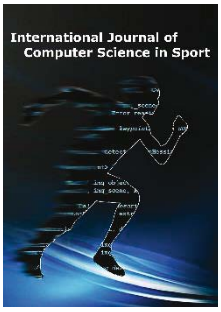
International Journal of Computer Science in Sport

Volume 20, Issue 1, 2021

Journal homepage: http://iacss.org/index.php?id=30

sciendo

DOI: 10.2478ijcss-2021-0006



Optimizing Team Sport Training With Multi-Objective Evolutionary Computation

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Abstract

This research introduces a new novel method for mathematically optimizing team sport training models to enhance two measures of athletic performance using an evolutionary computation based approach. A common training load model, consisting of daily training load prescriptions, was optimized using an evolutionary multi-objective algorithm to produce improvements in the mean match-day running intensity across a competitive season. The optimized training model was then compared to real-world observed training and performance data to assess the potential improvements in performance that could be achieved. The results demonstrated that it is possible to increase and maintain a stable level of match-day running performance across a competitive season whilst adhering to model-based and real-world constraints, using an intelligently optimized training design compared a to standard human design, across multiple performance criteria (BF+0 = 5651, BF+0 = 11803). This work demonstrates the value of evolutionary algorithms to design and optimize team sport training models and provides support staff with an effective decision support system to plan and prescribe optimal strategies to enhance in-season athlete performance.

KEYWORDS: TRAINING LOAD; GENETIC ALGORITHMS; EVOLUTIONARY COMPUTATIONS; ARTIFICIAL INTELLIGENCE

Introduction

A core responsibility of every sports coach is to design and conduct training sessions that effectively develop an athlete's performance. Coaches will routinely use training models to assist them in completing this important task. A training model can consist of planning, analysis and assessment, which are important components in the overall development of athletes (Bompa & Buzzichelli, 2019). It has been repeatedly demonstrated that effective training can enhance an athlete or teams performance. A large volume of research has been dedicated to studying the effects that suitable modifications in training models and interventions can have on specific measures of physiological performance and adaptation (Jaspers et al., 2017; Borresen & Ian Lambert, 2009). In practice, the manipulation of training model variables are typically conducted by a coach with sufficient domain-specific knowledge and experience, selecting what they consider to be effective combinations of training frequency, mode and load to enhance their athletes' performance. However, when the number of variables in a training model become too large and non-independent, it can be difficult for coaches to select the optimal set which will result in an athlete achieving a significant enhancement in performance. Additional complexity arises when we consider managing multiple training variables across an entire season whilst reducing the risk of overtraining and injury. For example, a coach may desire to maintain a high level of athlete readiness and performance across a season, while also peaking for specific competitions and events. Techniques commonly utilised in the field of operational research, such as mathematical optimization, can assist coach's in finding the best possible combination of training model variables to achieve a well defined and measurable performance goal. Recently Carey et al. (2018) utilised such a method to investigate the effects optimizing pre-season training load had on player performance in Australian rules football. Their defined objectives were to maximise the total distance covered over a range of days spanning the pre-season training period and to maximise a model-based prediction of performance on the first day of the competitive season. The authors effectively demonstrated the utility of this approach and produced optimized training plans that were in agreement with previous research-based recommendations. However, the authors only sought to optimize pre-season training load prescriptions. Whilst this is an important period for players to prepare for the upcoming season, the approach of Carey et al. (2018) provides limited operational utility during the in-season competitive period given the increased complexity of the training and competition schedule.

