Generating eating plans for athletes using the particle swarm optimization

Dušan Fister[1], Iztok Fister[2], Samo Rauter[3], and Iztok Fister Jr.[2]

[1]Faculty of Mechanical Engineering, University of Maribor, Smetanova 17, 2000 Maribor
Email: dusan.fister@student.um.si
[2]Faculty of Electrical Engineering, and Computer Science, University of Maribor, Smetanova 17, 2000 Maribor
Email: {iztok.fister,iztok.fister1}@um.si
[3]Faculty of Sport, University of Ljubljana, Gortanova 22, 1000 Ljubljana
Email: samo.rauter@fsp.uni-lj.si

***Abstract*—This paper presents the automatic generation of optimal eating plans for athletes. The automatic generation of the eating plans is introduced as an optimization problem, where particle swarm optimization is taken as the problem solver. Inputs for the proposed particle swarm optimization algorithm are generated training plan and list of the potential meals, while the output of the algorithm represents a list of meals that should be consumed by the athletes. The first practical experiments showed that this solution is very promising.**

I. Introduction

This year is an Olympic year. The Olympics are going to be organized in Rio de Janeiro (Brazil), where more than 200 nations with more than 10,000 athletes will compete in various sports to achieve medals. In fact, the Olympics are the sport event that has probably the most valuable or prestigious name. Its origins, the Olympic games, are drawn from ancient Greece, where these games had religious and mythical roles. The modern Olympic games (also Olympics) was revived by Baron Pierre de Coubertin, the founder of the International Olympic Committee (IOC) in 1894. The Olympic movement showed its strengths with the realization of the first Olympics of the modern era in 1896 in Greece. Until recently, thousands and thousands of athletes competed in Olympic events in the past 100 years. To gain a place in an Olympic team, athletes have to work harder in the previous 4 years in order to fulfil the criteria for selection. Usually, these criteria are connected with particular times in particular disciplines. Especially team sports are qualified on other bases (mostly on Olympic Tournament qualification or automatically if they won any important Tournament). Athletes must be really well prepared if they want to ensure their participation in this big competition. In the preparation part, however, the most important factor is training. The training is a basic duty of the professional athletes that is very complex in its nature. However, there are also other important factors besides the training that include eating, massages, resting and similar activities. Training is usually done using the help of a professional Sport Trainer, who also takes care about resting and eating. Unfortunately, there are many types of Sport Trainers, i.e., some trainers are magnificent, while some trainers are very bad. However, the best trainers are very expensive and some athletes cannot afford them.

In line with this, a substitution for the human Sport Trainer was proposed not so long ago, by introducing the so-called Artificial Sport Trainer [1] (AST). At the beginning, the AST was designed to plan sport trainings for short and long periods, but later more and more features were added to the AST. Among other things, these features include things such as, for example, generation of sport routes or viisualization of training sessions.

In the previous years some attempts were made to devise an eating plan by Swarm Intelligence (SI), Evolutionary Algorithms (EAs) and even other computer-based solutions. Mostly, researchers were concentrated on the generation of healthy nutrition. Thus, most of the solutions are connected with medicine and a healthy lifestyle (especially in the current unhealthy era). The papers of Seljak et al. [10], [11] propose multi-objective evolutionary algorithms for dietary nutrition planning. The results in these studies were very interesting and it encouraged more research in this direction. On the other hand, the paper of Pop et al. [8] discusses the problem of avoiding cardiovascular diseases. Particle Swarm Optimization (PSO) was used to generate the healthy lifestyle recommendations that are adjusted to the persons parameters. Additionally, fuzzy logic based menu planning was also presented in a paper by Kljusurić et al. [6], while computer-generated vegan menus were presented in paper by Orešković et al. [7]. As far as we know by searching through the existing literature, a pure connection between eating and sport training plans have not been revealed until now. Therefore, our pilot study might also encourage other researchers to apply swarm intelligence based and evolutionary computation algorithms for the generation of eating plans for athletes in training.

In this paper we are proposing a new feature that would help athletes in the automatic generation of eating plans. The solution is based on the Particle Swarm Optimization [4] algorithm that takes the proposed training plan and list of potential meals as input parameters. As a result, it generates the optimal eating plan that corresponds to the existing training plan.

