.79	25.90	35.62
2	40.33	32.87	972.82	264.88	20.23
3	74.01	16.23	908.05	56.41	19.72
4	40.00	43.64	1172.54	223.69	27.94
5	41.41	18.25	690.97	181.17	17.90
6	63.14	17.47	1043.55	53.78	15.57

Dietary recommendations often consider the average acceptable glycemic load of a balanced diet to be less than 100 per day, so it's clear that all the food combinations identified by our model generate acceptable average glycemic loads to help prevent glycemia-related diseases.

The application of (MOPSO) approaches in multi-criteria optimization often enables efficient exploration of the solution space in search of diversified solutions that also respect the possible problem requirements, From Table 6, we can see that almost all the diets generated are generally diversified and healthy, rich in vegetables, fruit, and lean proteins, so they are beneficial and recommended for people with diabetes, as well as being part of a daily diet and

Table 6. Penality parameters and different obtained diets

Diet	GLp	Cstp	Favp	Unfavp	Diet
1	0.4	0.4	0.8	0.6	Lime (6) ;Cooked zucchini (6) ; Grapefruit juice (6) Goat's milk (4);Onion (6) ; Tea(2) ; Tomato(6) .
2	0.4	0.6	0.8	0.2	Sesame seed (1);Coconut(6); Orange(6); Raw whiting fish (2) ;.
3	0.6	0.6	0.2	0.6	Eggplant (6);Clementine(6); Sesame seed(1); Melon(6) ; Roasted pigeon(1).
4	0.6	0.8	1	0.2	Egg white cooked (6);Sesame seed (1); Orange juice (6); Goat milk (6); Soy milk (6); Salad (2); Green salad without oil (2)
5	0.8	0.2	0.6	0.8	Cooked zucchini (6); Crab (1); Raw lamb liver (1); Sesame seed (1); Grape juice (6); Green salad without oil (4)
6	1	0.4	0.4	0.4	Clementine (6) ; Sesame seed (1); Green salad without oil(2)

well known in Moroccan eating habits. On the other hand, people should limit their intake of fatty, carbohydrate-rich foods, and reduce alcohol consumption. In addition, the prices presented in table 5 show that the cost of food in the diets found is within reach of the cost of living in Morocco. The results obtained by the multi-objective particle swarm optimizer for 500 iterations with the following Penalization parameters of the glycemic load GLp= 0.8, the diet price Cstp=0.2, the favorable nutrient deviation Favp=0.6 and the unfavorable nutrient deviation Unfavp= 0.8 are shown in the following figures 6, which provide a best-value function.

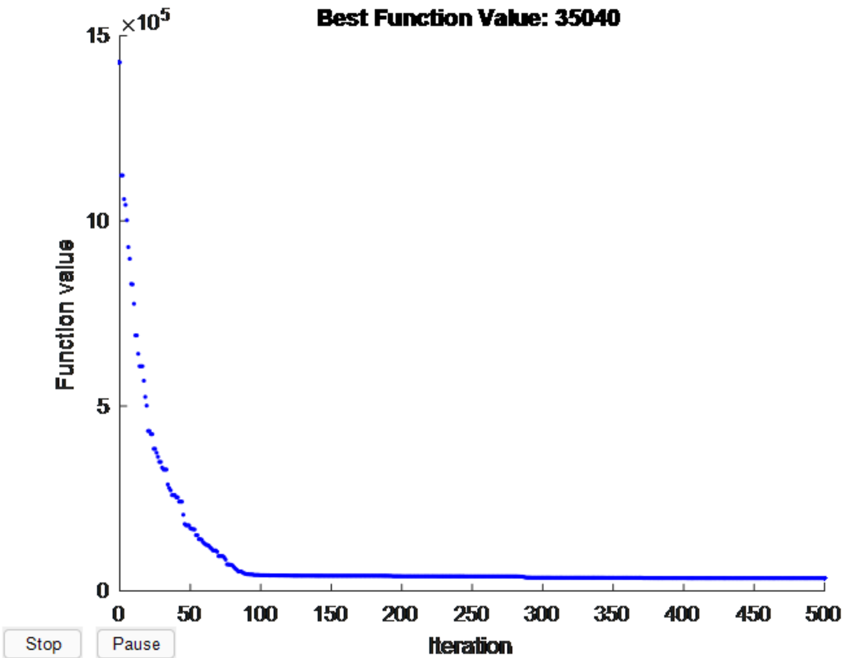

Figure 6. : Multi-objectives Particule Swarm Optimizer with GLp=.8 ; Cstp=.2 ; Favp=.6 ; Unfavp= .8

5. Conclusion

In this article, we aim to address a dietary problem for diabetics that focuses on minimizing glycemic load while taking into account food costs and the essential nutritional requirements for the human body recommended, this problem is presented with the aim of a multi-objective diet model. Applying a particle swarm optimization approach enables us to find better trade-off solutions that provide healthy diets that are better at controlling blood sugar levels and preventing diabetic complications. on another hand, the costs of the different diets found are appropriate for an economically comfortable diet in the Moroccan region. The nutrients in the different diets found are fruits, vegetables, and whole grains. This type of diet is the best diet for almost everyone.

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