Scholar Publishing Group
International Journal of Sports Technology
https://doi.org/10.38007/IJST.2022.030301
ISSN 2789-7141 Vol. 3, Issue 3: 1-20

Wireless Network Multimedia Communication and Multi-Objective Evolutionary Algorithm and Its Female Athlete's Nutritional Diet Model

Jumshid Ulah Khana*

Commune d'Akanda, Gabon

**corresponding author*

Keywords: Wireless Network Multimedia, Multi-objective Evolutionary Algorithm, Nutritious Diet, Nutritional Structure

Abstract: With the improvement of people's living standards and quality of life, health and health care as an emerging industry has begun to flourish, and people have begun to pay attention to dietary nutrition issues to improve their physical fitness and quality of life. This article aims to study wireless network multimedia communication and multi-objective evolutionary algorithm and its female athletes' nutritional diet model. This article first introduces the multimedia organization model in wireless networks, and studies the transformation of the planning problem of the multi-objective evolutionary algorithm, and proposes the preferred multi-objective evolutionary algorithm. A flow chart of the realization process of the dietary nutrition model of the multi-objective evolutionary algorithm is given, and then the nutritional diet of athletes is investigated based on wireless network multimedia communication, and the dietary nutritional status of the athletes is studied based on the multi-objective evolutionary algorithm. The experimental research results show that based on wireless network multimedia communication and multi-objective evolutionary algorithm, the research findings of its female athletes' nutritional diet model, basically, only 50% of the athletes' diets meet the needs of athletes' sports, which indicates that it is necessary to strengthen the propaganda of athletes' dietary rules and health, so as to ensure that athletes can compete on the field with sufficient energy.

1. Introduction

Since the beginning of the new century, food has gradually been regarded as an important source of health. In recent years, with the development of a sustainable economic system, people's living standards have been greatly improved. There is an increasing demand for health care doctors, but due to the high fees for health care, some people below the middle level cannot afford such expenses. At the time, it is necessary to develop a dietary decision support system that combines information technology with dietary nutrition. Promoting the popularization of nutrition knowledge will bring huge economic value and social significance to social development.

Scientific and reasonable dietary nutrition is very important to human health and social development. Today, food production is developing rapidly, and humans have also made considerable progress in nutrition. However, in some poor areas, malnutrition is still widespread. In some affluent areas, certain over-nutrient diseases are also on the rise. Guiding people to eat reasonably is an arduous task undertaken by society.

According to the research progress at home and abroad, different scholars have also made corresponding investigations in the research of multi-objective algorithms and female athletes' nutritional diet model: Pilis K introduced nutritional status and its relevance to the physical determinants of training athletes and sports students. It was found that the examined women used an abnormally low energy diet with too low carbohydrate content, which was more useful relative to the absolute amount of protein, fat and carbohydrate consumed [1].Barrett SL used 218 former NCAA first-level female college athletes who had retired 2-6 years to empirically test an established theoretical model of eating disorders. Through the structural equation model, the author examined the direct and indirect relationship between the latent variables, while controlling the body mass index and the number of years after retirement. The model fits the data well and supports the direct and indirect relationship between the assumed variables [2].In order to study the influence of dietary patterns on athletes' nutritional status, Kaur H collected data on athletes' general profiles, anthropometric measurements, hemoglobin levels, diet and nutritional intake. Various parameters of the nutritional status of vegetarian and non-vegetarian male and female athletes were compared [3].Jake B studied the nutritional status and cardiovascular health indicators of two groups of female athletes of the same age and competition period, and found that the dietary intake of gymnasts was not ideal. This may be reflected in the differences in anthropometric and cardiovascular indicators between gymnasts and swimmers [4].The purpose of the Dickey JP study was to measure the impact of the combination of sports nutrition counseling and active life guidance on sports nutrition knowledge and the resulting changes in the dietary behavior of a group of female college rowers. The results of the study showed that the current interventions had a positive impact on participants' knowledge of sports nutrition, but did not lead to positive changes in dietary behavior [5].Escalante discussed the damage to health and exercise caused by lack of proper nutrition, and discussed recommendations on proper nutrition guidelines to safely reduce body fat, increase muscle mass, and improve overall athletic performance [6].Cao B proposed a distributed parallel co-evolutionary multi-objective evolutionary algorithm based on message passing interface MPI, using multi-objective test suites Deb-Thiele-Laumanns-Zitzler and Walking-Fish-Group to check the proposed algorithm. Experimental results show that the new algorithm has better performance consumption in terms of optimization results and time [7].Wang P proposed a multi-objective evolutionary algorithm based on dual space density. Define the dual-space density to reflect the diversity of the target space and decision space. Based on the dual-space density, propose TSD mating options to balance the convergence and diversity of the population; Experimental results show that the algorithm is competitive with the most advanced design selected [8].However, these studies did not discuss the multi-objective evolutionary algorithm in the nutritional diet of athletes, and did not combine the two to illustrate the problem.

The innovations of this article are mainly reflected in:(1) Introduced the multimedia organization model of heterogeneous wireless networks, studied the transformation of planning problems of multi-objective evolutionary algorithms, and proposed a preferred multi-objective evolutionary algorithm;(2) Based on wireless network multimedia communication, the athlete's nutritional diet was investigated and researched, and the athlete's dietary nutritional status was studied based on the multi-objective evolutionary algorithm.

2. Methods of Wireless Network Multimedia Communication and Multi-Objective Evolutionary Algorithm and Its Female Athletes' Nutritional Diet Model

2.1. Multimedia Organization Model of Heterogeneous Wireless Network

The organization of heterogeneous wireless networks is mainly manifested in three aspects: The physical expansion of wireless networks, the collaboration of wireless network resources, and the interoperability of wireless network protocols, currently focus on different researches [9].This chapter will mainly discuss the first two aspects. Network protocol intercommunication will be discussed in detail in Chapter 5 Network Protocol. Judging from the evolution of the current heterogeneous wireless network organization, it can be roughly divided into three categories: networks with cellular networks as the core; wireless Mesh networks; and wireless ad hoc networks based on P2P. The descriptions are as follows [10].

Currently, there are mainly three types of heterogeneous wireless network organization models centered on cellular networks: ICAR, ODMA, and A-GSM.

(1) ICAR

The integrated cellular ad hoc relay system (ICAR) is an integrated ad hoc system proposed by the cellular system for the unbalanced traffic and expanding the system capacity. For the cell with heavy load, the mobile terminal transfers the traffic to other cells with the help of ad hoc relay station (ARS).In this way, the imbalance of business flow can be avoided, and the probability of network congestion can be reduced. While the system balances network traffic, it effectively improves system capacity, expands coverage, and reduces node energy consumption. In order to improve the success rate of load transfer and improve the stability of the system, three relay strategies are proposed: active relay, backup relay and overlapping relay [11].

In this organizational model, by designing a reasonable number of nodes, ARS placement and coverage ratio can greatly increase the system capacity. However, because the location of ARS depends on the cellular network, it can only increase the capacity of the cellular network, but cannot expand the wireless network coverage. In addition, if the hot spot area is large and multiple adjacent cells are involved, multi-hop ARS relays are required, which affects communication efficiency and delay. In the ICAR system, node roles are not equal. Regardless of the mobile terminal's computing power, it needs to be forwarded through ARS, which cannot make full use of the terminal's resources [12].