The structure of the paper is as follows. Section II discusses the basics of sport nutrition. In Section III the basics are explained of the Particle Swarm Optimization algorithms. The generation of eating plans for athletes using the PSO algorithm is presented in Section IV. The initial experiments and results are illustrated in Section V. The paper concludes with a summary of the performed work and directions for the future work.

II. Sport nutrition

Nutrition [3], [9] can be an incredibly important factor in sport. Nutrition continues to be a much discussed topic amongst endurance athletes. In fact, when you talk to athletes who did not have a good race, they will often mention nutrition as the main reason why things did not go as planned. Questions about what to eat before, during, and after the endurance races that can last more days are asked commonly by beginners and even advanced athletes. Nutrition planning strategy starts many weeks before a specific competition. The first step in the planning is to figure out what nutrition works best for an athlete. This includes not only the amount of nutrition, but timing as well. We will discuss the basics briefly, a few general rules for managing the nutrition. During endurance training, for instance, an athletes body relies on two basic fuel sources in varying degrees, i.e., carbohydrates and fats. Although both are always utilized together (fat burns in carbohydrates flame), the amount of carbohydrate used relative to fat depends upon the intensity level of the athletes movement. The higher the intensity of the effort, the more carbs burned relative to fat [2]. The lower the intensity, the greater the percentage of fat. This means, using the carbs during exercise depends upon both the intensity and duration of the sports activity. Carbohydrates (carbs) are an athletes main fuel. His/her body changes according to the glucose eaten in the form of sugar that is stored in the athletes muscles as glycogen. When he/she exercises, the body changes glycogen into energy. In the days before the race, the athlete should make sure that his/her fuel stores (muscle glycogen) are full. In the old days, extreme carbo-loading regimes were followed with days of no carbohydrate, days of extreme carbohydrate, a depletion run a week before, etc. However, this practice is not necessary any more. Very high muscle glycogen levels can be achieved by just eating more carbohydrates. Eating more carbohydrate does not mean overeating or eating as much as possible. It just means that the athlete‘s amount of daily calories that are coming from carbohydrate are consumed at the cost of fat. On the other hand, proteins do not provide a lot of fuel for energy, but they are needed for maintaining the athletes muscles. Actually, proteins are large complex molecules that make up up to 20% of body weight. Some research has found that inclusion of small amounts of protein during prolonged activity can help enhance performance by sparing muscle glycogen, as well as aiding fluid uptake.

III. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is one of the first members of the SI-based algorithm family. It was proposed by Kennedy and Eberhart [4] in 1995. The PSO algorithm mimics the behavior of flocks of birds. Therefore, it is a member of the stochastic nature-inspired population-based algorithms, where the population consists of n particles consisting of real-coded elements representing the solution of the problem to be solved.

The PSO algorithm explores a new solution by moving the particles throughout a search space in the direction of the current best solution. Thus, two sets of particles are managed by the algorithm, i.e., the local best solutions $\mathbf{p}_i^{(t)}$ and the current positions of the particles $\mathbf{x}_i^{(t)}$. Moreover, the best solution in the population $\mathbf{g}^{(t)}$ is determined in each generation. The new particle position is generated as presented in Eq. (1).

$$\begin{aligned} \mathbf{v}_i^{(t+1)} &= \mathbf{v}_i^{(t)} + C_1 U(0,1)(\mathbf{p}_i^{(t)} - \mathbf{x}_i^{(t)}) + C_2 U(0,1)(\mathbf{g}^{(t)} - \mathbf{x}_i^{(t)}), \\ \mathbf{x}_i^{(t+1)} &= \mathbf{x}_i^{(t)} + \mathbf{v}_i^{(t+1)}, \end{aligned} \tag{1}$$

where $U(0,1)$ denotes a random value drawn from the uniform distribution in interval $[0,1]$, and C_1 and C_2 are learning factors. The pseudo-code of the original PSO algorithm is illustrated in Algorithm 1.

