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Adaptive Athlete Training Plan Generation: An intelligent control systems approach.

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ABSTRACT

Objectives: The planning and control of team sport training activities is an extremely important aspect of athletic development and team performance. This research introduces a novel system which leverages techniques from the fields of control systems theory and artificial intelligence (AI) to construct optimal future training plans when unexpected disturbances and deviations from a training plan goal occur.

Design: Simulation-based experimental design

Methods: The adaptation of training load prescriptions was formulated as an optimal control problem where we seek to minimize the difference between a desired training plan goal and an observed training outcome. To determine the most suitable approach to optimise future training loads the performance of an AI based feedback controller was compared to random and proportional controllers. Robust computational simulations (N=1800) were conducted using a non-linear training plan spanning 60 days over a 12-week period, the control strategies were assessed on their ability to adapt future training loads when disturbances and deviations from an optimal planning policy have occurred. Statistical analysis was conducted to determine if significant difference existed between the three control strategies.

Results: The results of a repeated measures analysis of variance demonstrated that an intelligent feedback controller significantly outperforms the random ($p < .001$, ES = 7.41, very large) and proportional control ($p < .001$, ES = 7.41, very large) strategies at reducing the deviations from a training plan goal.

Conclusions: This system can be used to support the decision making of practitioners across several areas considered important for the effective planning and adaption of athletic training.

KEYWORDS

Training Load; Planning; Decision Support; Evolutionary Computation; Artificial Intelligence; Control Systems

Practical Implications

- Practitioners can use the novel control system presented in this study to support key decisions concerned with the planning and adaption of athlete training loads.
- Training loads are automatically generated from higher level training goals over medium to long term horizons.
- The model introduced in this study is responsive to feedback and adapts future training to ensure that athletes are only exposed to highly controlled and feasible loads.
- Intelligent control-based approaches are more effective at reducing the effect of unplanned disturbances compared to proportional and random methods.

1. Introduction

The planning and control of team sports training is an important aspect in the development of athletes and the enhancement of performance.[1] Team sports typically present a greater challenge than individual sports for coaches, scientists and support staff, as multiple training goals need to be accounted for and satisfied.[2] The quantity or volume of training load accumulated during a training session is a primary variable that requires considered manipulation to achieve long-term adaptations and reduce the risk of injury.[3] The prescription of training load is therefore prioritised as a higher level goal in the preparation and development of athletes by coaches and support staff. Training load has also shown to be a key factor in the regulation of fatigue[4] and is routinely manipulated in a training plan to achieve desired adaptions across a training phase. The construction of training plans and prescription of training loads across a training phase has largely been guided by instinct and experience.[5] While this is suitable for simple higher level goals, research has shown that when the complexity of a planning task starts to increase, our performance at constructing an optimal policy over a medium to long term duration exponentially decreases.[6] It is also common for planned training goals to not be realised during a training session, week or phase. These unplanned deviations can accumulate disrupting the complex balance between fatigue, adaption and athlete performance.

Previous work has sought to address the problem of planning training prescriptions and several contributions have been made which have leveraged the utility of mathematical optimization to produce optimal training plans.[7,8] Whilst the methods detailed in previous research have contributed to addressing the problem of optimally planning training sessions, these approaches do not include any provisions to account for disturbances and deviations away from an optimal or desired planning policy. In control system theory this approach is described as an open-loop control system, where the system does not adapt its control actions based on the system's outputs. In an open-loop control system, once an optimal training plan has been designed it cannot be adjusted based on an athletes response or external factors, which disrupt the realisation of a training plan goal.[9] This type of approach may be suitable to prescribe training loads to athletes when there is limited feedback available. However, currently, it is common practice in elite sport to have extensive athlete monitoring data available pre, during and post-training.[10,11] This information can be effectively utilized to dynamically inform the future training plans and load prescriptions of athletes. To utilise the vast quantity of athlete training data currently available and address the problem of minimising deviations from optimal training plans, we have sought to design and implement an intelligent control system. Intelligent control refers to approaches that use artificial intelligence techniques such as fuzzy logic, neural networks and genetic algorithms in the design and operation of a control system.[12] The aim of these systems is to produce rational control actions to achieve a goal or maintain a goal state, typically in an autonomous fashion or as part of a man-machine interface. Intelligent control systems have shown to be more effective at controlling complex dynamical systems compared to conventional methods and have been deployed in several real world applications including autonomous driving, utility power and health care.[13]

