Population-Based Metaheuristics for Planning Interval Training Sessions in Mountain Biking

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Abstract. Stochastic population-based nature-inspired metaheuristics have recently revealed that they are a very robust tool for planning sport training sessions in various sports, e.g. running, cycling, triathlon. Most of the existing solutions in literature are focused on planning training sessions for a particular training cycle. Until recently, no special attention was paid to planning interval training sessions, where the high-intensity intervals are followed by low-intensity periods of recovery. This kind of training sessions increases the aerobic capacity of an athlete. In this paper, we propose planning interval training sessions using stochastic population-based nature-inspired metaheuristics. The proposed bat algorithm was tested on an archive of interval training sessions realized by a younger mountain biker, where two different scenarios were taken into account.

Keywords: Planning sport training sessions · Metaheuristics · Optimization

1 Introduction

Sport trainers are crucial components in the process of an athlete's sports training, that is a required precondition for achieving success in the sport competitions. The primary task of the modern sport trainer is offering assistance for athletes, helping them by planning sport training sessions, analyzing the past training sessions, and also racing. Typically, it is very difficult to become an excellent sport trainer. Therefore, the majority of them are past athletes with many training, as well as racing, experiences. Besides these experiences, each good trainer must have a deep knowledge about nutrition, human anatomy, sociology, psychology, and so on.

Nowadays, we live in a society where modern Information Technology (IT) can be found in almost every domain of life. Therefore, it is no wonder that the

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modern computer technology has also been applied into the domain of Sport. A recent book [4] has introduced the concept of the Artificial Sport Trainer (AST), based on stochastic population-based nature-inspired metaheuristics [3,6]. Automatic planning of the sport training sessions that is a part of the AST is still considered as a very hard task. For an efficient automatic planning of sports training sessions, algorithms have to deal with archives of existing sports training sessions, which were obtained by measuring the performance data obtained during the real ones by wearable mobile devices (e.g., sports watches, mobile phones). Additionally, these algorithms are able to deal with several constraints that could arise during the process of sport training. In some cases, athletes are injured and the existing training plan needs to be adapted accordingly.

Until recently, no special attention was devoted to automatic planning of interval training sessions, where the high-intensity intervals are interspersed with recovery periods, due to increasing the aerobic capacity of the athlete in sports training. In this paper, the automatic planning of interval training sessions in mountain biking presents the main challenge. Thus, this planning is represented as an optimization problem, which combines the high-intensity intervals and corresponding low-intensity recovery periods from existing interval training sessions collected within an archive, such that the sum of all *TRIMP* values of the proposed intervals does not exceed the prescribed maximum value. Let us notice that the *TRIMP* value represents an intensity measure of the specific interval training session expressed as a product of average Heart Rate (HR) by its duration (t).

Although the proposed algorithm could be implemented using any stochastic population-based nature-inspired algorithm [5], the Bat Algorithm (BA) [12] was selected due to its simplicity. The algorithm for planning the interval training sessions was applied to an archive of 40 existing interval training sessions produced by a young mountain cyclist. However, the results were commented by real cyclist trainers, who confirmed that these training plans could be applied in practice. To the authors' knowledge, this is the first study that operates with population-based metaheuristics for the interval training sessions planning.

In summary, this paper presents the following main novel contributions:

- to elucidate the problem of planning the interval training sessions,
- to present planning the interval training sessions as an optimization problem,
- to propose a new method for particular problem based on the BA.
- to apply the proposed algorithm on a real archive of collected interval training sessions.

The structure of this paper is as follows: Sect. 2 deals with the fundamentals of interval training in mountain biking. In Sect. 3, the optimization problem of planning the interval training sessions is discussed in detail. Experiments and results are subjects of Sect. 4, while Sect. 5 summarizes the performed work and outlines directions for the future work.

2 Fundamentals of Interval Training in Mountain Bike

Interval training has a very long tradition. In general, for successful endurance athletes must balance the overall frequency and volume of training with the high-intensity interval training sessions [11]. The interval training session intersperses the high-intensity intervals (i.e., exercises of intensity equal to or higher than the maximal lactate steady-state threshold) with recovery periods (i.e., low-intensity exercises or recovery). Interval training was first described by Reindell and Roskamm [2], and was popularized by the Olympic Champion Emil Zatopek in the 1950s. Indeed, aerobic interval training is defined as an interval training which elicits aerobic metabolism at a higher ratio than anaerobic metabolism.

