Optimising Team Sport Training Plans With Grammatical Evolution

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***Abstract*—We present a novel approach to generating seasonal training plans for elite athletes using the grammatical evolution approach to genetic programming. A grammatical encoding of a team sport training plan dictates the plan structure. The quality of the training plan is calculated using the widely adopted fitness-fatigue model, which in this study incorporates four performance metrics, namely *distance covered at low to medium speed*, *distance covered at high speed*, *distance covered accelerating*, and *distance covered decelerating*. We compare performance of the evolved training plans to a control setup which generates plans using a pseudo-random search process, and baseline against the training plan adopted by an elite team of Gaelic Football Players. Significant potential performance gains are achieved over the control setup and baseline elite team plan.**

***Index Terms*—sports analytics, genetic programming, grammatical evolution**

I. Introduction

Planning seasonal training for athletes has traditionally been guided by periodisation theory research which is fundamentally an extension of the study of stress, specifically stress arisen from an imposed physical training stimulus and the potential fitness adaptations which may develop through adequate recovery [1]. In the 1970s the first physiological based mathematical model was developed with the aim of predicting an athletes performance occurring from adaptation to a training stimulus, utilising measures which estimate the subsequent stress brought about as a result of that stimulus, typically referred to as a 'training load' [2]. This fitness-fatigue model developed by Banister et al. is still the most widely used in professional sport today, all be it in several different modified versions. In principle the model asserts that the response to a training stimulus is a combination of a negative (fatigue) and a positive (fitness) adaptation from the accumulated training stress an athlete is exposed to during a single session. Optimal performance is considered to be a balance between the two mechanisms of the model [3]. Performance in any training session will be governed by the adaptions from the previous one, if the resulting fatigue was greater than the body's ability to adapt then performance will be negatively affected until a time point at which fatigue has dissipated and a positive adaptation can been achieved. Therefore careful and considered design of an athlete's training plan is extremely important as to minimize the potential detrimental effects of accumulated fatigue such as excessive muscle tissue damage, changes in hormonal dysregulation and autonomic nervous system imbalance [4]. This is particularly relevant in the case of team sport athletes due to varying levels of stress induced by the quantity, intensity and variety of training activities they are exposed to, plus the regularity of competitive games. Therefore the use of the fitness-fatigue model is common place in guiding the preparation of seasonal training plans in elite team sports today.

The original fitness-fatigue model was designed to be utilised with only a single global measure of training load in arbitrary units [2]. In the present day, advancements in athlete tracking technology has allowed sports scientists and coaches to extensively quantify a wide variety of training stressors. Wearable devices equipped with global positioning system (GPS) chips and inertial sensors are routinely worn by professional team sport athletes during training and competitive match's to track a large quantity of external training load metrics [5]. The over or under accumulation of these metrics are used routinely to infer to what extent an athlete has been subjected to a specific internal stress. To date a strong body of research has shown that the accumulation of distance covered at high rates of velocity and changes in velocity has a significant relationship with important physiological markers of athlete well-being including muscular tissue strain [6], changes in blood bio-markers of muscle damage [7] [8] and reductions in neuromuscular performance [9].

1) Purpose of the Paper: Therefore the importance of ensuring that players receive significant doses of training stress to develop a strong output capacity during matches, while reducing the occurrences of a negative over exposure, is an ongoing priority for medical and coaching staff. Thus the purpose of this paper is: (i) to present a flexible framework which can be used to generate optimised training plans for professional teams and athletes adhering to real world and model-based constraints. And (ii) compare generated training

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plans against a human implemented plan to quantify its suitability and feasibility.

2) Statement of Novelty: The novel contribution to this approach is three fold, firstly this is the first paper to explore the use of grammatical evolution to generate optimised team sport training plans, and by extension map the real world training structure of an elite sports team into the optimisation algorithm. Secondly the novel use of a fitness function which captures a physiological based model of performance, for multiple measures of training stress, is introduced. The approach allows for the simultaneous optimization of these measures by considering the relationship between them. Given these measures infer the stress placed on the bodies subsystems, this allows for the compartmentalization of training stress within a session, as opposed to the use of a single global measure which may not fully capture the extent to which an individual subsystem has been exposed. This approach also allows multiple different parameters of the fitness-fatigue model to be applied to the different measures of training stress, and thus more precisely represent the associated subsystems response to a training stress. Thirdly this is the first approach to apply the concept of training load thresholds to constrain generated plans for the purpose of producing feasible and appropriate load prescriptions with respect to the training session type. These thresholds can be applied to any training session through out the length of the plan which helps reinforce the use of a periodisation strategy, specifically the practice of tapering training loads pre-competition.

