International Core Journal of Engineering Volume 6 Issue 12, 2020
ISSN: 2414-1895 DOI: 10.6919/ICJE.202012_6(12).0040

Research on Optimization of Nutritional Meal Based on Particle Swarm Optimization

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Abstract

Nutritional catering is of great significance to ensure that customers absorb enough nutrition and satisfy people's nutritional diversity. This article analyzes the basic requirements and rules of nutritional catering, constructs a mathematical model of the catering problem, optimizes the nutritional catering system with the help of particle swarm algorithm, gives the results of nutritional catering, and verifies the feasibility of the system model.

Keywords

Particle swarm algorithm; Mathematical model of nutritional catering; Optimal solution.

1. Introduction

With the development of society and economy, people want to improve the unscientific dietary structure and obtain more scientific and reasonable nutritional meals to ensure the nutritional requirements needed for daily life and work. Meal catering, in fact, is to ensure a considerable amount of calories to meet the physical consumption of the day, and also to meet the balance of various nutrients in the food, that is, to adopt scientific nutritional catering [1]-[3].

Due to the wide variety of nutritional requirements and to meet the needs of multiple customers in a short time, it is necessary to find an optimized nutritional catering system to improve the efficiency of nutritional catering. This paper studies the optimal design of nutritional catering based on particle swarm algorithm, so that the designed catering system can meet the requirements of different nutritional elements required by the human body.

2. Nutritional Catering Model

2.1 Brief Description of the Problem

People have to consume a certain amount of nutrient element food every day to meet people's normal needs for daily energy and nutrient elements. If the nutritional requirements of food are not met for a long time, the energy intake is not nutritious, which will damage the health of the body. Therefore, a scientific diet structure is very important to support the health of the body.

Nutrition refers to the natural process of growth and development, body metabolism, etc., through the intake of nutrients in food. Nutrition is a discipline that studies this field and related fields. Nutrients, including protein, fat, trace elements, etc., are called nutrients. Nutritional catering is to calculate the nutrient content of the food according to the substances needed by the individual, to help us formulate the menu and get more beneficial energy and nutrients.

2.2 Mathematical Model

Assuming there are *n* types of food, each type of food has *m* nutritional components, and a_{ij} is used to represent the actual quantity of the *i*-th nutrient contained in each gram of the *j*-th food, and the total nutrition of all foods is described as [4]:

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$$A_{m*n} = \begin{bmatrix} a_{11} & a_{12} \cdots & a_{1n} \\ a_{21} & a_{22} \cdots & a_{2n} \\ a_{m1} & a_{m2} \cdots & a_{mn} \end{bmatrix} = a_{ij}, i = 1,2,\cdots,m; j = 1,2,\cdots,n \quad (1)$$

Assuming that the set of actual weights of n kinds of food is X, then $\mathrm{x}_{n*1} = (\mathrm{x}_1, \mathrm{x}_2, \cdots, \mathrm{x}_n)^T \in R^n$ is the decision quantity (x_j is the weight of the j-th food, and $\mathrm{x}_j \geq 0$).

The total number of nutrients is represented by the set B, then B is the expected value vector $B_{m*1} = (b_1, b_2, \cdots, b_m)^T$, which is the daily nutrient requirement.

The goal of nutritional catering is to minimize the error between the nutrition contained in the food and the expected nutritional value, that is, the objective function is described as,

$$\min z_i = \left|\sum_{j=1}^{n} a_{ij} x_j - b_j\right| i = 1,2,\cdots,m \quad (2)$$

3. Particle Swarm Optimization Algorithm

3.1 Fundamental Theory

Particle Swarm Optimization (PSO) was proposed by Kennedy and Eberhart by mimicking the migration and gathering activities of birds in the hunting process of human life. The calculation method of the particle swarm is a search algorithm among species groups. In the process of evolution, the particle uses the method of catching up with two extreme values to innovate itself. The individual extreme value is the optimal solution found by the particles themselves, and the group extreme value is the optimal solution found by all particles. With the help of individual extremum and group extremum, each particle searches for the optimal value.

In a D-dimensional search range, N particles form a group, and the position of the i-th particle is represented as a D-dimensional vector,

$$x_i = (x_{i1}, x_{i2}, \cdots, x_{id}), i = 1,2, \cdots N \quad (3)$$

The flying speed of the i-th particle is also a D-dimensional vector, denoted as,

$$v_i = (v_{i1}, v_{i2}, \cdots, v_{id}), i = 1,2, \cdots N \quad (4)$$

The individual extreme value of the i-th particle is recorded as,

$$P_{best} = (p_{i1}, p_{i2}, \cdots, p_{id}) i = 1,2, \cdots N \quad (5)$$

The group extremum of all particles is denoted as,

$$g_{best} = (g_1, g_2, \cdots, p_d) \quad (6)$$

After finding the individual extremum and the group extremum, the particles update their speed and position in the following way,

$$v_{ij}(t+1) = v_{ij}(t) + c_1 r_1(t)\left[p_{ij}(t) - x_{ij}(t)\right] + c_2 r_2(t)\left[p_{gj}(t) - x_{ij}(t)\right] \quad (7)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (8)$$

Among them, c1 and c2 are learning factors, also known as acceleration constants; r1 and r2 are average random numbers in the [0, 1] space, which increases the chance of particle flight.