(2) ODMA

ODMA is an opportunity-driven multiple access mechanism proposed by the UMTS standardization organization 3GPP in the TR25.924 specification [13]. ODMA is not a true multi-access technology. ODMA divides a long communication path transmission into a series of shorter communication path transmissions through a relay mode, thereby reducing transmission energy consumption, reducing coverage blind spots, and avoiding mutual interference as much as possible [14]. In this mechanism, both Node-B and mobile terminals with stronger capabilities can be used as relay nodes. ODMA also divides the coverage area of Node-B into a high-rate coverage area and a low-rate coverage area according to the transmission rate between the terminal and the Node-B, as shown in Figure 1.The mobile terminal located in the low-rate coverage area passes through the Node-B and other mobile terminals in the area through multi-hop relay, and its transmission rate can be improved [15].

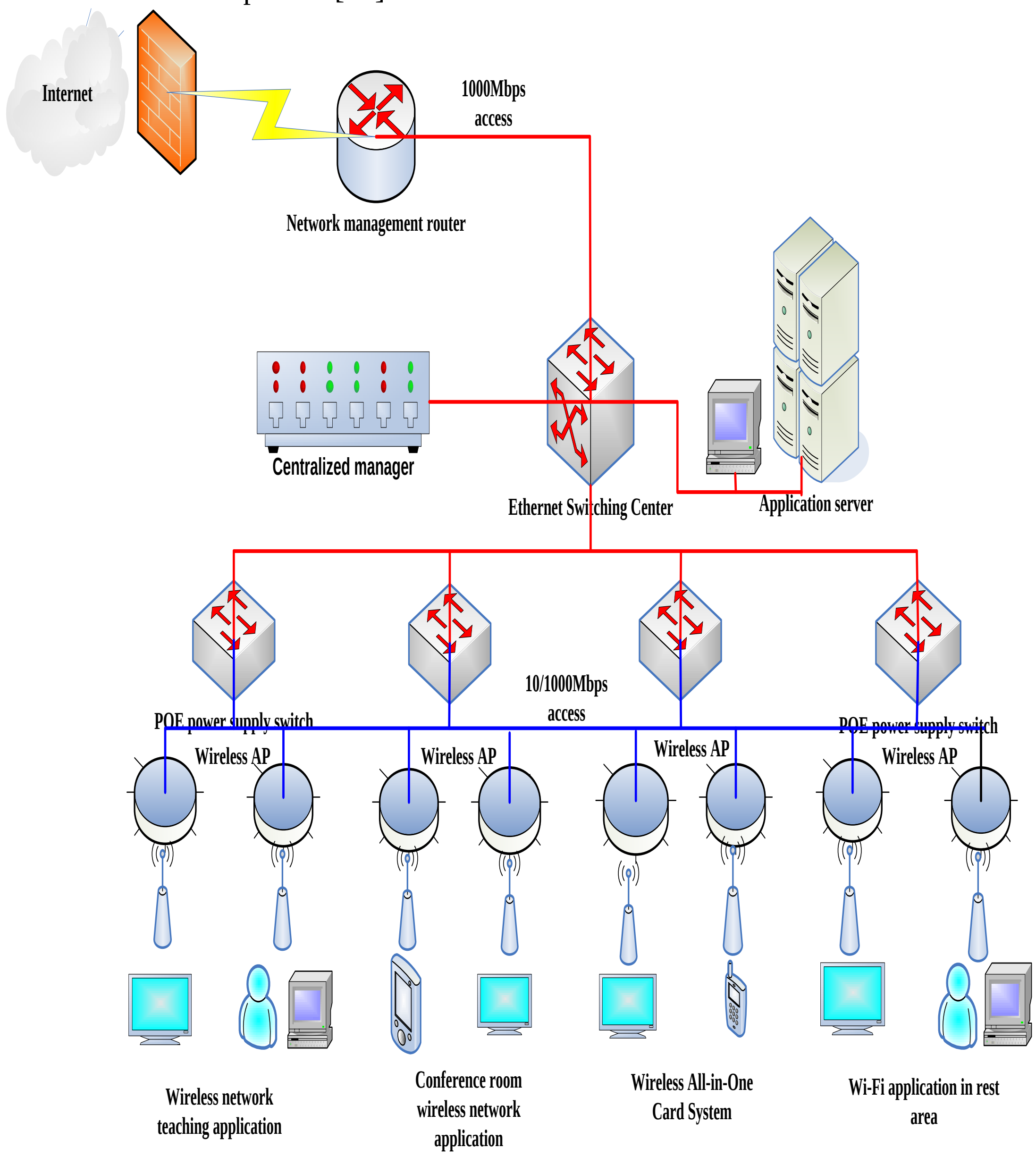


Figure 1. Wireless network multimedia communication coverage

(3) A-GSM

There are blind areas in the GSM network (such as subway, indoor or basement, etc.). To eliminate blind areas, base stations can be deployed, but the cost is relatively high [16].The wireless relay method can extend the end of the wireless network, reduce the transmission power and interference between adjacent cells, thereby reducing the complexity and cost of the base station, and improving the network capacity and stability [17].Based on this consideration, Ad hoc can be used to expand GSM access, that is, A-GSM. The organization design idea is similar to ODMA, as shown in Figure 2.

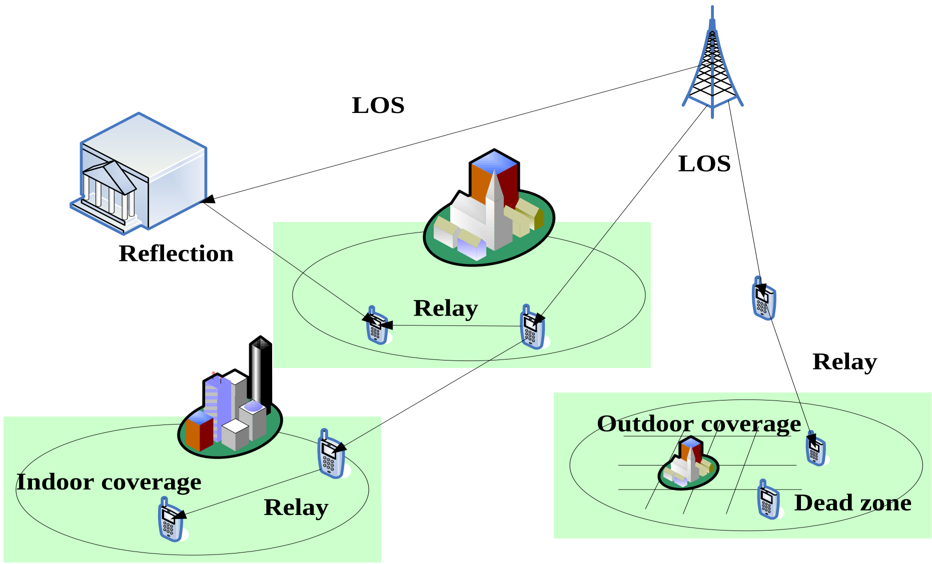


Figure 2. GSM and A-GSM extended network

The difference between A-GSM and ODMA is that A-GSM does not change the connection characteristics of the terminal. A-GSM makes full use of the existing GSM functional entities with only a few changes. In addition, in A-GSM, a set of reconfigurable and dynamic control protocols are also designed to adapt to changes in wireless signals in various scenarios and dynamically allocate bandwidth according to the needs of multimedia services. Because of the transmission overhead on the wireless interface, the A-GSM link layer adopts the Beacon method, which can determine the mobility of the terminal and the number of hops of the connection path. In addition, the A-GSM protocol has designed a set of A-GSM encapsulation protocol on the third layer of the wireless interface, adding a dedicated resource management module and a specific protocol framework [18].Through this agreement framework to guarantee the connection of GSM network and ad hoc network. A-GSM aims to extend the end of the wireless network, but does not involve multi-hop routing, and does not give detailed instructions on how to select and switch the network [19].