II. Related Work

There has previously been several different algorithms purposed to solve the problem of generating optimized training plans to increase performance based on training models focused around individual sports, and more recently team sports. The following section will give a broad over view of that work as to familiarise the reader with what is a relatively new area of research.

A. Fitness-Fatigue Model

The initial approach taken to model the relationship between training and performance was based on the assertion that a single training session carries both a positive and negative physiological response, typically refereed to as "fitness" and "fatigue", and that combining these two responses gives a measure of performance [10]. This is represented mathematically in the following way:

$$p_t = p_0 + K_1 \sum_{i=1}^{t-1} w^i e^{-\frac{n-i}{r1}} + K_2 \sum_{i=1}^{t-1} w^i e^{-\frac{n-i}{r2}}$$

With K_1 and K_2 being a positive weighting factor for fitness and fatigue, these values can be fit per individual and represent the rate at which they can recover from a training stress, r_1 and r_2 represent the time decay until fitness and fatigue return to baseline, and finally w_i being the measured training work load for a single session. One particular limitation of the original model was that its parameters had to be fit to a particular athlete. Because of the requirement to individualise the model to a single athlete, a simplified version of the model know as the *Training Stress Balance (TSB)*, was widely adopted in team sports because of its relatively simple implementation, generalizability and supporting research [11]. The TSB model considers performance as the ratio between two exponentially weighting moving average scores, representing the fitness and fatigue components (See section titled *Fitness Function* for a detailed breakdown). Both models of performance do have some flaws and overlook some important training concepts, namely in the Banister model some parameters need to be adapted to the athlete and also the performance metric being used. Both the Banister and TSB model ignore the concept of over training, assuming that a training stimulus will always produce a increase in fitness, which is not always the case. The training stress of a session is also only represented in both models as a single global value, which dose not capture the varying levels of stress and rates of recovery on the bodies subsystems. Acknowledging these limitations, both models have shown in practice to be effective at guiding the planning of team sport training prescriptions [12] [13].

B. Mathematical Optimisation

Recognizing the rise in fitness based smartphone applications and adoption of wearable tracking devices, the authors of this publication [14] developed a mathematically based optimisation method to plan appropriate doses of training load with the goal of peaking a runners performance over a 100 day period. The following interpretation of the fitness-fatigue model was used to describe the relationship between training load and performance:

$$p(t) = p^* + w(t) * g(t)$$

Where $p(t)$ is the potential performance response to the training load at time (t), p^* describes the initial state of the athlete, $w(t)$ is the measured training load and $g(t)$ describes the response to that training load, which can be further broken down in to the relationship between the time decay factors of fitness and fatigue. A dynamical programming algorithm was used to solve the formulated optimisation problem, where by the decision at each successive stage is set to select the optimal amount of training load that enhances fitness while minimising fatigue. The results of simulation studies showed that training plans which utilised the fitness-fatigue model out preformed a training plan in which the loads where constant.

A multi-objective optimization model has also recently been explored to generate training plans which reduce the risk of injury as opposed to enhancing performance in Australian rules football (AFL) [15]. This approach used a sequential quadratic programming algorithm to generate daily training load values which (A) maximise the total amount of distance run over the specified training period (125 days), and (B) maximise the forecast performance on match days using a fitness-fatigue model. Several constraints where also applied to the optimization of the training plans in order to increase the feasibility of the plans, these primarily focused on limiting the short term accumulation of running distance to amounts that were achievable by humans and reduced the risk of over training. The algorithm was able to generate training plans that satisfied both objectives (A) and (B) between 400-600 iterations, the training load values produced were comparable to those of previously reported by AFL teams, however no direct comparison was completed to access the effectiveness of the algorithm generated plans.