The problem of constructing optimal training models to enhance in-season physical performance is considered complex from a number of physiological and operational perspectives (Wright, 2009). For example, previous research has shown there to be a negative relationship between increased acute training load and physical output during a simulated soccer match (Slattery, Wallace, Bentley, & Coutts, 2012; Jones, Greig, Maw´en´e, Barrow, & Page, 2019). The effects of an accumulation of training load on match performance were also previously reported by (Lazarus et al., 2017), who concluded that periods of high acute load, as well as sustained increases in load, lead to negative match performances in elite AFL competition. Paradoxical research on the importance of having high physical outputs during games was reported by Chmura et al. (2017) who detailed that during the 2014 FIFA World Cup tournament, winners Germany, covered significantly more distance at higher relative intensity than players from other teams. Similarly, Konefal et al. (2019) showed that, during the 2014/2015 Bundesliga domestic season, having a higher mean and peak speed in the second half of a match significantly increased the odds of winning that match. Furthermore, Longo et al. (2019) reported that high-intensity running activity was associated with a higher probability of achieving a top-three end of season ranking in the 2016/2017 Serie A season.

Therefore, the effective construction of a training model that included the planning and management of training load has an important role to play in supporting positive performance outcomes throughout the competitive season and slowing the rate of progressive deterioration's in physical conditioning typically observed as the season advances (Meckel, Doron, Eliakim, & Eliakim, 2018; Mara, Thompson, Pumpa, & Ball, 2015).

This research seeks to advance the approaches applied in previous research (Connor, Fagan, & O'Neill, 2019), (Carey et al., 2018), (Schaefer, Asteroth, & Ludwig, 2015) (Ladany, 1975) to the problem of enhancing performance in competitive matches during the in-season period using a form of multi-objective evolutionary computation.

This study introduces a new approach to the problem of constructing an optimal training plan model, that can be used by coaches and support staff to enhance the in-season physical performance of their players. To test the utility of the optimized training plan model we compare it to the observed training of a competitive team sport athlete designed by a professional coach. We hypothesise that the artificially designed training models will out perform the human designed model.

Methods

In order to generate training models which enhance physiological performance, the problem is constructed as a multi-objective optimization. This type of problem seeks to find the maximum or minimum of two or more objective functions, subject to a set of constraints (Deb, 2001). In this experiment, we aim to maximise the average model predicted performance on match days across the entire season and minimise large fluctuations in the daily training load prescribed to the athlete. The schematic in Figure 1.0 provides a visual overview of the optimization process and the modular multi-model setup. The following sections will detail the structure of the multi-objective optimization and the approach used to solve it.

Quantifying Performance

To quantify physiological performance during a match, two measures were calculated that capture differing aspects of running intensity; velocity based running intensity (VRI) and acceleration based running intensity (ARI). All data was collected using a GNSS based wearable device (STATSports Apex 10Hz, N.Ireland). The validity and reliability of this device has previously been established (Beato, Coratella, Stiff, & Dello Iacono, 2018; Beato & de Keijzer, 2019). The VRI measure is defined as the sum of all distance run above $5.5ms^{-1}$ divided by the total active playing time. The ARI measure was calculated as above were all distance run above $3.0ms^{-2}$ is summed and divided by the active playing time to produce two intensity measures in units of metres per minute m/min. These threshold values represent an industry norm and are in line with previous methods used to quantify running intensity in other sports (Tierney, Tobin, Blake, & Delahunt, 2017; Trewin, Meylan, Varley, & Cronin, 2018).