2.2. Transformation Research of Multi-Objective Evolutionary Algorithm Planning Problem

For the objective function, it is generally called a single-purpose planning problem. However, in the process of actual engineering problems, and at the same time in our growth process, many problems encountered are multi-purpose problems [20].For example, at any given time, how students plan their body, study and work to achieve the best state can be set as a three-target planning problem [21].

Under normal circumstances, to achieve a minimum value, in order to optimize a set of conflicting solutions, then the following formula must be used to achieve:

Generally, MOP consists of i decision variables, L objective functions and H constraints. The optimization objectives are as follows:

$$\begin{cases} ming(a) = (g_1(a), g_2(a), \cdots, g_m(a)) \\ \quad s.t.\, k_n(a) \leq 0 \; n = 1,2,\cdots,q \end{cases} \tag{1}$$

In the learning process of advanced mathematics (or mathematical analysis), readers all know that the conditional extreme value problem under the constraint of equality can be transformed into an unconditional extreme value problem by using the Lagrange multiplier method. However, the relationship between the optimal solution of the problem before and after the transformation was not discussed in depth at that time. It was only based on the necessary conditions for obtaining the extreme value of the multivariate function, and the constrained equation was transformed into an unconstrained equation system [22].

The equality constraint is like

$$\begin{cases} min\ g(a) \\ s.t.\ k_n(a) = 0, n = 1,2,\cdots,n \end{cases} \tag{2}$$

The equivalent question showing this question is

$$\begin{cases} min\left\{\{g(a) + {}^{L}\!/_{2} \sum_{n=1}^{N} k_n^2(a)\right\} \\ s.t.\ k_n(a) = 0, n = 1,2,\cdots,N \end{cases} \tag{3}$$

Among them, L is a normal number, and by the classical (in advanced mathematics) Lagrangian multiplier method, the unconstrained programming problem corresponding to this equivalent programming is

$$MinG(a,\varphi,L) = g(a) + {}^{L}\!/_{2} \sum_{n=1}^{n} k_n^2(a) + \sum_{n=1}^{n} \varphi_n k_n(a) \tag{4}$$

Among them, $a = (a_1, a_2, \cdots, a_i)$ and $\varphi = (\varphi_1, \varphi_2, \cdots, \varphi_n)$ are called multipliers, and the normal number L is also called the penalty parameter.

To plan the relationship between the optimal solutions, use the following theorem to characterize.

Let a^h be

$$minF(a,\varphi^h, L_h) = {}^{L_h}\!/_{2} \sum_{n=1}^{N} k_n^2(a) + \sum_{n=1}^{N} \varphi_n^h k_n(a) \tag{5}$$

Then a^h must be the optimal solution of the following plan

$$\begin{cases} ming(a) \\ s.t.\ k_n(a) = k_n^{(a^h)}, k = 1,2,\cdots,N \end{cases} \tag{6}$$

Among them, L_h is a given positive integer, which can be large enough, and the multiplier $\varphi^h = (\varphi_1^h, \varphi_2^h, \cdots, \varphi_N^h)$ is a constant vector.Although the theorem does not directly give the relationship between planning (1) and (2), it gives the idea of how to construct a series of optimal solutions of unconstrained problems to approximate the optimal solutions of the original constraint problem: If the values of L^h and φ^h can be changed continuously, the optimal solution a^h of unconstrained programming can meet the constraint conditions

$$G(a, L_h, \varphi^h) k_n(a^h) = 0, n = 1,2,\cdots,N \tag{7}$$

At this time, the solution of (3) is also the solution of (1). How to take L_h and φ^h to achieve this goal?

Since a^h is the optimal solution of $minG(a, L_h, \varphi)$, according to the necessary conditions for obtaining the extreme value of the function, there are

$$\beta G(a^h, \varphi^h, L^h) = 0, m = 1,2, \cdots, s \tag{8}$$

$$\beta g(a^h) \Big/ \beta a_m + L_h \sum_{n=1}^{N} k_{n(a^h)} \beta k_n(a^h) \Big/ \beta a_m + \sum_{n=1}^{n} \varphi_n^h \beta k_n(a^h) \Big/ \beta a_m = 0 \tag{9}$$

Namely

$$\beta g(a^h) \Big/ \beta a_m + \sum_{n=1}^{N} (\varphi_n^h + L_h k_n(a^h))^{\beta k_n(a) / \beta a_m} = 0, m = 1,2, \cdots s \tag{10}$$

Therefore, inspired by the classical Lagrange multiplier method, the next multiplier can be taken

$$\varphi_n^{h+1} = \varphi_n^h + L_h k_n(a_h), n = 1,2, \cdots, N \tag{11}$$

It can be proved that as long as L^h is large enough, for φ_n^{h+1} given in equation (11), a^h satisfies

$$minG(a, \varphi^h, L_h) = G(a, \varphi^h, L_h) \tag{12}$$

For every $1,2, \cdots, N$ there is

$$lim_{h \to \infty} k_n(a^h) = 0 \tag{13}$$

In the actual calculation, $L_{h+1} = tL_h$ can be used, and t is a constant greater than 1. From this we can get a series of unconstrained programming

$$\begin{cases} minG(a, \varphi^h, L_h) \\ \varphi_{h+1} = \varphi_n^h + L_h k_n(a^h) = G(a^h, \varphi^h, L^h), n = 1,2, \cdots, N \\ n \end{cases} \tag{14}$$

$$L_{h+1} = tL_H, h = 0,1,2, \cdots \tag{15}$$

We can get the optimal solution a^h of genetic unconstrained programming, to approximate the optimal solution of the original plan, and the ending criterion:

$$max|k_n(a^h)| < \sigma, 1 < n < N \tag{16}$$

In summary, this is the transformation of a constrained programming problem into an unconstrained programming problem.

2.3. Preference for Multi-Objective Evolutionary Algorithms

There are three methods for decision makers to introduce preference information:(1) A priori method: introduce preference information before the search process starts;(2) Posterior method: After the search process is over, the solution that the decision maker is interested in is selected according to the preference information;(3) Interactive method: Preference information is added to the search process in an interactive manner.

The ASF function was first proposed by A.P. Wierzbicki, and is now used in most multi-objective algorithms. The ASF function can map any given reference point (in the feasible region or outside the feasible region) to the Pareto surface and any effective solution can be found by the ASF function.This method can transform any goal problem into the following single goal problem:

$$MinT_r(j(a)) = max_{n=1,\cdots,q}\{\{E_n(j_n(A) - d_n)\} + \mu\sum_{n=1}^{q}(j_n(A) - d_n) \quad (17)$$

Among them, $\mu > 0$ is a small incremental coefficient, and $E_1, \cdots, E_q$ is the weight vector on each target.