3.2 Main Parameters

(1) Population size

The selection of the particle population size depends on its own topic, the number of particles under normal circumstances is 20-50. When the research problem is relatively simple, the population size is selected as 10, and a better result can be obtained. When the research problem is relatively complex, 100~200 particles can reach a better solution, but the algorithm runs longer.

(2) Inertia weight

Inertial weights are used for the development and exploration capabilities of control algorithms. When the inertia weight is small, the global optimization ability is weaker, and its local optimization ability is stronger. There are two types of inertial weights, fixed weights and time-varying weights.

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The fixed inertial weight enables the particles to maintain the same exploration and development capabilities, while the time-varying inertial weight enables the particles to have different development and exploration capabilities.

(3) Acceleration constants c1 and c2

The acceleration constants c1 and c2 adjust the maximum step length of flight in $\mathrm{P_{best}}$ and $\mathrm{g_{best}}$ directions respectively, reflecting the information exchange between particles. If c1=c2=0, the particles are far away from the boundary or even fly away from the boundary, and it is difficult to find the optimal solution. When c1=0, it belongs to the "social" model, the particle cognitive ability is lacking, and there is group experience. Although the convergence speed is faster, it is easy to fall into the local optimum. When c2=0, it is a "cognitive" model, there is no social shared information, and the probability of finding the optimal solution is small.

(4) Maximum speed of particles

The maximum speed limit of the particle is $\mathrm{V_{dmax}}$, keeping the speed in [-$\mathrm{V_{dmax}}$, +$\mathrm{V_{dmax}}$]. The $\mathrm{V_{dmax}}$ parameter is very important. If the value is too large, the particles will fly out of the predetermined search space, making it difficult to find the optimal solution. If the value is too small, the particles may not be able to adequately detect areas outside the local optimal area.

(5) Boundary condition processing

When the orientation or velocity of one dimension or many dimensions is higher than the set value, the boundary condition processing strategy can be selected to limit the particle orientation within the searchable range. In this way, the expansion and divergence of the species population can be prevented, and at the same time, the blind follow-up search in large areas of particles can be prevented, and the search efficiency can be improved. The general approach is to set the maximum azimuth constraint $\mathrm{X_{max}}$ and the maximum velocity constraint $\mathrm{V_{max}}$. When the maximum azimuth or the maximum velocity is higher, a value is randomly generated in the interval instead, or it is set to the maximum value, that is, boundary absorption.

4. Nutritional Catering based on Particle Swarm Algorithm

4.1 Implementation P

The food is divided into three categories: porridge, vegetables and staple food, and several dishes from each category are randomly selected to form a recipe for the day. There are 7 foods in the recipes studied in this article, including steamed buns, rice, pancakes, spinach, potatoes, chicken, and eggs. There are 13 kinds of nutrients involved in this study, including calories, protein, fat, carbohydrates, vitamin A, vitamins, calcium and iron. The expected output of catering is shown in Table 1.

According to formula (1), combined with the research content of this article, the nutrition coefficient matrix is described as,

$$A_{13*n} = \begin{bmatrix} a_{11} & a_{12} \cdots & a_{2n} \\ a_{21} & a_{22} \cdots & a_{3n} \\ a_{131} & a_{132} \cdots & a_{13n} \end{bmatrix} \tag{9}$$

Each particle represents a way of catering, and the fitness function is,

$$\min z_i = \left|\sum_{j=1}^{n} a_{ij}x_j - b_j\right| i = 1,2,\cdots,13 \tag{10}$$

Evaluate each particle according to the fitness function, and record the individual extreme value and the group extreme value.

The flow chart of using particle swarm algorithm to realize nutritious meal [5] [6] is shown in Figure 1. The steps are summarized as,

(1) Set algorithm parameters, including population size, number of iterations, etc.;

(2) Initialize the particles randomly, and calculate the initial individual extreme value and population extreme value according to the fitness function;

ISSN: 2414-1895 DOI: 10.6919/ICJE.202012_6(12).0040

(3) According to individual extreme value and population extreme value, update each particle;

(4) Calculate the fitness of the updated particles, record individual extreme values and population extremes;

(5) Judge whether it reaches the maximum number of iterations, if it reaches, stop the iteration and output the population extremum; otherwise, return to step (3).

(6) According to the extremum of the population, get the current way of nutrition catering.