C. Swarm Intelligence

The use of swarm intelligence algorithms has also been purposed to generate optimised athlete training plans due to the simple implementation and minimal time complexity for a variety of problems. Previously a modified version of the bat algorithm (MBA) has been used to search for a training plan constructed as an integer vector that minimises the error rate (er) between an intensity factor K and a training load for a generated training plan [16]. This was formally defined as:

$$er = min|K - hr|$$

where K was set as the desired maximal heart rate and hr in this instance was the heart rate generated by a specific training plan. Experimental results showed that with in 50,000 evaluations the bat algorithm was capable of generating training plans with an $er = 0$, how ever this was only the case when the intensity factor was set between an interval $K \in [135, 147]$. Using the same mapping process from search space to candidate solution the results of the bat algorithm was compared against particle swarm optimisation (PSO), differential evolution (DE) and deterministic algorithms (DET). The comparison showed that results from the PSO, DE and MBA all significantly outperformed the DET, with the PSO and DE also outperforming the MBA by a non-significant margin.

Building on the aforementioned work, recently a framework for planning training sessions in the multidisciplinary sport of triathlon using a PSO was purposed [17]. Similar to the bat algorithm a modification was made to the PSO so that problem solutions could be generated as real valued vectors. A single training load metric was generalized across all disciplines (swimming, running, cycling) with a weighting applied to indicate priority of training. The PSO algorithm was capable of maximizing the training load for the defined number of training days devoted to each discipline using the following fitness function:

$$f(x_i) = max \sum_{k \in D} w_k \cdot TRIMP_k(x_i)$$

Where w_k for k is the importance weighting of the discipline and $TRIMP_k(x_i)$ is the training load metric for that sporting discipline. The results of which were evaluated by a professional triathlon coach to determine the potential to enhance performance, further experiments will need to be conducted before the effectiveness of the PSO derived plans can be determined.

D. Evolutionary Algorithms

The use of evolutionary algorithms to generate optimal training plans has been explored by Schaefer et al. [18] investigating the potential of several different training load models to enhance fitness and performance. The optimisation problem was constructed as finding a training plans which results in achieving a specified performance goal, four constraints were set to three of which relate to the training structure of training periods i.e on/off days, and a maximum achievable training load per day was also set. The fitness function was formalised to reward solutions which limit the difference between a performance goal and the models predicted performance given its generated training loads:

$$f(p, g) = 1 - |g - f_m(p, p_m)| - \alpha \cdot \sum_{i=1}^{n} (p_i)$$

with $p \in \Omega$, g the intended performance goal, f_m representing the performance model used and p_m its parameters. A weighting factor α is also used to ensure plans with higher training loads with good precision don't get rated poorly compared to low loads with bad precision. Three different evolutionary approaches were taken, firstly a *Hill Climbing* approach was used with a population size of one, three variants of mutation operators were implemented over the evolved plan to randomly increase the training load for a given day, while supporting the constraint boundaries. The second approach was to employ a Differential Evolution algorithm which created a new solution from the differences between four members' of the population in a given generation. The third approach utilised a Covariance Matrix Adaptation Evolution Strategy (CMA-ES), candidate solutions were sampled from a multivariate normal distribution, and the search path was directed by the sum of consecutive update steps. Comparative results over 10 generations showed that the DE and CMA-ES algorithms were capable of solving the optimisation problem in this instance significantly faster than two constraint satisfaction problem (CSP) solvers (Bonmin, Couenne) with similar levels of quality while adhering to all formalised constraints. The Hill Climbing algorithm's performance suffered from a tendency to converge on a local optimum, and thus was out preformed by all other algorithms used in the experiment.

III. Experimental Framework

The purposed framework to evolve optimised training plans for team sports based on performance models and defined constraints, consists of three main parts, an evolutionary algorithm, a formalised grammar and a fitness function, which are detailed further in this section.

In this study we focus on generating training plans for an elite team in the field sport of Gaelic Football. Data for the team has been captured during a competitive season using STATSports Apex units [19] for each of the four training load measures, namely, *distance covered at low to medium speed*, *distance covered at high speed*, *distance covered accelerating*, and *distance covered decelerating*. This collected data covers both an inter-county football league and All-Ireland championship competition spanning eight months from the end of January to the start of June.

A. Grammatical Evolution

Grammatical Evolution is an evolutionary algorithm that takes a novel approach to Genetic Programming (GP) by utilising a formalised grammar when executing the genotype to phenotype mapping process [20]. PonyGE2 is a highly flexible open source Python implementation of grammatical evolution which is capable of encoding information by mapping linear genomes to phenotype outputs, through the use of a context free grammar notated in Backus-Naur form (BNF). The extensive modular nature of PonyGE2 allows for a variety of search strategies to be experimented with and progressive changes in behaviour to be achieved by implementing trivial changes in the supporting grammar. For a detailed over view of PonyGE2, see [21].