G-domiance is a way to introduce preference information through reference points. It has the characteristics of simple and effective operation, but also has disadvantages such as the position of the reference point and the shape of the Pareto surface. The detailed description of this method is as follows:

Given a reference point $k \in R^q$ and a point $e \in R^q$, define $Flag_k(e)$ as follows:

$$Flag_k(e) = \begin{cases} 1 \ if \ e_n <= k_n \ \forall n = 1, \cdots q \\ 1 \ if \ e_n >= k_n \ \forall n = 1, \cdots q \\ 1 \ Other \ cases \end{cases} \quad (18)$$

From the above definition, it cannot be seen that the feasible space for a given reference point is divided as shown in Figure 3(a).

As shown in Figure 3(b) and Figure 3(c), no matter the reference point is in the feasible region or outside the feasible, it can search for the Pareto solution in the preference region. And this method can be easily used in other multi-objective algorithms, and only needs to modify the dominance relationship or modify the evaluation of the objective function. This latter method is the easiest method to implement on the basis of the existing code, and only needs to make small changes to the evaluation of the objective function [23].

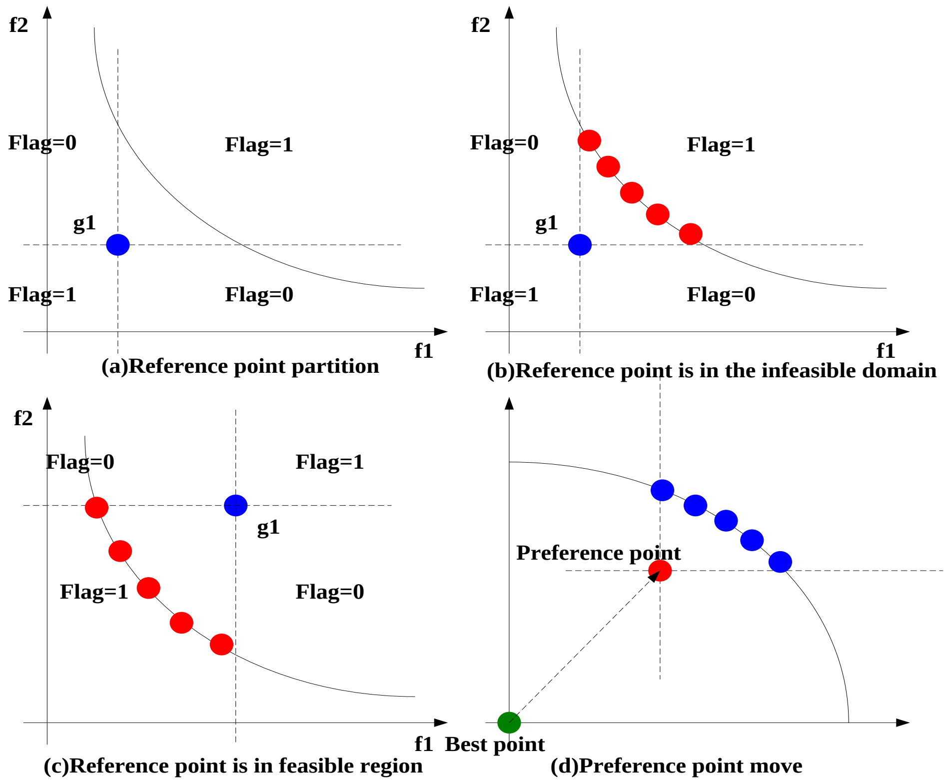


Figure 3. Preference multi-objective evolutionary algorithm research diagram

From the definition of g-dominance, we can see that it is a relatively simple and classic method, but it also has many problems. First, the location of the reference point has a greater impact on the search results. When the decision maker sets the reference point on the Pareto surface, only one or even an ideal preference solution can be obtained, that is, the preference area is uncontrollable; Secondly, after setting the reference point, it will affect the convergence of the algorithm, which is mainly because the Flag partition limits the diversity of the population [24].For problems with more local optima, it will be more difficult to converge; In order to solve the second problem, we also made some improvements to g-dominance, setting the reference point to be mobile, The starting point of the movement is set at the best point, and then it continues to move to the preference point set by the decision maker along with the iteration, as shown in Figure 3(d).When comparing the modified method with the original method, it is found that the problems with more local optima and difficult to converge, such as: Dtlz1 and Dtlz2, the modified method has better convergence [25].

In order to define the distance between the reference point and the solution, an ASF function is also required. The calculation method is as follows:

$$Dist(A,b)=\sqrt{\sum_{n=1}^{R}e_n(\frac{j_n(A)-j_n(b)}{j_n^{max}-j_n^{min}})^2},e_n\in[0,1],\sum_{n=1}^{R}e_n=1 \tag{19}$$

Where A is the individual to be calculated, b is the user-defined reference point, j_n^{max} is the previous value of the nth target value, j_n^{min} is the lower bound of the nth target value, and e_n is the weight of the nth target.

The main feature of r-dominance is to create a strict partial ordering relationship between Pareto's non-dominant solutions. Therefore, decision makers can set preferences to distinguish non-dominated solutions and further stratify the original Pareto stratification. R-dominance not only does it strengthen the Pareto dominance relationship, but it also introduces the preferences of decision makers into the search process.

$$D(A,F,b)=\frac{Dist(A,b)-Dist(F,b)}{Dist_{max}-Dist_{min}} \tag{20}$$

$$Dist_{max}=max_{w\in q}Dist(w,b) \tag{21}$$

$$Dist_{min}=min_{w\in q}Dist(w,b) \tag{22}$$

From the above algorithm, it is not difficult to see that the method requires the decision maker to provide too many parameters, which is not desired by the decision maker. In order to reduce the input of the parameters, Deb proposed that only the critical value of the difference is required to be used in NSGA-II. The algorithm flow is as follows:

$$g=max\{\varphi_n(j_m-w_n^t)\}+q\sum_{n=1}^{L}(j_n-w_n^t) \tag{23}$$

$$l_u(w^s,j)=card\{n:j_n-w_n^t>=u_n,n=1,\cdots,L\},jSw^t,if\ l_u=0 \tag{24}$$

If any individual j satisfies jSw^t, then j is as good as w^t, that is, it is mostly in a non-dominated level. If j is better than w^t in some goals, it must be worse than it in other goals.

In order to comprehensively consider the closeness of individual m to the positive preference point and the distance to the negative preference point, the following closeness calculation formula is defined:

$$T_m=\frac{h_m^-}{h_m^+ + h_m^-} \tag{25}$$

If the closeness T_m of the individual m is larger, it indicates that it is closer to the positive preference point and farther from the negative preference point, and vice versa.

The realization process of the dietary nutrition model of the multi-objective evolutionary algorithm is shown in Figure 4.