Table 1 Expected output of nutritional catering

Number	Nutrient	Expected Output
1	calories (kcal)	2000
2	protein (g)	60
3	fat (g)	40
4	carbohydrates (mg)	600
5	iron (mg)	18
6	Zinc (mg)	13
7	selenium(μg)	40
8	Retinol (μg)	600
9	vitamin E(mg)	8
10	Thiamine (mg)	1.0
11	Riboflavin (mg)	1.0
12	niacin (mg)	20
13	vitamin C(mg)	40

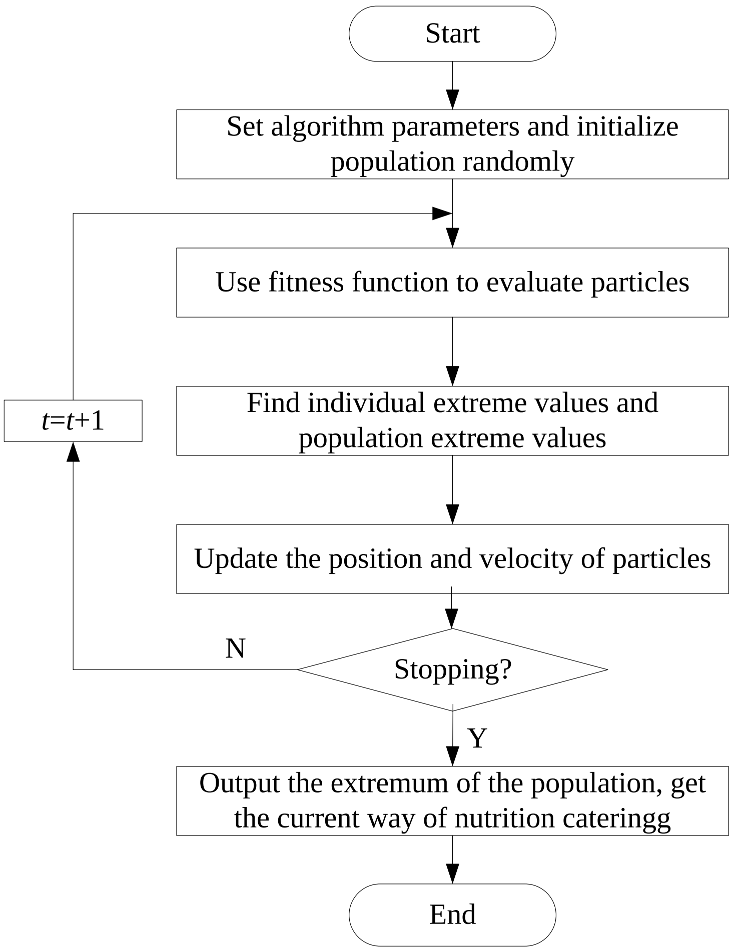

Figure 1 Flow chart of nutrition catering based on particle swarm

ISSN: 2414-1895
DOI: 10.6919/ICJE.202012_6(12).0040

4.2 Experimental results

Using MATLAB software to simulate, according to the calculation process shown in Figure 1, the optimal results obtained are: steamed bread 230g, rice 550g, pancake 215.57g, spinach 56.02g, potato 171.28g, chicken 96.98g, egg 51.61g. The comparison of nutrient output and expected output of this nutrient catering method is shown in Table 2. It can be seen that, except for the larger errors of thiamine and riboflavin, the errors of other nutrients are all smaller, indicating that the particle swarm algorithm can be used to obtain a more balanced meal preparation method.

Table 2 Comparison of expected output and actual output of nutritional catering

Nutrient	Expected Output	Actual output	Catering deviation	error(%)
calories (kcal)	2000	2057.91	57.91	2.41
protein (g)	60	67.63	7.63	9.53
fat (g)	40	42.31	2.31	3.85
carbohydrates (mg)	600	588.45	-12.55	1.56
iron (mg)	18	18.83	0.83	4.15
Zinc (mg)	13	8.80	-4.20	28
selenium(μg)	40	49.98	9.98	19.96
Retinol (μg)	600	571.55	-28.45	3.55
vitamin E(mg)	8	7.98	0.02	0.2
Thiamine (mg)	1.0	0.29	-0.71	59.1
Riboflavin (mg)	1.0	0.53	-0.47	39.1
niacin (mg)	20	19.31	-0.69	2.76
vitamin C(mg)	40	44.16	4.16	6.93

5. Conclusion

This paper discusses the problem of nutritional catering based on particle swarm algorithm, and constructs a mathematical model according to the goal of nutritional catering. The basic principles and main parameters of the particle swarm optimization algorithm are introduced, and the nutrient catering problem is optimized with the aid of the particle swarm algorithm. MATLAB software is used for simulation calculation, and the results show that the error between the actual output nutrient and the expected nutrient is small, and the purpose of nutritious meal is achieved.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (grant number 61901350); Science Research Fund of Xi'an Aeronautics University (grant number 2019KY0208).

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