Algorithm 1 Pseudocode of the PSO

Input: PSO population of particles $\mathbf{x_i} = (x_{i1}, \ldots, x_{iD})^T$ for $i = 1 \ldots Np$, MAX_FE.
Output: The best solution $\mathbf{x}_{best}$ and its corresponding value $f_{min} = \min(f(\mathbf{x}))$.

```
init_particles;
eval = 0;
while termination_condition_not_meet do
   for i = 1 to Np do
      f_i = evaluate_the_new_solution(x_i);
      eval = eval + 1;
      if f_i ≤ pBest_i then
         p_i = x_i; pBest_i = f_i; // save the local best solution
      end if
      if f_i ≤ f_min then
         x_best = x_i; f_min = f_i; // save the global best solution
      end if
      x_i = generate_new_solution(x_i);
   end for
end while
```

IV. Particle Swarm Optimization for the generation of eating plans

The following section outlines the process of eating plan generation using the PSO algorithm. For this problem, the following modifications were applied to the basic PSO:

- Preparing the input datasets,
- Representation of individuals,

TABLE I
AN EXAMPLE OF THE GENERATED SPORT TRAINING PLAN.

DAY	AVERAGE HR [bpm]	DURATION [min]
1	150	120
2	167	100
3	125	110

- Evaluation of the fitness function.

In the remainder of the paper the modified elements of the PSO algorithm are presented in detail.

A. Input datasets

Two different datasets are needed for input as follows:

- A training plan,
- A list of the potential nutrition.

In the remainder of the paper the mentioned datasets are described in detail.

1) The training plan: The first input for our algorithm is the training plan generated by an Artificial Sport Trainer. Table I presents an example of the generated sports training for three days, where the first column depicts the training days, the second the average Heart Rate (HR) in beats per minute (bpm) for this training and the third the training duration in minutes. The latter two parameters are then converted into the burned calories. This conversion is performed using the formulas taken from the website **www.calories-calculator.net** and the reference proposed by Keytel et al. [5]. Let us notice that the formulas are different according to the mentioned sex, as follows:

- Man:

$$\begin{aligned} \mathit{CalorieBurned} = [(AGE\_IN\_YEAR \times 0.2017) + \\ (WEIGHT\_IN\_KILOGRAM \times 0.1988) + \\ (HEART\_BEAT\_PER\_MINUTE \times 0.6309) - 55.0969] \times \\ DURATION\_IN\_MINUTE / 4.184 \end{aligned}$$

- Woman:

$$\begin{aligned} \mathit{CalorieBurned} = [(AGE\_IN\_YEAR \times 0.074) + \\ (WEIGHT\_IN\_KILOGRAM \times 0.1263) + \\ (HEART\_BEAT\_PER\_MINUTE \times 0.4472) - 20.4022] \times \\ DURATION\_IN\_MINUTE / 4.184 \end{aligned}$$

In equations, the variable $\mathit{CalorieBurned}$ denotes an amount of burned calories, AGE_IN_YEAR is the age of the athletes in years, $WEIGHT\_IN\_KILOGRAM$ his/her weight in kilograms, $HEART\_BEAT\_PER\_MINUTE$ average HR, and $DURATION\_IN\_MINUTE$ duration of training in minutes.

2) A list of the potential nutrition: The second input for the PSO algorithm is the created list of the potential nutrition. Actually, there are four lists according to different daily meals, as follows:

- Breakfast,
- Snack,
- Lunch and
- Dinner.

TABLE III
PARAMETER SETTING OF THE PSO ALGORITHM.

Parameter	Value
MAX_FE	70,000.00
Np	70.00
D	15.00
C_1	2.00
C_2	2.00
AGE_IN_YEAR	30.00
$WEIGHT\_IN\_KILOGRAM$	75.00

Note that there is only one list for snacks, although each athlete eats a snack two times per day. Table II presents an example of lists for breakfasts and dinners. The first row in the Table consists of an ID of breakfast or dinner, while the second row contains a food, mass of food and corresponding calories for that particular food. (calories are delimitered by -). Note that calorie values were mostly taken from **OPEN Platform for Clinical Nutrition - www.opkp.si**

B. Representation of individuals

Individuals in the PSO are represented as real-valued vectors $\mathbf{x}_i = \{x_{i,j}\}$ from $i = 1 \ldots Np$ and $j = 1 \ldots D$, where each element of vector is taken from the interval $x_{i,j} \in [0, 1]$, and Np denotes the population size and D the dimensionality of the problem. These real values are later, in fitness function, mapped into the identifier of food $\mathit{generatedFood}_j$ as follows:

$$\mathit{generatedFood}_j = \lceil x_{i,j} * MAX\_ID \rceil, \tag{2}$$

where $x_{i,j}$ denotes the corresponding j-th element of the vector $\mathbf{x}_i$ and *MAX_ID* is the maximum number of foods in the list.