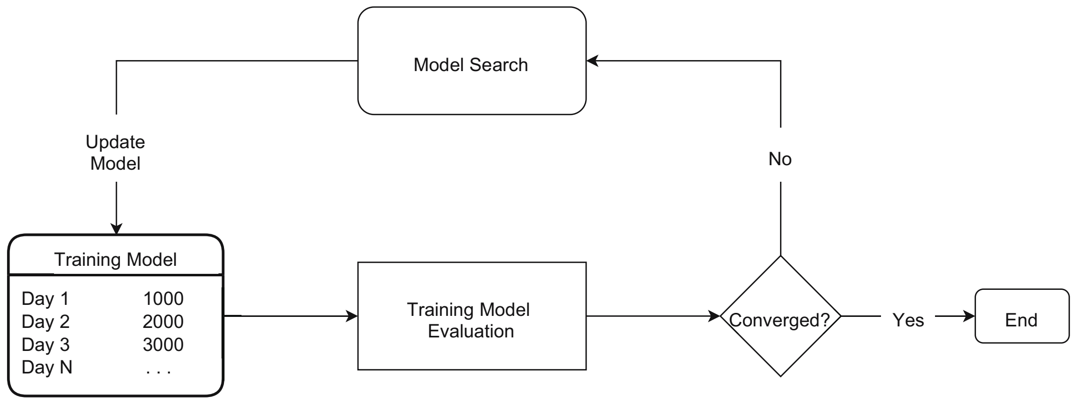


Figure 1.: Schematic of the optimization process.

Training Models

To produce training models that adhere to real-world operational constraints, the training and match schedule of a female soccer player competing in division one of the National Collegiate Athletic Association competition was replicated exactly to form the structure of the training model. The training model spanned 120 days of the inseason competitive period. Each day in the training model was categorised using a match-day minus system to allow microcycle specific constraints to be incorporated into the optimization process. The training load prescriptions on each day is split into two sets containing six values. The values in each set consist of the running distances in metres accumulated in six different manufacturer defined velocity and acceleration zones (Table 2.0 Appendix). The two sets of zones are then aggregated using a training impulse (TRIMP) exponentially weighted (Appendix Table 3.0) calculation (Stagno, Thatcher, & van Someren, 2007), to form two daily training load variables: $TRIMP^{Vel}$ and $TRIMP^{Acc}$ (Graham, Cormack, Parfitt, & Eston, 2018). This process is conducted in order to ensure that running intensity in higher zones receive a higher weighting as those zones represent a larger physiological load on the player. These variables are inputted into the objective functions to predict an athletes performance, the optimization process will find the set of variables that maximise predicted performance subject to constraints.

Training Model Optimization

In order to generate optimized training models, an evolutionary computing algorithm was implemented using the open-source PonyGE2 program written in the Python 3 programming language (Fenton et al., 2017). The following sections will describe the specifics of the algorithm and its application to the problem.

```
<inseason> ::= <GEN>;<md-5>;<md-2>;…<MD15>
<GEN> ::= <DZ1H>,<DZ2H>,<DZ3H> … <ADZ6H>
<DZ1H> ::= GE_RANGE:3500
<DZ2H> ::= GE_RANGE:500
<DZ3H> ::= GE_RANGE:200 …
<ADZ6L> ::= GE_RANGE:200
```

Figure 2.: The grammar adopted to encode an in-season training plan. The number and order of training and match days are replicated using the observed training plan of an elite soccer player. The non-terminals generate a random integer from 0 to an upper limit using a special python operator.

Evolutionary Computing

Evolutionary computing is a subfield of artificial intelligence focused on the use of biologically inspired population-based heuristic search algorithms. A genetic algorithm is one such type of population-based heuristic which seeks to emulate in part the Darwin principles of evolution. Genetic algorithms operate by generating an initial population of candidate solutions, fitter solutions are selected to progress on to the next generation based on an objective function score. Research has shown that genetic algorithms are capable of solving complex optimization problems in a timely and satisfactory manner (Coello Coello, Lamont, & Van Veldhuisen, 2007; Schaefer et al., 2015). Grammatical Evolution is an extension of the canonical genetic algorithm which seeks to direct the search to a space of potential solutions by employing a mapping function using a formalised grammar (O'Neill & Ryan, 2001, 2003; Dempsey, O'Neill, & Brabazon, 2009). The advantage of this technique is that it allows for domainspecific knowledge to be encoded into the grammar, which helps uncover more desirable solutions in the search space. Figure 2 shows an example of the grammar used in this experiment.