B. Grammar Design

In order to evolve a valid structure for an athletes training plan a BNF grammar was initially defined and is outlined in Figure 1. The grammar was designed to replicate the training plan structure of an elite inter-county Gaelic Football team, spanning over twenty two weeks of competition. Gaelic Football is a field based team sport native to Ireland, it is contested between two teams of 15 players and is characterised by its fast pace and skill [22]. When notating the training habits of an elite team into the formalised grammar each training session which took place was represented a series of non-terminals, which further mapped to a set of four non-terminals representing measures of external training load captured by a wearable GPS unit. These four training load measures detailed the distances in metres an athlete could potentially run when their speed was: $< 5.5\,\mathrm{m\,s^{-1}}$, $\geq 5.5\,\mathrm{m\,s^{-1}}$, acceleration was $\geq 3.0\,\mathrm{m\,s^{-2}}$ and deceleration was $\geq 3.0\,\mathrm{m\,s^{-2}}$. Each training session had a type associated with it based on how far it was away from a match day (i.e. MD-2, two days preceding a competitive match), based on the training day type, load measures where constrained between an upper or lower bound. This ensured that training plans were evolved containing feasible training load values and that tapering prior to games could be achieved. The ten match day load values were calculated using the actual elite team match day data from the median of all combined players who were on the pitch for longer than 50 minutes and encoded into the grammar for specific match day types, preserving the authenticity of the retrospective training plan.

C. Fitness Function

As was the case with previous work, an implementation of Banisters' fitness-fatigue model know as Training Stress Balance was used to assess the fitness of a given population of solutions. The model's fitness and fatigue components were represented as exponentially weighted moving averages calculated per session (54 sessions in total), for each of the four training load measures, values for the fatigue component are divided by the fitness component to give a ratio value:

$$f = \sum_{sess=1}^{54} \sum_{met=1}^{4} \left| \frac{fatique}{fitness} - 1.3 \right| \tag{1}$$

Where f is the sum of the summation of residual values, after the ideal ratio 1.3 has been taken from the absolute ratio of each training stress balance score representing the total training load of that session, calculated as follows:

$$fatigue = Load_{ts} * \lambda_{fat} + ((1 - \lambda_{fat}) * fatigue_{ts}) \tag{2}$$

$$fitness = Load_{ts} * \lambda_{fit} + ((1 - \lambda_{fit}) * fitness_{ts}) \tag{3}$$

Where $fatigue$ and $fitness$ are the values for a single training session, $fatigue_{ts}$ and $fitness_{ts}$ are the calculated loads for the previous training session, $lambda$ is a value between 0 and 1 specifying the degree of decay for both fitness and fatigue. In this experiment lambda values were specified as follows based on previous research [23]:

$$\begin{aligned} \lambda_{fat} &= 2/(7+1) \\ \lambda_{fit} &= 2/(28+1) \end{aligned} \tag{4}$$

A fixed ratio value between the fitness and fatigue of the training load measure was set at 1.3, for all four training measures in a session, to enable progressive increases in performance with acceptable levels of fatigue [23]. This is the first study to explore the use of a fitness function that seeks to compartmentalise training load to represent adaption across different subsystems of the body. No other previous work [18] [17] has consider this approach, which could also be extended, to account for the varying rates of adaptation by changing the lambda parameters of a training measure's TSB calculation, to more accurately model specific rates of fitness accumulation and fatigue decay. For example based on previous research highlighting that mechanical loads experienced during deceleration's can be up to 65 % greater than that of other match play activities [24], the lambda parameters of the fitness function could be easily adapted to account for increased fatigue and slower rates of adaptation due to the enhanced muscular tissue trauma.