C. Fitness function

Fitness function is calculated according to Eq. 3 as follows:

$$f(x) = |\sum_{j=0}^{n} (\mathit{trainingCalories}_j + 1500) - \mathit{generatedFood}_j|, \tag{3}$$

where the $\mathit{trainingCalories}_j$ denotes the training calories, the $\mathit{generatedFood}_j$ the calories of the generated meals and n is the number of days.

V. INITIAL EXPERIMENTS

The purpose of the experimental work was designed to show that the PSO algorithm can be used successfully for generating the eating plans for athletes in sports training. In line with this, the PSO algorithm written in Python programing language was developed and applied to a Sports Training Program for a professional cyclist generated by the Artificial Sport Trainer proposed by Fister et al. in [1]. Table II was applied as a nutrition dataset. The PSO algorithm was written in Python programing language with the setting of parameters as presented in Table III.

The results of the initial experiments are illustrated in Table IV, from which it can be seen that our solution is able to plan eating plans successfully. The proposed plans

TABLE II
LIST OF MEALS THAT CAN BE USED FOR BREAKFAST AND DINNER.

Breakfast	Food	Amount	Calories	Food	Amount	Calories	Food	Amount	Calories
1	Banana	225 g	196.93	Oat flakes	150 g	591.45			
2	Wheat bread	100 g	242.57	Plum jam	100 g	244.08	Vegan sandwich	-	315.87
3	Poached egg	57 g	126.05	Corn salad	149 g	36.89	Yogurt	245 g	163.37
	Soya milk	200 g	66.00	Avocados	150 g	325.74			
4	Almonds	100 g	576.18	Peach	154 g	70.42	Oats beverage	300 g	185.85
5	Pasteurized milk	244 g	156.74	Corn flakes	122 g	463.04			
Dinner	**Food**	**Amount**	**Calories**	**Food**	**Amount**	**Calories**	**Food**	**Amount**	**Calories**
1	Vegan sandwich	-	315.87	Mushrooms millet	450 g	581.14			
2	Cheese pies	-	388.61						
3	Lentil	200 g	547.56	Coconut pancakes	200 g	435.53			
4	Soya milk	200 g	66.00	Avocados	150 g	325.74			
5	Oats beverage	300 g	185.85	Chicken steak	300 g	536.97			

were validated by a Sport Trainer who accepted them. The proposed food is located within normal borders and the food is diverse enough. However, repetitions of the same food are a small problem that should be solved easily by extending our food databases. In conclusion, these eating plans‘ generation solutions help to make the Artificial Sport Trainer more powerful and more comprehensive.

VI. CONCLUSION

In this paper, we introduced a solution for generating an eating plan for athletes in training. The proposed solution is based on the PSO algorithm and takes various input datasets for returning the optimal food selection for the particular training day. First experiments showed that we are on the right path and, thus, this solution might be appropriate for the real-world. However, the research also showed some pitfalls and open problems that should be taken into account in the future. The following remarks must be pointed out in the further research:

- More input data: In order to obtain better and more richer meals, we should collect more data and use it as input parameters.
- The eating plan based on three main ingredients, i.e., proteins, carbohydrates, fats: These three ingredients in the food should be a stepping stone for more optimal calculation of meals. For example, if someone conducted an interval training, then this athlete should eat more carbohydrates than fats.
- Enable athletes to reject a particular food, i.e., if one athlete does not like to eat cucumber, then this food should be removed from the input data and meal plans should adapt themselves according to his/her wishes.

Although, there are so many tasks for further research, we can conclude that our solution is promising. In the further work, we could focus on solving the mentioned problems.