Objective Functions & Constraints

In order to evaluate the quality of a training model, it is scored by using multiple objective functions. This is stated mathematically in the following form:

$$\begin{aligned} &max\ f_1(x), \qquad min\ f_2(x) \\ &\text{s.t} \quad x_i \leq a_j\, \forall j \\ &x_i \geq 0\ \forall j \end{aligned} \tag{1}$$

Where, x is a training model, x_i is a set of training load variables, a_j is an upper bound on training load that can be prescribed on the i^{th} day preceding a match (i.e. MD-1), in the set j of match-day type constraints (See appendix Table 1.0). Constraints were selected by selecting high but feasible training load values using unpublished data. The first of the two objective functions is based on the seasonal mean of the impulse response (IR) model predicted match-day performances. This model asserts that a training stimulus will have a dose-response type effect on an athletes' performance. A single training input to the impulse response model results in two antagonistic responses, an increase in fitness and an increase in fatigue. The balance between the two responses, which have varying rates of decay, form a prediction of the athletes current level of performance. The objective function is then the mean of the model predicted performances for both the velocity and acceleration based running intensity measures, as follows:

$$f_1(x) = \frac{P_1 + P_2}{2} \tag{2}$$

Where P_1 & P_2 are each the sum of the average seasonal match-day predicted velocity and acceleration based running intensity performances, calculated as follows using the impulse response model:

$$P = \frac{\sum_1^n p(t)}{n} \tag{3}$$

Where P is the overall average seasonal performance

$$p(t) = p* + k1 \cdot w(t) - k2 \cdot g(t) \quad (4)$$

Where $p(t)$ is the predicted performance 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 into the relationship between the time decay factors of fitness and fatigue. The parameters of the models were fit by minimising the residual sum of squares between the model predicted and observed performances using a differential evolution stochastic global optimization method (Storn & Price, 1997) in a custom Python script. In order to evaluate the predictive accuracy of the fitted parameters, the Bootstrap method was utilised (Tsamardinos, Greasidou, & Borboudakis, 2018). Briefly, this involved re-sampling the original data set to create a bootstrapped replicate data set of the same size as the original to which we apply the impulse response model. Samples which are not chosen, known as out of bag samples, are used to evaluate the accuracy of the model by calculating the root mean square error (RMSE) between the observed and predicted out of bag samples. This method was repeated 1000 times to calculate the mean impulse response model error with 95% confidence intervals (Harrell, 2006). For further information on the impulse response model see Banister, Calvert, Savage, and Bach (1975).

The second objective function implemented to evaluate the quality of a training model was the regulation of daily training load prescriptions using a method known as the acute chronic workload ratio (ACWLR). The ACWLR is routinely used to restrain the prescription of daily or weekly training load in order to avoid large fluctuations which could potentially cause detrimental effects to an athletes' performance. Research conducted by Lazarus et al. (2017) has demonstrated that match-day performances are typically higher when the ACWLR on a match-day is closer to the seasonal mean. This makes intuitive sense as the seasonal mean value represents a reasonable baseline fluctuation in training load that is tolerable for the athlete and provides a suitable method of restraining the ramp rate of training load accumulation. We state this objective function mathematically as:

$$f_2(x) = P_1 + P_2 \quad (5)$$

Where P_1 & P_2 are the performances of the algorithm, scored on its ability to prescribe a training load distribution that results in match-day ACWLR values being closer to the seasonal mean, calculated by the following equation (6):

$$P = \frac{\sum_{i=1}^{n} |y_i - \hat{Y}|}{n} \quad (6)$$

Where n is the number of match days in the season, y_i is the ACWLR value on the i^{th} match-day of the season and $\hat{Y}$ the mean ACWLR across the entire season. The ACWLR is calculated using the exponentially weighted moving average method as detailed in Williams, West, Cross, and Stokes (2017).

Experimental Parameters

The following experimental parameters were used when running the grammatical evolution algorithm over 30 experimental runs to generate optimized solutions: Generations - 500, Population Size - 500, Cross Over - Fixed One Point, Mutation - Integer Flip Per Individual, both Cross Over and Replacement were performed using a version of the non-dominated sorting genetic algorithm (NSGA-II) (Deb, Pratap, Agarwal, & Meyarivan, 2002). For further information about the experimental parameters used see Fenton et al. (2017).