This paper introduces a new method to assist coaches, scientists and support staff in the planning and control of training load prescriptions to their athletes. This new method seeks to address the problem of constructing optimal training plans over medium to long term durations and the requirement to adapt those plans when real world disturbances force a deviation away from the optimal policy. We hypothesise that an intelligent controller (IC) will be superior to both a random controller (RC) and a proportional controller (PC) when applied to the task of prescribing and adapting training loads to realise a higher level training plan policy goal. The specific control strategies of the IC, RC and PC will be discussed in more detail in the proceeding sections.

2. Methods

This section will detail the intelligent control model (Figure 1), how a training plan is initially formulated using a hierarchical training goal and the structure of the controller which is used to adapt training loads in response to feedback. The model is then subject to robustness testing using a traditional training plan incorporating both linear increases in training load and a nonlinear taper. The purposed method consists of a hierarchical policy goal (U), which is expected to be achieved at the mesocycle level, and realised through the optimization and adaptive control of training loads (OPL) at the microcycle level using a closed-loop feedback control model (Figure 1).

Please Insert Figure 1 Here.

A training plan goal can be explicitly defined by a coach in a hierarchical fashion, for example, a coach may plan a linear increase in the total weekly training load over X number of weeks which is then realised through the accumulation of training sessions during those weekly periods.

A training plan goal can also be implicitly defined using the following variables and mathematical formulation:

$$G = B \times R \tag{1}$$

Where G is the desired goal load, B is a base load and R is a ramp rate or uplift factor. For example, a coach may want to increase the current weekly base training load by an uplift factor of 15%.[14] We can further define sub goals in a similar manner whereby an overall goal G is a linear combination of subgoals as per equation 2.

$$G = G_1 + G_2 \ldots G_n \tag{2}$$

Numerous sub goals can also be combined in a piecewise style to form a combination of both linear and non-linear loading strategies. A sub goal will then consist of a number of variables $x \in u_i$ that are representative of the training session load values which when aggregated should equal the overall sub goal load. The training session load x can then be intelligently prescribed and subsequently adapted using mathematical optimization and feedback control so that a hierarchical goal set by the coach can be fully realised.

The process of mathematical optimization consists of finding a set of variables that either minimize or maximizes a defined goal commonly referred to as an objective or fitness function. In control problems, the goal is typically to minimize the difference between an observed trajectory and the planned or preferred trajectory. In this instance, we define our objective function as a minimization of the root mean squared difference between the optimal or desired training plan goal G and an observed training outcome O, where the manipulated variables are the set U of future daily training session load values.

$$min\ f(G,\ O) = \sqrt{\frac{1}{n}\sum_{i}^{n}(G_i - O_i)^2} \tag{3}$$

Constraints can also be added such that for any training session $x \in u_i \subset U$ an upper and lower bound can be placed on the possible value it can take to ensure it is feasible and realistic. For example $0 < x < 1000$.

In order to perform the minimization we need to find some set of optimal inputs U subject to constraints, to do this we utilize an algorithm from a branch of artificial intelligence known as evolutionary computation to search the space of possible solutions. The field of evolutionary computing utilizes biologically inspired population based heuristic search algorithms to find solutions to complex problems in a time efficient manner.[12,15] In this experiment we have utilized the differential evolution (DE) algorithm. DE operates by generating an initial population of solutions to a problem and then proceeds to iteratively find better solutions by traversing a search space of all potential solutions through the use of mutation, recombination and selection based operators. Once a globally optimal solution is found, or the algorithm can not improve on the current solution after a set number of attempts, the best solution thus far is returned.[15,16] DE has shown to be a simple and effective optimization method across a number of different domains and applications,[17] thus we have chosen it to perform the intelligent adaptation/prescription of future training loads in the IC. The RC consists of generating random future training load values from a discrete uniform distribution with the same upper and lower bounds as the IC. Finally, the PC uses a proportional strategy to adapt future training loads by calculating the difference between an optimal session load and the realised/ observed load, the difference is then added (subtracted) to the next sessions optimal value, if the future session value is negative a zero value is applied to indicate no training should be conducted.