The Olympic format of cross-country mountain bike racing (XCO) is a fairly different sport in comparison to road cycling, because it changes also the basic principles of mountain bike training by including high-intensity workouts beside the endurance ones. A cycling race requires cyclists to possess the ability to generate a relatively high power output of short duration during steep climbing and in accelerations [10]. It can be characterized as a high-intensity, intermittent activity that requires riders to compete over varying terrains, including rocky paths, a technical single-track, and open forestry roads. Frequently, this also includes obstacles such as jumps and vertical drops, with high-intensity, high-power ascending sections that are separated by relatively lower-intensity descents [1,7,8].

In sports theory, it is well known that mountain bikers need to adapt, and to simulate competitive conditions during their training sessions. Especially, there are a lot of short periods of acceleration. Typically, mountain bikers have to overcome up to 120 of such accelerations within 90 min of racing. Consequently, special attention needs to be paid to the development of speed (with emphasis on high intensity training), as well as specific strength (special strength training) and coordination, which becomes particularly important during the downhills [9].

A typical endurance training session consists of repeated 1 to 8 min runs at 90 % to 100 % speed of maximal oxygen uptake, with recovery intervals of 2 to 3 min). This is the most effective program for improving maximal oxygen uptake and performance for endurance athletes [2]. On the other hand, studies of anaerobic intervals divide the interval training into two categories. The first category (the older studies) examined this kind of training at a fixed work-rate. Thus, the time limit, or the number of repetitions, was suitable to sustain a different pause duration. The intensities used in these studies were not at the highest intensity level, but were at about 130 % to 160 % of the maximal oxygen uptake speed. Moreover, they used high-intensity intervals of 10 to 15 s in duration that were interrupted by short recovery intervals of 15 to 40 s in duration. The second category (the more recent studies) demanded that the high-intensity intervals of 30 s be interspersed with different recovery intervals of 4 to 5 min in duration. These studies examined the changes in maximal dynamic power during successive exercise periods, and characterized the associated metabolic changes in muscle [2].

3 Problem Definition and Proposed Solution Method

An interval training consists of a sequence of exercises, where each high-intensity exercise is followed by a low-intensity exercise that is dedicated to resting. For instance, if the typical interval training session in cycling lasts 60 min and there are 10 intervals, the duration of each interval is 6 min, where the high-intensity interval lasts 5 min and the low-intensity one 1 min. Formally, each interval of an interval training session can be expressed as $IT_i = \langle I_i, R_i \rangle$, where the high-intensity period is defined as couple $I_i = \langle HR_i^{(I)}, t_i^{(I)} \rangle$, and the low-intensity period as $R_i = \langle HR_i^{(R)}, t_i^{(R)} \rangle$. In both couples, the first element $HR_i^{(\cdot)}$ determines the average heart rate, while the second element $t_i^{(\cdot)}$ the duration of i-th interval. In summary, the whole interval training session is defined as:

$$IT = \left[\left\langle HR_1^{(I)}, t_1^{(I)}, HR_1^{(R)}, t_1^{(R)} \right\rangle, \ldots, \left\langle HR_n^{(I)}, t_n^{(I)}, HR_n^{(R)}, t_n^{(R)} \right\rangle \right], \tag{1}$$

where n describes the number of intervals in the interval training session IT.

All the interval training sessions realized in one training cycle are accumulated into an archive of interval training sessions, in other words:

$$A = \begin{cases} IT_1 = \left[\left\langle HR_{1,1}^{(I)}, t_{1,1}^{(I)}, HR_{1,1}^{(R)}, t_{1,1}^{(R)} \right\rangle, \ldots, \left\langle HR_{1,n}^{(I)}, t_{1,n}^{(I)}, HR_{1,n}^{(R)}, t_{1,n}^{(R)} \right\rangle \right], \\ \ldots \\ IT_m = \left[\left\langle HR_{m,1}^{(I)}, t_{m,1}^{(I)}, HR_{m,1}^{(R)}, t_{m,1}^{(R)} \right\rangle, \ldots, \left\langle HR_{m,n}^{(I)}, t_{m,n}^{(I)}, HR_{m,n}^{(R)}, t_{m,n}^{(R)} \right\rangle \right], \end{cases} \tag{2}$$

where m determines the number of interval training sessions in archive A.