Statistical Analyses

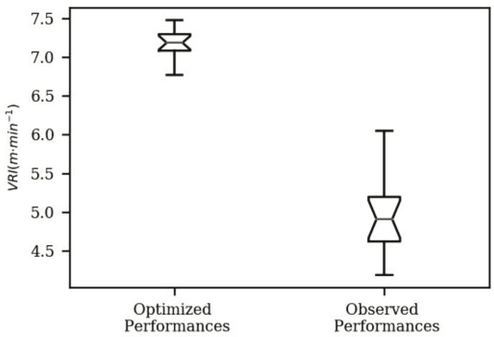
The bootstrapped root mean squared error of the impulse response models is reported as the mean ± s.d. with 95% confidence intervals. The converged objective function values of the 500th generation over 30 experimental runs is reported as the mean ± s.d. Statistical analysis of the difference between training model optimized performances and the observed performances are reported using a directional Bayesian paired samples t-test with a Cauchy prior of 0.7 (Kruschke, 2013). A two-sided KolmogorovSmirnov test was used to test the hypothesis that the two distributions of prescribed training load are the same, the alpha values were set at 0.05 (Hodges, 1958). All analysis was conducted using the Python 3.7 programming language.

Results

The mean bootstrapped impulse response model error for high velocity running was 1.65 ± 0.12 (CI 1.45, 1.87). The error for high accelerated running was 0.97 ± 0.02 (CI 0.94, 1.02). Over the 30 experimental runs, the mean Pareto front on the 500th generation has a value of 8.90 ± 1.30 (a value of zero is a fully satisfied solution), this shows the stability of the algorithm to consistently converge on an optimal solution space. The impulse response model based objective reached convergence between 11.3 - 11.4 (AU). While the ACWLR objective appeared to converge to an optimal value of between 0.5 - 0.6 (AU) in fewer generations. The model optimized and observed performances can be seen in Figures 3 and 4. The first observation displays the summary of the optimized and observed seasonal performances for velocity based running intensity, while the second observation displays optimized and observed seasonal performances for acceleration based running intensity. The standardized mean difference between the model optimized and observed performances are displayed in Table 1.0 as a Bayes factor in favour of the alternative hypothesis, which in both instances was a directional hypothesis stating that the optimized performances would be greater than the observed. The Bayes factor in both cases demonstrates that the alternative hypothesis explains the data substantially better than the null hypothesis.

			BF_{+0}	**error %**
Optimized VRI	-	Observed VRI	5651.222	NaN
Optimized ARI	-	Observed ARI	11803.009	NaN

Table 1.0 Bayesian Paired Samples T-Test



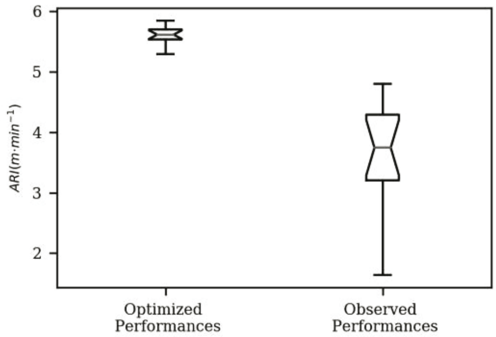


Figure 3.: Velocity Based Running Inten- Figure 4.: Acceleration Based Running Intensity

Training Load Distributions

An aggregation of the daily zonal training load prescriptions can be seen in Figures 5 and 6. The Kolmogorov-Smirnov test results show that there are significant differences