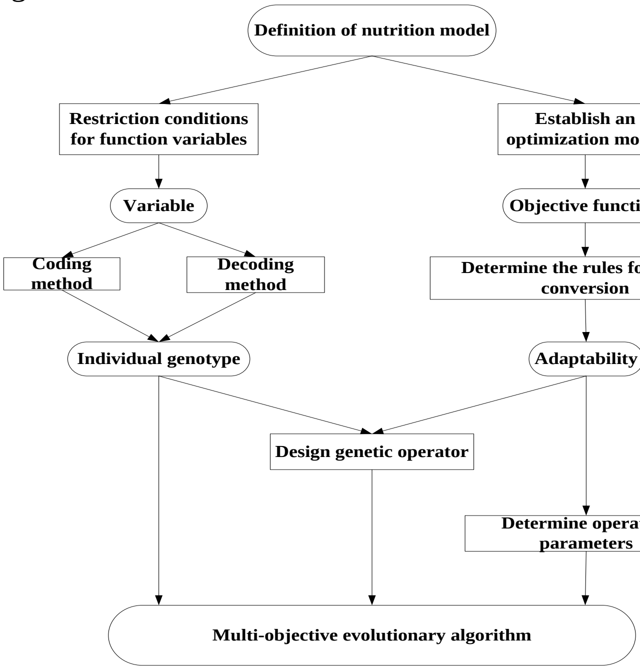


Figure 4. Schematic diagram of the realization process of the nutritional diet model

3. Experimental Results of Wireless Network Multimedia Communication and Multi-Objective Evolutionary Algorithm and Its Female Athletes' Nutritional Diet Model

3.1. Investigation and Research on Athletes' Nutritional Diet Based on Wireless Network Multimedia Communication

In order to better understand the healthy diet of athletes, this article firstly investigates the diet of athletes based on wireless network multimedia communication. Athletes and normal people must eat a lot of food every day to maintain physical strength and physical activity. Therefore, the five types of food such as cereals are the common choice of athletes and normal people. Among them, the five types of food meet the human demand for sugar, protein, fat and other foods. The standard intake has a very high reference value for measuring nutritional needs. Figure 5 shows that from the perspective of grain, vegetable and fruit requirements, intake of athletes are about 1.5 times that of the normal population. In terms of the demand for meat, poultry, fish, beans, milk and fat, there is not much difference between the needs of athletes and ordinary residents. This is because meat, poultry and fat are rich in fat and protein. A large intake of meat will cause excessive fat and protein intake, which will reduce physical fitness to a certain extent and cause edema. If these foods are eaten in large quantities, it will also destroy the nutritional balance of the human body and reduce the intake of other nutrients in foods such as fruits and vegetables.

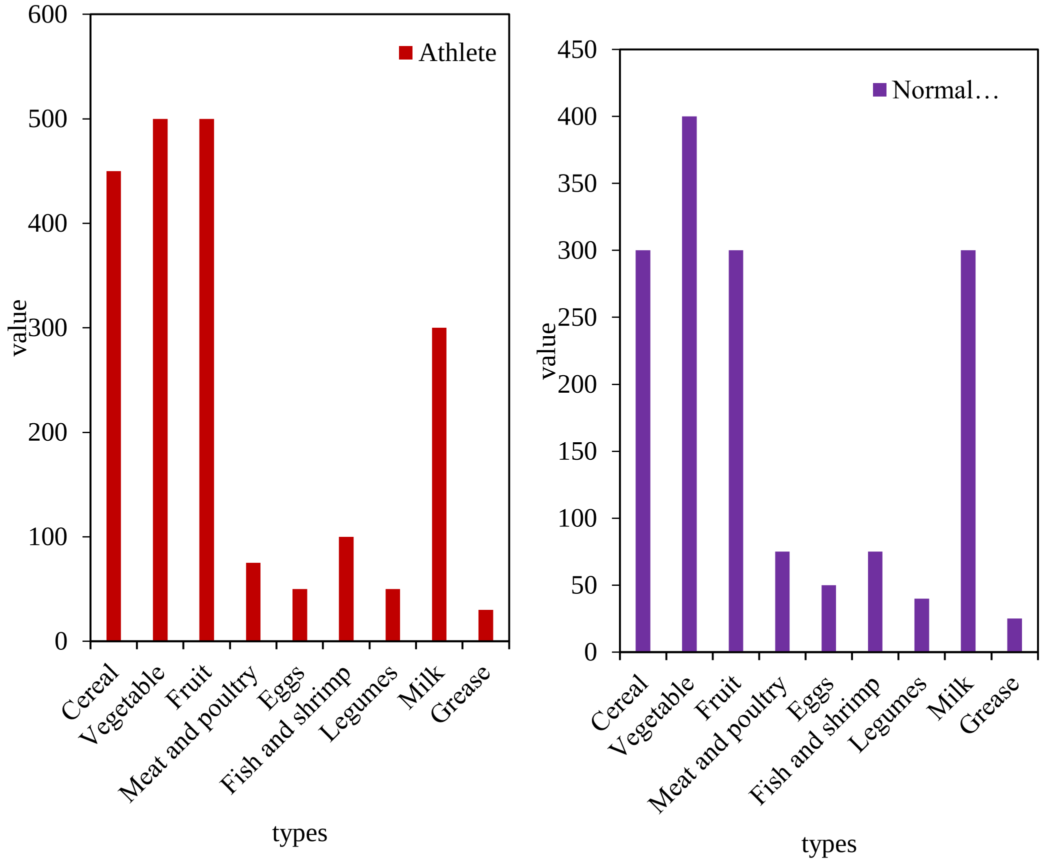


Figure 5. Comparison of staple food intake between athletes and normal people (g/day)

Good eating habits have a certain promoting effect on athletes' balanced diet. In the survey, as shown in Figure 6, female athletes eat better breakfast, and 68% of female athletes can guarantee to eat breakfast every morning. Breakfast is the most important of the three meals a day. When people get up in the morning, blood sugar levels are very low. Inappropriate complementary foods can cause many adverse reactions. As an athlete, it will directly affect the morning exercise plan. Regarding extra meals, most athletes do not have the habit of adding meals, and 56% of female athletes will not choose to add meals. This may be related to the weight control of female athletes. Extra meals are very important for athletes. Athletes carry out high-intensity and long-term training every day. It is not enough to rely on the supply of three meals. But it is necessary to control the amount of food and snacks, try to eat digestible, non-greasy food, so as not to fall asleep after eating.