3.1 Problem Definition

Planning the interval training sessions in mountain biking is presented as an optimization problem in the following way: Let us assume, an archive of interval training sessions in mountain biking to be A, and the desired values $TRIMP_0$ are given, where the measure $TRIMP$ determines the intensity of the interval training session according to the following equation:

$$TRIMP = HR \cdot t. \tag{3}$$

Then, the total intensity of the interval training session is expressed as follows:

$$TRIMP(IT) = \sum_{j=1}^{n} \left(HR_{k_j}^{(I)} \cdot t_{k_j}^{(I)} + HR_{k_j}^{(R)} \cdot t_{k_j}^{(R)} \right), \tag{4}$$

subject to

$$\sum_{j=1}^{n} \left(t_{k_j}^{(I)} + t_{k_j}^{(R)} \right) \leq TD, \text{ and} \tag{5}$$

$$t_0^{(I)} \leq t_{k_j}^{(I)} < 0, \text{ for } j = 1, \ldots, n, \tag{6}$$

where k_j determines the j-th interval of the selected k-th interval training session from the archive A, TD is the duration of the interval training (typically $\leq$60 min), and $t_0^{(I)}$ the maximum duration of the high-intensity interval that cannot be zero.

Objective function is expressed as:

$$f(IT) = |TRIMP(IT) - TRIMP_0|. \quad (7)$$

The task of the optimization algorithm is to find the minimum value of the objective function, in other words:

$$f^*(IT) = \min f(IT). \quad (8)$$

In the remainder of the section, the design of the stochastic population-based nature-inspired algorithm for planning the interval training is illustrated in detail.

3.2 Algorithm for Planning the Interval Training

As said before, the algorithm for planning interval training can be any stochastic population-based nature-inspired algorithm. However, the BA [12] was used in our study, due to its simplicity. The following modifications must be applied to the original algorithm.

Representation of Individuals. The individuals representing the interval training session IT are represented as vectors:

$$\mathbf{x}_i = [x_{i,1}, \ldots, x_{i,n}], \quad \text{for } i = 1, \ldots, Np, \quad (9)$$

where each of $x_{i,j} \in [0, 1]$ for $j = 1, \ldots, n$ determines the index of the interval training session, from which the $IT_{k,j}$ elements of the interval training k belonging to the specific interval j are taken, n is a dimension of the problem, and Np denotes the number of individuals within the population.

Evaluation of Objective Function. The objective function is expressed by Eq. (7). In order to evaluate this function, each element of the vector $x_{i,j}$ needs to be mapped into the corresponding elements of the interval training $IT_{k,j}$ according to the following equation:

$$k_j = \lfloor x_{i,j} \cdot m \rfloor + 1, \quad (10)$$

where $k_j \in [1, m]$ determines the j-th interval of the k-th interval training session within the archive A.

Repairing the Infeasible Solutions. Often, the solution generated by the stochastic population-based nature-inspired algorithms, can be infeasible, when the constraints according the inequalities in Eqs. (5) and (6) are violated. Let us assume that we generate 10 intervals that must be finished in one hour. When the generated interval training exceeds the limitation of one hour, the constraint presented in Eq. (5) is violated. In this case, the infeasible solution is repaired, such that one of the intensity intervals in the violating solution is selected randomly. This interval is then modified with the interval of lower duration in the randomly selected interval training from the archive.

The second constraint violation occurs when the duration of the high-intensity interval exceeds the maximum duration $t_0^{(I)}$. Also, in that case, the randomly selected high-intensity interval violating constraint is changed with the high-intensity interval from the randomly selected interval training from the archive that does not violate the constraint.

However, the additional constraints could be incorporated into Eq. (4) that determine the characteristics of the interval training in more detail. Obviously, the constraints remain as a direction for the future.