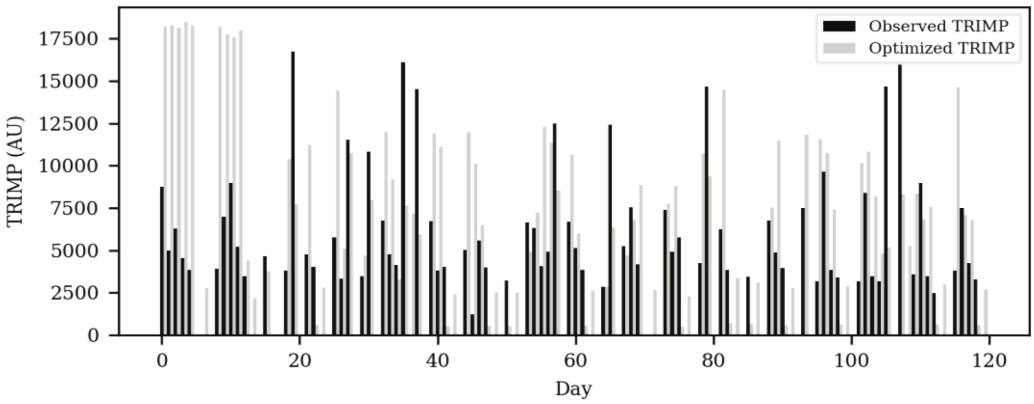


Figure 5.: Optimized and observed aggregated velocity based training loads (TRIMP) over the in-season period.

in the seasonal distributions of both the velocity ($p < 0.001$) and acceleration ($p < 0.001$) daily training load values, which likely attributed to the differences in matchday running performances.

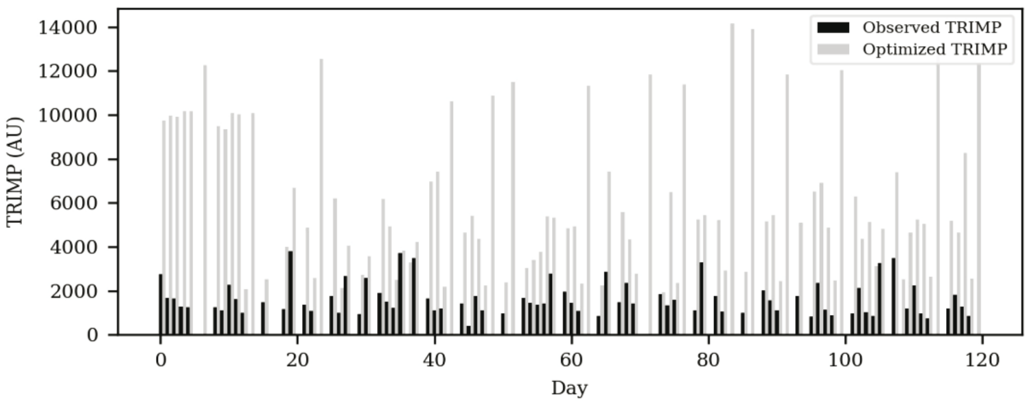


Figure 6.: Optimized and observed aggregated acceleration based training loads (TRIMP) over the in-season period.

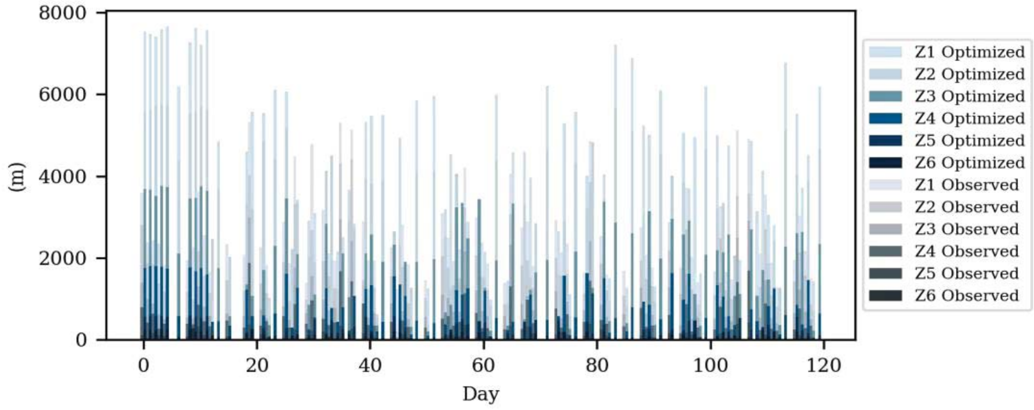


Figure 7.: Optimized and observed velocity based training loads (m) distributed across zones 1-6.