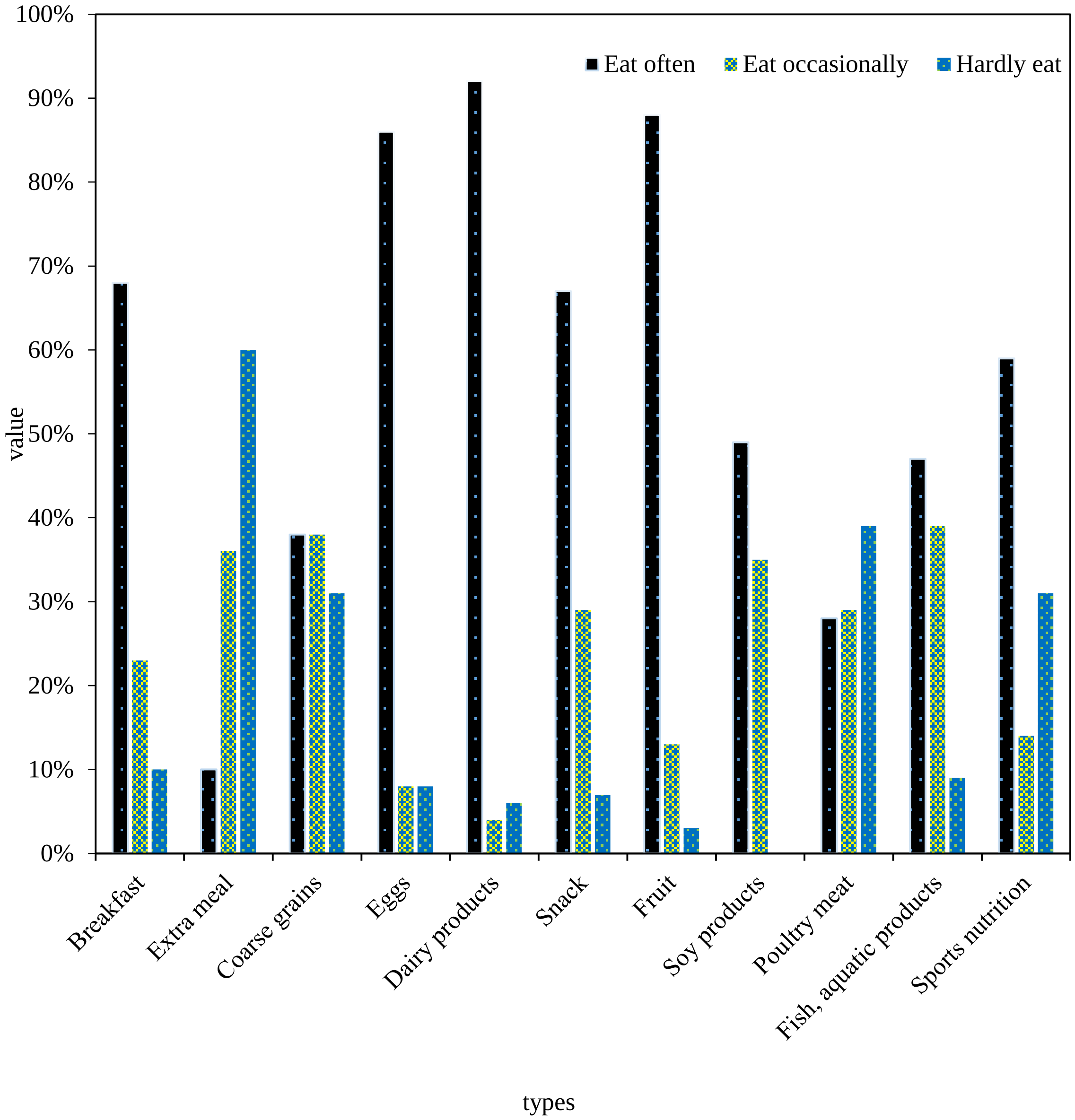
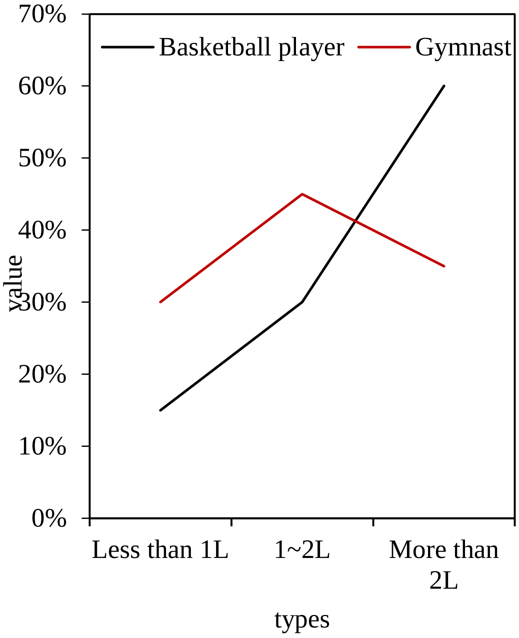


Figure 6. Statistical chart of survey of dietary conditions of female athletes

The average daily water consumption of athletes and the survey on drink selection are shown in Figure 7. 11% of basketball players and 27% of gymnasts drink less than 1L of water per day; the daily drinking water of basketball and gymnasts is between 1 and 2L, 28% and 42%, respectively. Among the options exceeding 2L, 61% are basketball players and 31% are gymnasts.



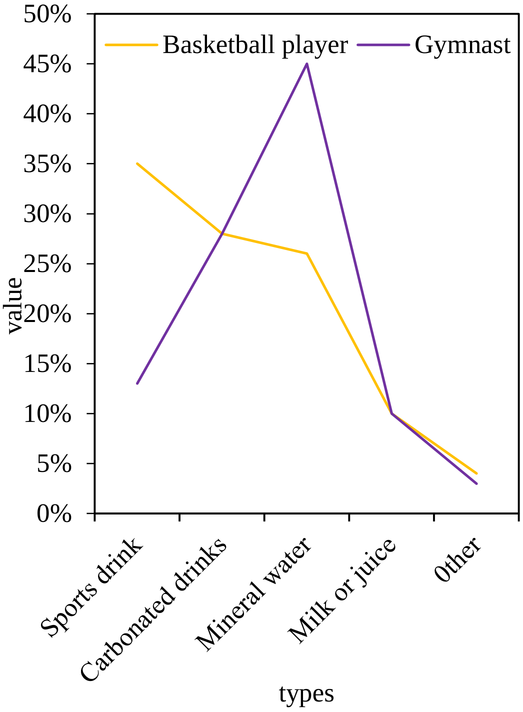


Figure 7. Survey of athletes' daily water consumption and drink selection

Among them, 36% and 13% of basketball and gymnasts choose sports drinks. The difference between the two options is 23%, which is a huge gap; in the choice of carbonated drinks, the ratio of the two is the same, both are 27%; the proportion of basketball players using mineral water is 24%, and the proportion of gymnasts using mineral water is 46%. The difference between the two is 22%, which is a big difference. When choosing milk or juice, the ratio of the two is the same, both 10%; the choices of other beverages are similar.

3.2. Athletes' Dietary Nutrition Status Based on Multi-Objective Evolutionary Algorithm

The article is based on a multi-objective algorithm to study the dietary and nutritional status of athletes. Thermal energy is the basis of all functions of the human body. Thermal energy mainly comes from the consumption of three essential nutrients that provide energy, namely sugar, fat and protein. The energy consumed by the athlete must maintain a dynamic balance with the energy consumed by the body. Insufficient energy will reduce the athlete's exercise function, poor physical condition, and too much energy will increase body fat, which is not conducive to improving athletic ability.

As shown in Table 1, the average daily intake of total calories for the 4 female athletes is far from the recommended value. Among them, the intake ratio of athletes No. 2 and No. 3 is too low, accounting for only 59% and 58% of the minimum recommended value respectively; In addition, the fluctuation of the daily caloric intake of No. 2 athlete is also serious. When the total intake in a single day is the least, it is only 1102.09kcal, which accounts for 31.09% of the lowest recommended value.

Table 1. Calorie intake situation

Athlete Number	Total intake on the first day (kcal)	Total intake on the second day (kcal)	Total intake on the third day (kcal)	Three-day total intake (kcal)	Average daily total intake (kcal)	Average daily recommendation value (kcal)
1	3949.97	2459.66	2631.04	9058.27	3012.09	3015~3685
2	3012.03	1102.09	1929.18	5935.20	1959.37	3330~4070
3	2298.59	1591.01	1999.67	5817.17	1939.86	3375~4125
4	3699.79	2631.59	2099.98	8476.36	2829.12	3420~4180
Average	3241.02	1910.23	2179.34	7333.09	2439.03	-

The reasonable dietary requirements for athletes are: the heat energy provided by carbohydrates, fat, and protein should account for 50%-60%, 25%-30%, and 12%-15% of the total heat energy respectively. For sports with higher requirements, foods with high protein nutrient density should be appropriately selected to meet the needs. The calories of protein foods can reach 19% of the total calories, while reducing the proportion of fat calorie intake.

As shown in Table 2, the protein energy supply ratio of athlete No. 1 meets the recommended value, and the protein energy supply ratio of the other three athletes is slightly higher; however, the fat energy supply ratio of the four female athletes was significantly higher; and the carbohydrate energy supply ratio was significantly lower.