D. Experimental Parameters

The specific parameters used in this experiment with the PonyGE2 algorithm described in section III.A were: Population size = 1000, Generations = 500, Runs Completed = 30, Selection = Tournament, Tournament Size = 2, Replacement = Generational, Elite Size = 10%, Crossover = Fixed One Point, Crossover Probability = 90%, Mutation = Int Flip Per

```
<inseason> ::= <md-5>;<md-2>;<md1>;
               <md-5>;<md-2>;<md2>;
               <md+2>;<gen>;<gen>;<md-5>;<md-2>;<md3>;
               <md+2>;<gen>;<gen>;<md-5>;<md-2>;<md4>;
               <md+2>;<gen>;<md-5>;<md-2>;<md5>;
               <md+2>;<gen>;<gen>;<md-4>;<md6>;
               <gen>;<gen>;<gen>;<gen>;<gen>;<gen>;<gen>;
               <gen>;<gen>;<gen>;<gen>;<gen>;<gen>;
               <md-5>;<md-2>;<md7>;
               <gen>;<md-4>;<md-1>;<md8>;
               <md+2>;<md9>;
               <md+2>;<gen>;<gen>;<md-2>;<md10>
<md1> ::= 6331,1197,391,64
<md2> ::= 7895,543,261,97
<md3>::= 8876,629,362,123
<md4>::= 8665,613,336,120
<md5>::= 9157,1007,426,149
<md6>::= 10541,672,350,136
<md7>::= 8775,783,306,125
<md8>::= 9836,1169,356,140
<md9>::= 8642,706,432,147
<md10> ::= 9858,938,471,139
<md+2> ::= <td_u>,<hsr_u>,<acc_u>,<dec_u>
<md-6> ::= <td_u>,<hsr_u>,<acc_u>,<dec_u>
<md-5> ::= <td_u>,<hsr_u>,<acc_u>,<dec_u>
<md-4> ::= <td_u>,<hsr_u>,<acc_u>,<dec_u>
<md-2> ::= <td_l>,<hsr_l>,<acc_l>,<dec_l>
<md-1> ::= <td_l>,<hsr_l>,<acc_l>,<dec_l>
<gen> ::= <td_u>,<hsr_u>,<acc_u>,<dec_u>
<td_l> ::= GE_RANGE:3500
<hsr_l> ::= GE_RANGE:500
<acc_l> ::= GE_RANGE:200
<dec_l> ::= GE_RANGE:200
<td_u> ::= GE_RANGE:10000
<hsr_u> ::= GE_RANGE:1500
<acc_u> ::= GE_RANGE:500
<dec_u> ::= GE_RANGE:500
```

Fig. 1. The grammar adopted to encode an in-season training plan. The number and ordering of training and match days is as adopted by the elite Gaelic Football team. The ten match day load metrics, across the four dimensions of load, are encoded in the non-terminals `<md1>..<md10>` and are generated from the elite teams actual load data on each match day. The `<gen>` non-terminal encodes general training sessions which occur outside the seven-day pre-match window with `<md-` and `<md+` encoding pre- and post-match day training sessions. The four `_l>` and four `_u>` non-terminals are used to set lower and upper bounds for each of the four load metrics in each session.

Ind, Mutation Events = 1. A pseudo-random search control experiment was also conducted as a performance baseline, the parameters were matched for both experiments aside from the following adjustments: Population size = 10000, Generations = 1, Runs Completed = 1.

IV. Experiment Results

The results of the experiment show that the purposed framework detailed in section III is capable of generating training plans with an superior fitness score, compared to a random control and a real world elite team seasonal plan, subject to the following constraints set out in the grammar:

- Elite team periodization structure
- Enforced match training loads
- Upper training load bounds
- Lower training load bounds (MD-1, MD2)

The average rate of convergence can be seen in Figure 2. This was calculated by taking the population with the lowest fitness score per generation from each experimental run and compiling the average of those score over all 30 runs. Error bars displaying the 95% confidence intervals are also shown, displaying the extent to which the evolved scores differ from the elite team and random search across generations. Based on this figure we can also assert that this optimisation method outperforms a random search within a short number of generations and continues to sharply improve its performance until a leveling off begins to occur at approximately the 200th generation. This demonstrates that the current implantation of the PonyGE2 algorithm has the ability to offer a fast and precise solution to evolving optimised team sport training plans. An interesting observation is present when comparing the evolved training plan fitness scores to that of the elite team, the performance of the elite team when analysed in the context of the fitness-fatigue model detailed in section III.C is considerably worse than the random search control. Based on this observation one might speculate that a performance improvement could potentially be obtained simply through the implantation of constraints, based on sound scientific principles of training load management, and the adherence to those constraints.