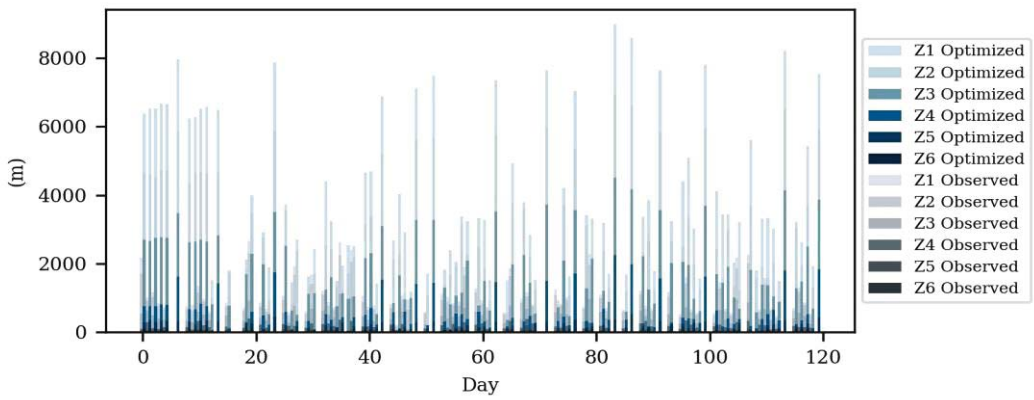


Figure 8.: Optimized and observed acceleration based training loads (m) distributed across zones 1-6.

Discussion

This research demonstrates that it is possible to generate feasible training models that can enhance multiple athlete performance criteria, while also satisfying microcycle upper load constraints. This is the first study to demonstrate the ability of an evolutionary computation based algorithm to optimize training models for an athlete during the in-season competitive period. This study is also the first to construct novel multi-model objective functions and converge on solutions, over several dimensions, that are considered important for the effective design of a training model to enhance athlete performance. The findings of this study appear to be in agreement with other researchers (Connor et al., 2019; Carey et al., 2018; Schaefer et al., 2015) who demonstrated that training load prescription values can be optimized utilising mathematical models that map the effects of training stimuli to a change in athlete performance.

The flexibility of using grammatical evolution to solve this problem can't be understated, with trivial changes to the grammar the training model structure can be altered or updated to reflect real world changes. Similarly, the objective functions can be swapped out and altered with ease if model parameters need to be changed, or new models are developed to help to direct the planning of training activities. The multi-objective nature of the problem also presents a Pareto front of possible solutions, the choice can be made to use a solution that achieves a higher performance in one objective at the cost of another or a balanced solution from the middle of the front. This characteristic may be desirable for coaches given that different situations can arise during the season which requires one objective to prioritised over another. Or if the objectives are not equally weighted by coaching staff. For example, higher fluctuations in training load may be tolerated achieving enhanced performance in the lead up to important matches.

When examining the model optimized daily training load values, displayed in Figures 7 and 8, we observe similar distributions of daily training load in velocity zones 1-6 as actually completed by the player. The training model optimized daily prescriptions appear to have a slight positive skew towards higher loads in zones 1-4, these zones represent distance covered at a velocity under 4.0 ms^{-1}, which is typically a velocity below the maximal aerobic threshold for this population of athletes. And thus the increases in a training stimulus in these zones will predominantly bring about aerobic performance adaptations which have shown to differ elite from non-elite players. This type of behaviour is not programmatically encoded into the models or algorithms, yet on observation, it appears to emerge from the repeated evolution of optimal training models. Examining the daily training load prescribed in the acceleration zones we see a contrast in the distribution between the model optimized and observed values. The observed daily training load completed by the player occur predominantly in zones 2 & 3, the optimized training model prescribes a more even dispersion across zones 1-3 representing movement below 3.0 ms^{-2} and a less pronounced increase in accelerations between 3.0 - 4.0 ms^{-2}. The reasons for this is unclear as the dynamics of accelerations in team sports is not as well-studied as velocity. However, one theory may be that due to the metabolically taxing nature of accelerations, more varied exposure to acceleration stimuli across a range of zones could help develop a strong capacity to support a high consistent performance over the full competitive season (Harper & Kiely, 2018).