Comment. The principle of the proposed algorithm is simple: Actually, it selects the most suitable values of the HR and t for the specific interval from the interval training sessions accumulated into the archive. Thereby, this does not generate new values that were not realized in practice. Consequently, if we want to generate the interval training with maximum values, this could be achieved only to a certain extent, i.e., when all the maximum values were not achieved in the same interval training. This means that the algorithm never prescribes values which the athlete does not achieve in real training, but it is expected that the results of particular intervals will overcome the prescribed "hard" interval training sessions. Thus, the athlete increases the level of his/her achievements due to archiving each activity into the archive.

4 Experiments and Results

The aim of the experimental work was to evaluate the proposed stochastic population-based nature-inspired algorithm for planning interval training sessions. In line with this, two scenarios were defined:

- scenario A: deals with interval training of low-intensity $TRIMP$,
- scenario B: deals with interval training of high-intensity $TRIMP$.

Characteristics of both scenarios are described in detail in the remainder of the section. The results of scenarios were obtained by applying the BA for planning the interval training using the parameter setting as illustrated in Table 1.

The proposed BA was applied on an archive of interval training sessions consisting of $m = 40$ interval training sessions, realized by the professional young mountain biker. Part of the archive is presented in Table 2. Let us notice that

Table 1. Parameter setting of the BA

Nr.	Parameter name	Value
1	Population size	$Np = 50$
2	Individual size	$n = 10$
3	Pulse rate	$r_i = 0.5$
4	Loudness	$A_i = 0.5$

Table 2. Part of the archive

ID	$HR^{(I)}_{\text{ID}}$	$t^{(I)}_{\text{ID}}$	$HR^{(R)}_{\text{ID}}$	$t^{(I)}_{\text{ID}}$
1	185	5	147	3
2	186	5	148	2
3	186	4	149	2
4	187	5	148	3
5	188	4	150	2

the archive comprises interval training sessions of a wide spectrum, i.e., from the low-intensity and short-duration toward the high-intensity and long-duration. The same is also true for the resting period, where they are spread from shorter-duration to longer-duration. The intensities of this period are similar, and, therefore, can be ignored.

Although 25 runs of the proposed BA were performed for each scenario, we are interested only in the best solution according to the Eq. (8).

4.1 Scenario A

The characteristics of the interval training sessions in this scenario are used to generate an interval training plan of lower-intensity *TRIMP*. This means that the rational algorithm for planning the interval training session needs to select both the observed training periods (i.e., intensity and recovery) of either low-intensity or short-duration. Thus, the desired total intensity of the generated interval training was set to $TRIMP_0 = 9,000$. However, the interval training plan must be generated with $n = 10$ intensity and recovery periods.

Table 3. Generated interval training plan of lower-intensity *TRIMP*

ID	$HR^{(I)}_{\text{ID}}$	$t^{(I)}_{\text{ID}}$	$HR^{(R)}_{\text{ID}}$	$t^{(I)}_{\text{ID}}$	$TRIMP^{(I)}_{\text{ID}}$	$TRIMP^{(R)}_{\text{ID}}$	$TRIMP_{\text{ID}}$
1	183	5	140	2	915	280	1195
2	187	3	161	1	561	161	722
3	188	3	161	1	564	161	725
4	184	3	160	1	552	160	712
5	187	3	161	1	561	161	722
6	186	5	148	2	930	296	1226
7	183	5	140	2	915	280	1195
8	188	3	161	1	564	161	725
9	188	4	150	2	752	300	1052
10	188	3	161	1	564	161	725
$\sum$	186.2	37	154.3	14	6,878	2,121	8,999

The results of Scenario A are presented in Table 3, from which it can be seen that the total intensity of the best generated interval training amounts to $TRIMP = 8,999$. This means that the algorithm found the solution of intensity $TRIMP$, differing from the desired one by less than 1 % (more precisely 99.99 % matching). On the other hand, this training session is also of short-duration, due to endurance of $37 + 14 = 51$ min, where the average heart rate of the intensity period is 186.2 bpm, and the recovery period 154.3 bpm.