A comparison of the evolved training loads for the population with the best over all fitness from the 30 runs is shown in Figure 3. The total training load prescribed by the evolved training plan was 21% lower than that of the elite teams' plan across the entire season. With the differences being a 32% reduction in the amount of distance covered at a velocity greater than $5.5\,\mathrm{m\,s^{-1}}$, this was inline with a 25% reduction in distance covered less than $5.5\,\mathrm{m\,s^{-1}}$. A 142% increase in distance covered decelerating at a rate higher than $3.0\,\mathrm{m\,s^{-2}}$ contributed most to the over all difference in the total loads. Comparatively accelerations showed a minimal increase of 3%. Examining the distribution of training load values across the training sessions reveals the cyclical behavior of the evolved plan, which appears to follow a high low pattern compared to the elite team sport plan which also appears to fluctuate it's intensity but to a lesser degree. The effect of tapering can also be clearly observed in the behaviour of the evolved training plan, there was significant differences across all training load measures in sessions that occurred one or two days prior to a match. A 95-99% reduction in the distance covered at high speed, accelerating and decelerating can be observed when MD-1 and MD-2 training sessions are compared for the evolved and elite team training plans.

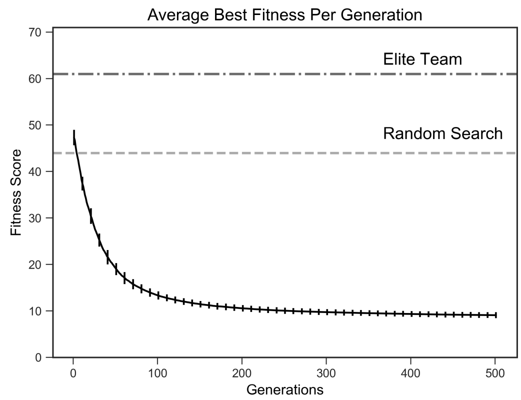

Fig. 2. The average fitness score of the best population per generation over 30 runs

V. Discussion

The purpose of this paper was to demonstrate the ability of grammatical evolution to generate optimised team sport training plans, using a fitness function based on a physiological performance model and adhering to formalised constraints set out in a BNF grammar. The results of experiments show that PonyGE2 can achieve a good performance for this formulated optimisation problem. The extremely flexible nature of grammatical evolution easily facilitates the modification of a problem, this has significant practical benefit given the dynamic nature of sports competition. The use of a grammar also makes it trivial to implement training periodization structures into the algorithm, macrocycles, mesocycles and microcycles can be easily notated in the grammar and evaluated within the fitness function to direct an athletes performance over multiple training periods. In the current experiment an elite Gaelic football teams' retrospective training structure was used to inform the construction of the grammar, the median value of the teams training load per match was enforced in the training structure for the purpose of comparing the evolved training plans to that of the elite team. The same process could be used by practitioners to inform training through the use of tactical periodisation, which aims to peak performance for matches which are perceived to be the most difficult or important during the competitive season [25]. This type of periodisation strategy can be easily implemented through the manipulation of the grammar, if predicted match loads are substantially different from the actual loads achieved then the algorithm can be rerun to update the team sport training plans accordingly. Based on the structure used to inform the distribution of training loads across the season, the PonyGE2 algorithm was able to generate feasible and practical solutions to planning training, however the current structure itself may not be the optimum way to construct a seasonal training plan. Refining the optimisation problem to allow the algorithm to choose other parameters such as the number of training days and the position of those days relative to a match could potential lead to an enhanced performance across the season, based on the current performance model. The novel use of a fitness function which accounts for multiple training stressors and considers the balance between them was an important part of this experiment. An evident flaw in both the Banister and TSB models are the use of a single global measure of training stress, and by extension a single rate of recovery and adaptation. Previous research has shown that this is an inaccurate assumption [26], our modification of the training stress balance model attempts to address this flaw, however further research and refinement is need to determine the optimal parameters for specific populations and training activities. The training stress balance model itself can be criticized for its over simplification of the complex relationship between training and performance, the model fails to account for important concepts such as over-training and monotony. However the intention of this paper was not to validate any