It is worth noting that the variations in daily training load do not fully explain match-day running performance, a limitation of the impulse response and ACWLR models is the requirement to have a univariate input which can restrict the predictive power of the models. Similarly, a limitation in our approach was the weightings we applied when combining the velocity and acceleration models, which in this experiment are both considered equal. However, the individual subsystems of the body will respond differently to specific external load stimuli such as those arising during high-intensity velocity or acceleration based running. Similarly, the rate at which adaptions to training can occur is also different for the body's different subsystems as previous research has shown (Issurin, 2008) thus the timing of exposures to stressors are an important consideration in maintaining fitness and avoiding high levels of acute fatigue. Ultimately these relationships are unique to an individual athlete and were outside of the scope of this research to explore fully. However, the flexible modular nature of our novel optimization process allows for the expansion and incorporation of new models which can capture this type of information and incorporate it into the planning process. In future work, we will seek to address some of these highlighted issues. The problem of finding optimal training models in this instance used a fixed training structure, however, this can be extended to incorporate other high-level variables such as the frequency and mode of training sessions or training drills. In this experiment, the generation of optimal training models that don't violate model-based and real-world constraints has been approached using a static optimization method. Future work will seek to develop this approach to account for the dynamic time-variant nature of the problem and explore the use of dynamic optimization algorithms with suitable performance models to find solutions that can adjust to the types of unpredictable scenarios encountered in professional sports.

Conclusion

In this study, we demonstrated the ability of an evolutionary computation based algorithm to optimize an athlete training model with the goal of finding values that minimise/ maximise multiple objective functions. We were able to achieve a high stable level of match-day running-based performance over the entire competitive season with only small to moderate manipulations in daily training load prescriptions. This paper further demonstrates the utility of evolutionary computation based optimization techniques applied to common models used in sports performance. Coaches and support staff can utilise techniques such as this, embedded in software packages, to support their decisions concerned with the optimal prescription of training to their athletes. And aid them in developing optimized training models to enhance performance, reduce player fatigue and improve physical fitness.

Disclosure statement

Authors B.Watters and F.McCaffery are currently employed by STATSports Group. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Funding

This work was supported by Science Foundation Ireland under grant 13/RC/2094 with Lero.

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Appendix

Table 1.: Upper TL prescription constraints for velocity and acceleration in metres.

Upper Load Constraints

Zones	1	2	3	4	5	6
Velocity Upper	3000	3000	3000	1500	500	250
Velocity Lower	2000	2000	2000	500	250	150
Acceleration Upper	2000	2000	2000	500	250	100
Acceleration Lower	1000	1000	1000	250	100	50

Table 2.: Zonal boundaries for velocity (ms−1) and acceleration (ms−2).

Locomotion Zones

Zones	1	2	3	4	5	6
Velocity	0-1.5	1.5-3.0	3.0-4.0	4.0-5.5	5.5-7.0	7.0-8.5
Acceleration	0.5-1.0	1.0-2.0	2.0-3.0	3.0-4.0	4.0-5.0	5.0-10.0

Table 3.: TRIMP calculation weighting coefficients for velocity and acceleration based TL per zone.

TRIMP Coefficient

Zone	1	2	3	4	5	6
$TRIMP^{Vel}$	1	1.2	1.5	2.2	4.5	9
$TRIMP^{Acc}$	1	1.2	1.5	2.2	4.5	9