Table 2. Energy supply ratio of energy supply materials for an average of three persons per day

Athlete Number	Protein (%)	Fat(%)	Carbohydrate (%)
1	16.01	37.82	46.01
2	22.02	33.98	44.99
3	19.92	40.02	39.97
4	22.03	41.01	36.96
Average	20.03	37.97	41.99
Recommended ratio	16~19	21~26	51~61

The energy distribution of each meal of the day should be set according to the athlete's training status for the day, and there is no certain share. In principle, the amount of food in the diet before exercise can be more.

Table 3. The average daily energy distribution of each meal for athletes

Athlete Number	Breakfast (%)	Lunch(%)	Dinner (%)	Extra meal (%)
1	22.01	33.91	24.89	19.01
2	10.11	54.87	29.99	4.02
3	0	60.02	31.78	8.05
4	12.02	47.98	34.22	5.99
Average	11.03	49.39	29.79	8.98
Recommend	25~30	30~35	30~35	5~10

As shown in Table 3, for breakfast intake, only athlete No. 1 had intake close to but slightly lower than the recommended value, while the intake of the other three athletes was much lower than the recommended value. The average intake of No. 2 and No. 4 only accounted for about 11% of the calorie intake throughout the day. Athlete No. 3 had no energy intake for breakfast and Chinese food at all, and only athlete No. 1 met the recommended value range. The calorie intake of the other three athletes' Chinese meals far exceeded the recommended value, and the Chinese meal intake of the No. 3 athlete was even closer to 60%.The intake of dinner, athlete No. 1 is slightly lower than the recommended value, and the caloric intake of the rest of the athletes is within the recommended range; The intake of extra meals was higher than the recommended value range for the No. 1 athlete, reaching nearly 20%, and the rest of the athletes basically met the recommended value level.

The main physiological function of hemoglobin is to transport oxygen and carbon dioxide, and to participate in the regulation of acid-base balance in the body. Routine measurement of hemoglobin helps to understand athlete's nutrition, adaptation to load, body function level and so on. Urea is the final product of the synthesis of amino groups in protein and amino acid compounds. Blood urea levels indicate the body's protein and amino acid catabolism. Serum total protein and albumin are biochemical indicators for detecting protein nutritional status.

Table 4. Results of blood test indicators during dietary survey (protein metabolism)

Athlete Number	Hemoglobin (g/dl)	Blood urea (mmol/L)	Serum total protein (g/L)	Serum albumin (g/L)
1	14.01	3.98	73.9	41.9
2	16.02	3.19	71.8	40.8
3	13.98	6.03	68.8	37.6
4	15.89	6.651	73.6	44.9
Normal value	12~16	4.0~7.0	65~75	35~50

Table 4 reflects the test conditions of the athletes' hemoglobin, blood urea, serum total protein and serum albumin during the diet survey. As shown in the table, the results of these four indicators of the 4 female athletes are all within the standard value range.

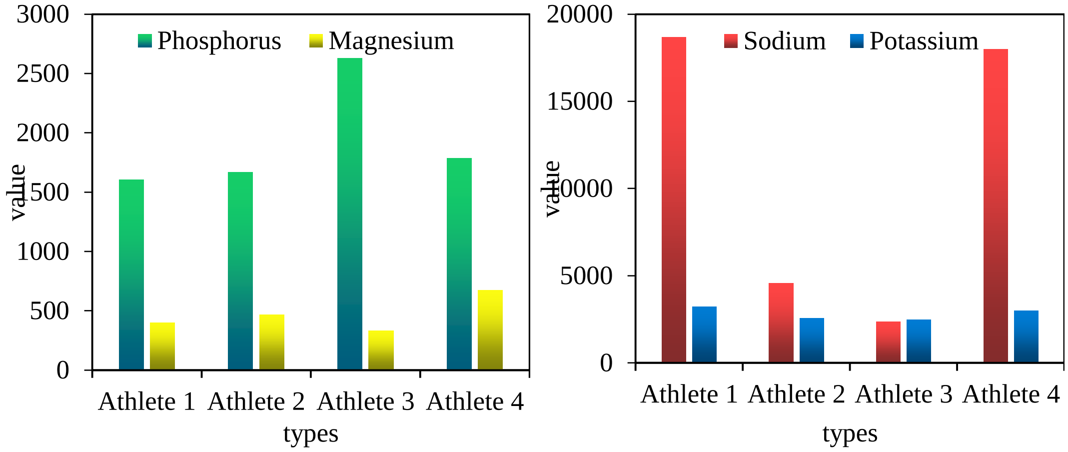


Figure 8. Athletes' intake of sodium, potassium, phosphorus and magnesium

As shown in Figure 8, except that the intake of athlete No. 4 was slightly higher than the recommended value, the P intake of the other three athletes was insufficient, reaching only about 80% of the recommended intake. The intake of Mg of the 4 athletes was different. The intake of athlete No. 1 was slightly insufficient, and the intake of athlete No. 2 was within the recommended range. The intake of athlete No. 3 only accounted for 81.2% of the recommended value, and the intake of

Mg for athlete No. 4 exceeded the recommended upper limit by about 32.9%.The Na intake of No. 2 and No. 3 athletes is within the recommended range of intake, while the Na intake of No. 1 and No. 4 athletes is far beyond the recommended range. They are about 4 times and 3 times the recommended value, respectively. The intake of No. 1 and No. 4 athletes K was within the recommended range, while the intake of No. 2 and No. 3 athletes was slightly insufficient.

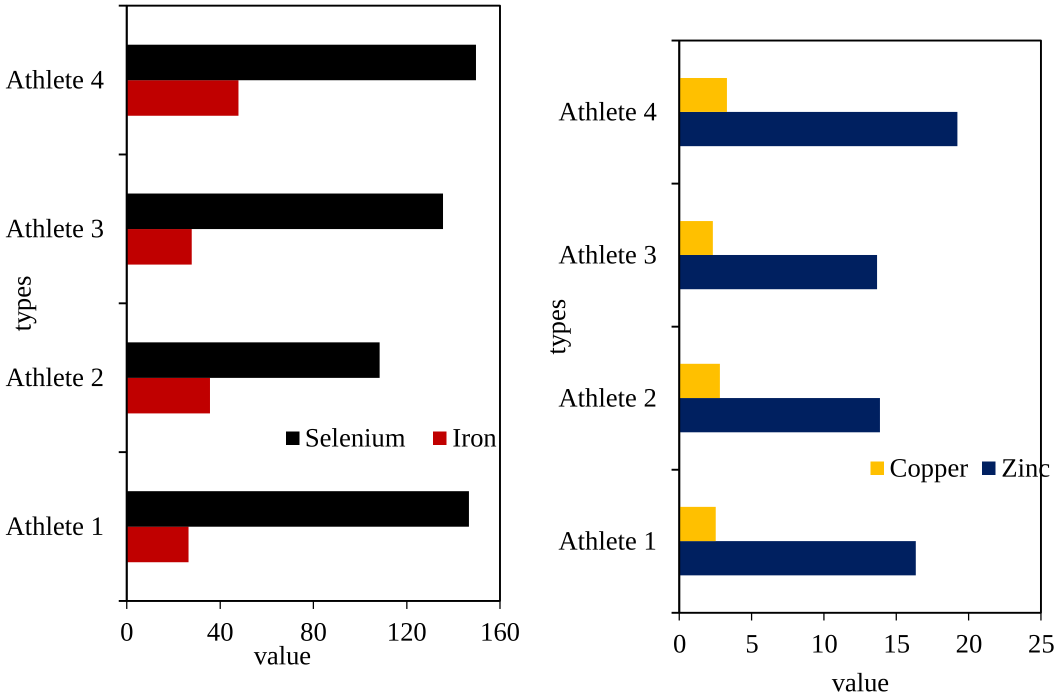


Figure 9. Athletes' intake of iron, selenium, zinc and copper

As shown in Figure 9, the Fe intake of athlete No. 1 and No. 3 slightly exceeded the recommended value, while the Fe intake of athlete No. 2 and No. 4 far exceeded the recommended value. The intake of Se of 4 athletes basically met the recommended level. The four athletes all had varying degrees of insufficient Zn intake, and their intake accounted for 75.9%, 63.9%, 62.8%, and 92.7% of the recommended value, respectively. The Cu intakes of athlete No. 1, 2 and 3 all met the recommended value range, and only athlete No. 4 had a slightly higher intake than the recommended value.