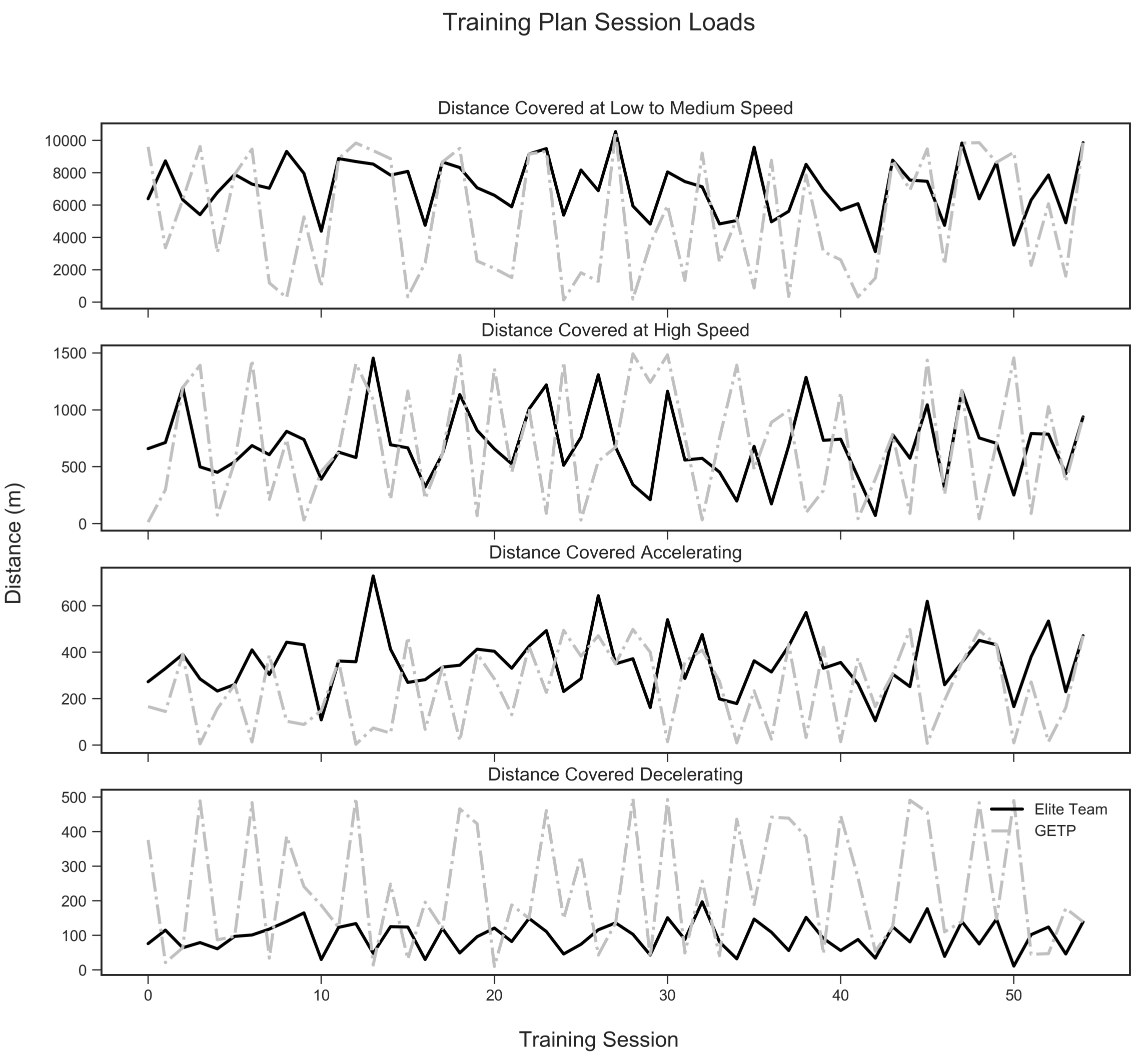

Fig. 3. Training plan session loads for an elite team, compared with evolved loads over a 22 week period

particular performance model, but to show that a framework based around grammatical evolution can be used to optimize team sport training plans with a large degree of flexibility and performance. This is supported by the generation of plans which out preform an elite team baseline, using established training science and performance monitoring methods.

VI. Conclusion and Future Work

A novel approach to elite team sport training plan generation is introduced using Grammatical Evolution with significant potential performance gains realised over a control and an elite team plan baseline. There is much potential for future work including the complexification of the grammar encoding to include periodisation cycles and strategies across the training year, expanding on the work presented here to include pre-season training periods. Further refinement of the fitness function to include relative weightings for the individual load metrics, and the implementation of more complex models of performance can be introduced. This approach can also be extended to other team sport training structures, which may have more complex training and competitive requirements. In summary the current methodology is capable of generating feasible team sport training plans with optimized training loads based on an implementation of the fitness-fatigue performance model and established constraints, through the use of the PonyGE2 Python implementation of Grammatical Evolution. This approach can be used to safely guide the training prescription of elite teams and athletes so that enhances in physiological performance maybe gained, while minimising the accumulation of fatigue associated with player overload and increases in injury risk.

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