The comment of the real sports trainer is as follows: Results in the table shows a high level of correlation with aerobic interval training, which is performed by mountain bikers very often, especially in preparation periods for competitions. The first type of training plan consists of repeated 3–5 min high intensity intervals with a relatively short-time of recovery (1–2 min). This training method ensures a successful adaptation to the level of high acidose by the athletes, which represents a similar effort as usually presented in the mountain bike races.

4.2 Scenario B

In this scenario, two demands were tested: (1) drastic increase of the demanded interval training intensity to $TRIMP_0 = 15,000$, and (2) at least one intensity period to be longer or equal to $t_{k_j}^{(I)} \geq 9$ min. Now, the BA must prefer the intensity and recovery periods of longer-duration on the one hand, and of higher-intensity on the other. Also here, the interval training must consist of 10 intensity, as well as recovery periods.

The results of Scenario B are depicted in Table 4, from which it can be seen that the total intensity of the best interval training needs to be realized at the intensity $TRIMP = 14,960$, that means 99.73 % matching with the demanded intensity. The slightly worse results than in Scenario A is a consequence of more constrained problem substituted with additional objectives. In this case, the total duration of

Table 4. Generated interval training plan of higher-intensity $TRIMP$

ID	$HR_{\mathrm{ID}}^{(I)}$	$t_{\mathrm{ID}}^{(I)}$	$HR_{\mathrm{ID}}^{(R)}$	$t_{\mathrm{ID}}^{(I)}$	$TRIMP_{\mathrm{ID}}^{(I)}$	$TRIMP_{\mathrm{ID}}^{(R)}$	$TRIMP_{\mathrm{ID}}$
1	179	5	120	6	895	720	1,615
2	188	5	151	2	940	302	1,242
3	178	6	148	3	1,068	444	1,512
4	174	8	138	4	1,392	552	1,944
5	186	4	143	2	744	286	1,030
6	172	9	131	5	1,548	655	2,203
7	185	4	145	2	740	290	1,030
8	177	7	135	4	1,239	540	1,779
9	186	5	148	2	930	296	1,226
10	187	5	148	3	935	444	1,379
$\sum$	181.2	58	140.7	33	10,431	4,529	14,960

the interval training increases to $58 + 33 = 91$ min, while the average heart rate of the intensity period settles at 181.2 bpm, and the recovery period 140.7 bpm.

The comment of the real sports trainer is now as follows. The second type of training consists of repeated 4–9 min intensity intervals, with recovery periods that last approximately 50 % less time than the intensity phase. Although this type of interval training slightly differs from the above mentioned Scenario A, it is the most effective for improving the maximal oxygen uptake and racing performance of the mountain bikers.

5 Conclusion

There is no doubt that stochastic population-based nature-inspired metaheuristics are a robust tool for planning the training sessions in various sports. In past, these metaheuristics have appeared for planning sports training sessions, where this training plan was generated for longer training periods.

In this paper, we investigated the possibility of planning the interval training sessions that consist of different intervals, and each interval is composed of an intensity interval and recovery period. Additionally, each intensity interval and recovery period are determined by the average heart rate and duration. The planning is represented as an optimization problem, where all intervals (i.e., intensity interval and recovery period) are composed from an archive of the interval training sessions, such that the total intensity of the training according to value $TRIMP$ does not exceed the desired intensity $TRIMP_0$. Let us mention that, in this preliminary phase, we do not generate the training plan for the whole training cycle, but for one interval training session only.

Although the algorithm for planning the interval training sessions could be implemented in any stochastic population-based nature-inspired algorithm, the BA was applied in this study. Experiments using the algorithm were divided into two scenarios, e.g. Scenario A and Scenario B, where both were conducted on an archive consisting of 40 interval training sessions realized by a younger mountain biker. The results confirmed our assumption that population-based metaheuristics can be applied for such type of planning.

The future of this area is still full of opportunities. Firstly, we should focus on the feedback of athletes who train on the training plan proposed by our method. Secondly, we should take into account more information about the already realized training sessions. From the initial observations, we see that there are many differences among athletes in the realm of endurance or speed. For that reason, some athletes prefer more interval sessions of more duration over intensity, while others vice-versa.

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