REFERENCES

[1] I. Fister Jr., K. Ljubič, P. N. Suganthan, M. Perc, and I. Fister. Computational intelligence in sports: challenges and opportunities within a new research domain. *Applied Mathematics and Computation*, 262:178–186, 2015.

[2] J. E. Hall. *Guyton and Hall textbook of medical physiology*. Elsevier Health Sciences, 2015.

[3] A. E. Jeukendrup. Nutrition for endurance sports: marathon, triathlon, and road cycling. *Journal of sports sciences*, 29(sup1):S91–S99, 2011.

[4] J. Kennedy and R. Eberhart. Particle swarm optimization. In *Neural Networks, 1995. Proceedings., IEEE International Conference on*, volume 4, pages 1942–1948. IEEE, 1995.

[5] L. Keytel, J. Goedecke, T. Noakes, H. Hiiloskorpi, R. Laukkanen, L. Van Der Merwe, and E. Lambert. Prediction of energy expenditure from heart rate monitoring during submaximal exercise. *Journal of sports sciences*, 23(3):289–297, 2005.

[6] J. G. Kljusurić, I. Rumora, and Ž. Kurtanjek. Application of fuzzy logic in diet therapy–advantages of application. In *Fuzzy Logic–Emerging Technologies and Applications*. INTECH Rijeka, Croatia, 2012.

[7] P. Orešković, J. G. Kljusurić, and Z. Šatalić. Computer-generated vegan menus: The importance of food composition database choice. *Journal of Food Composition and Analysis*, 37:112–118, 2015.

[8] C. B. Pop, V. R. Chifu, I. Salomie, A. Cozac, and I. Mesaros. Particle swarm optimization-based method for generating healthy lifestyle recommendations. In *Intelligent Computer Communication and Processing (ICCP), 2013 IEEE International Conference on*, pages 15–21. IEEE, 2013.

[9] I. San Millán, C. González-Haro, and J. Hill. Indirect assessment of glycogen status in competitive athletes. *Medicine & Science in Sports & Exercise*, 43(5):948–949, 2011.

[10] B. K. Seljak. Dietary menu planning using an evolutionary method. In *2006 International Conference on Intelligent Engineering Systems*, pages 108–113. IEEE, 2006.

[11] B. K. Seljak. Computer-based dietary menu planning. *Journal of Food Composition and Analysis*, 22(5):414–420, 2009.

TABLE IV

THE INITIAL RESULTS OF THE EATING PLAN FOR AN ATHLETE.

Day	Breakfast			Break			Lunch			Break			Dinner			Total
	Food	[g]	[cal]	Food	[g]	[cal]	Food	[g]	[cal]	Food	[g]	[cal]	Food	[g]	[cal]	
1	Poached eggs	56	126.05													
	Corn salad	149	36.89	Chocolate	22	130.28	Classic pizza	286	695.72	Kiwi	180	84.04	Lentil	200	547.56	
	Yogurt	245	163.37	White grapes	100	76.43	Green salad	103	41.31	Orange-Juice	248	116.24	Coco-Pancakes	200	435.53	
	Soya milk	200	66.00	Cheese pies	-	388.61										
	Avocados	150	325.74													
Total			718.05			595.32			737.03			200.28			983.09	3,233.77
2	Almond	100	576.18	Chocolate	22	130.28	Thick soup	-	120.30	Kiwi	180	84.04	Oats-beverage	300	185.85	
	Peach	154	70.42	White grapes	100	76.43	Pork minced meat	250	697.50	Orange-juice	248	116.24	Chicken steak	300	536.97	
	Oats-beverage	300	185.85	Cheese pies	-	388.61										
Total			832.45			595.32			817.80			200.28			722.82	3,168.67
3	Poached egg	56	126.05	Kiwi	180	84.04	Thick soup	-	120.30	Cheese pies	-	388.61	Cheese pies	-	388.61	
	Corn salad	149	36.89	Orange Juice	248	116.24	Pork minced	250	697.30	White grapes	100	76.43				
	Yogurt	245	163.37													
	Soya milk	200	66.00							Chocolate	22	130.28				
	Avocados	150	325.74													
Total			718.05			200.28			817.80			595.32			388.61	2,720.06