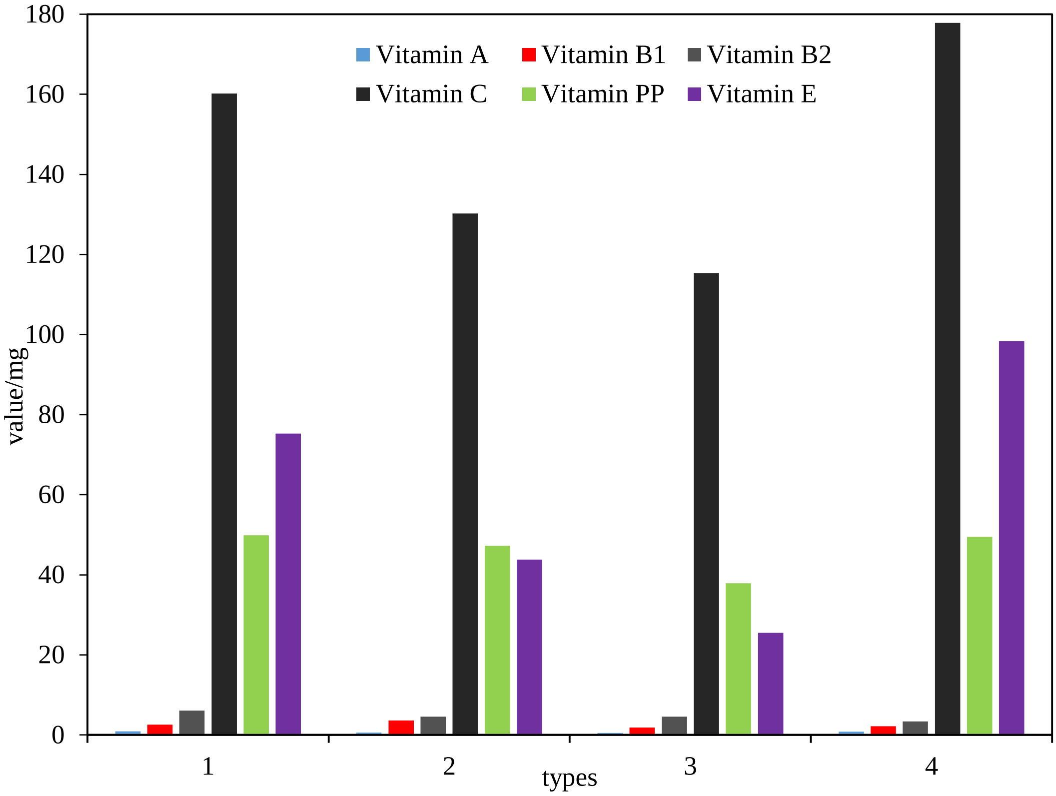


Figure 10. Average vitamin intake of female athletes

It can be seen from Figure 10 that the vitamin A intake of female athletes is not significant and does not meet the recommended dosage standard. Only one female athlete achieved a certain level of vitamin B1 diet. The vitamin B2 transfer amount of the 4 athletes all reached the recommended amount. The vitamin B2 transfer amount of the 4 athletes all reached the recommended amount. The intake of vitamin PP and vitamin E has exceeded the recommended value, and the intake of vitamin E has even exceeded 1 to 10 times. Therefore, athletes are obviously deficient in vitamin A, vitamin B1 and vitamin C are lacking in varying degrees, indicating that athletes do not pay enough attention to the intake of vegetables and fruits in their daily diet. In addition, the catering department may provide various types and quantities of vegetables and fruits, causing some athletes not to eat fruits after meals. There are also some athletes who do not like to eat fruit, which requires a branch of nutrition to provide athletes with juice to increase their vitamin intake.

Based on wireless network multimedia communication and multi-objective evolutionary algorithm, the research on its female athletes' nutritional diet model found that basically only 50% of athletes' diets meet the needs of athletes' sports. This shows that it is necessary to strengthen the propaganda of the healthy diet of athletes.

4. Discuss

Based on the wireless network multimedia communication, multi-objective evolutionary algorithm and its female athletes' nutritional diet model, the following suggestions for improvement are proposed based on the results of this dietary nutritional survey:(1) Adjust the diet of athletes; reduce the consumption of pork and other meats and greasy foods. Increase the consumption of staple foods such as rice and cereals, and increase the consumption of foods such as dairy products; green vegetables and fresh fruits.(2) Improve the eating habits of athletes, pay enough attention to breakfast, and develop regular breakfast habits.(3) When human and financial resources permit, conduct regular comprehensive dietary nutrition surveys in order to monitor and adjust the nutritional status of athletes in a timely manner.(4) Improve the diet of athletes, and use a combination of nutritious meals and elite athletes' buffet to make up for the lack of scientific and reasonable diet choices for athletes.(5) According to the results of nutrition surveys, the team's scientific researchers will provide targeted nutritional supplements to the elite athletes, especially the various vitamins and the detected calcium elements that the athletes may lack.(6) Athletes canteens improve the recipes for elite athletes, improve cooking methods, increase raw vegetables and black foods, etc., try to balance nutrition and taste, and better achieve "athlete-oriented" meals.

5. Conclusion

With the rapid development of innovation, the diseases of modern civilization and wealth have gradually increased. These chronic and intractable diseases require nutritious meals to be eaten every day. Diet therapy is one of the traditional therapies. In ancient times, many medical scientists believed that the influence of food on human health and medical care was not only confirmed by ancient medical scientists, but also confirmed by modern medicine. This article specifically introduces the research on the nutritional diet model of athletes. The Internet-based mass nutritional diet intelligent decision support system came into being under this situation. It has potential effects and multiple applications. Science and adequate dietary nutrition have an immeasurable impact on public health and future community development. With the development of society today, nutritious diets have developed fairly quickly, and this speed is also quite astonishing. The current dietary structure of people has been improved quite well. However, in some poor areas, certain nutritional deficiencies are not uncommon; in some richer multi-objective evolutionary algorithms and research fields applied to dietary nutrition decision-making, certain chronic diseases of over-nutrition are increasing every day. How to guide a reasonable diet and improve human health is an important task that society must solve. Internet-based intelligent decision-making for mass nutrition diet is a new research field, which will have a significant impact on traditional research, and will also have a significant impact on the development of nutrition, computer applications and Internet decision support. This Internet model has broad development prospects.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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