To test the robustness of the IC, and compare it to an RC and PC, we design a set of simulation experiments that replicate a real world training scenario. A training goal is defined consisting of several linear increases in weekly training load followed by a nonlinear taper. The training plan consisted of 60 training session over a 12-week period. This goal was chosen as it is thought to be representative of a typical athlete training plan.[18–20] The simulation experiment was conducted using a custom program written in the python programming language. To simulate a deviation away from an optimal training plan, individual training session load values were subject to added random noise generated from a Gaussian distribution with a mean of zero and a standard deviation equal to 50% of the original optimal training session load value. This process was designed to replicate unforeseen over and under accumulations of training session load as a result of several real world factors, such as the inclusion of extra training drills mid-session, a higher than expected training intensity or a within session change in training activities due to environmental conditions. In this experiment training load was quantified in arbitrary units, however the system will accept values in any unit of measurement the user prefers (Watts, Metres, TRIMP, etc). The system can also be easily adapted to accept multiple inputs and produce multiple training load values by adapting the fitness function to be compatible with multivariate optimal control procedures.

In order to quantify and compare the performance of each control strategy two quantitative outcome measures were used, first, the average of the root mean squared errors (RMSE) between the optimal planning policy and the adapted planning policy at every updated time step was calculated, this measure represents how close an adapted plan is to the desired or optimal planning policy, a score of zero indicates no difference [14]. The second outcome measure used was the average of the change in control signal power $P_{\Delta v}$, this measure represents the average change in the control signal [7], which in this experiment equates to the change in training load values between consecutive training sessions. Thirty experimental runs were conducted totalling N=1800 training plan simulations, the outcome measures were then collated and compiled for further analysis. The computational experiments were constructed using a bespoke program written in the Python 3.8 programming language and run on a high-performance computing cluster running a Linux operating system. The Storn and Price version of the differential evolution was implemented using the SciPy open-source software for mathematics, science, and engineering with the following custom parameters: maxiter=100, popsize=30, tol=.001. A repeated measures analysis of variance (RMANOVA) was used to test for significant differences between the IC, RC and PC training plan control strategies, significance was set at an alpha of 5%. If the assumption of superiority was violated Greenhouse-Geisser corrections were applied. Where applicable Bonferroni post hoc analysis was conducted. Results are reported using p-values, omega squared (ω^2) and absolute Cohen's *d* effect sizes. Cohen's *d* values, interpreted by Hopkins, are as follows: *trivial* < 0.2; 0.2 ≤ *small* < 0.6; 0.6 ≤ *moderate* < 1.2; 1.2 ≤ *large* < 2.0; *very large* > 2.0.[21] Descriptive statistics are reported using mean ± 95% confidence intervals (CI) unless otherwise stated. All statistical analysis was conducted using the JASP software (Version 0.14, Amsterdam, The Netherlands).

3. Results

The results of the RMANOVA indicated significant differences between the IC, RC and PC control strategies for the RMSE outcome measure (p <.001, ES = 0.71, *moderate*). Bonferroni post hoc analysis revealed significant mean differences between the IC and RC plans (p

<.001, ES = 7.41, *very large*), the IC and PC plans (p <.001, ES = 2.38, *very large*) in addition to the RC and PC plans (p <.001, ES = 1.18, *large*). Significant differences were also found between the control strategies for the second outcome measure $P_{\Delta v}$ (p <.001, ES = 0.79, *moderate*). Post hoc analysis revealed significant differences between the IC and RC plans (p <.001, ES = 1.43, *large*) and the IC and PC plans (p <.01, ES = 0.70, *moderate*), and the RC and PC plans (p <.001, ES = 9.34, *very large*). Figure 3 displays the distribution of the RMSE score values, for each control protocol, over the thirty experimental simulations employing the specified planning policy. Figure 4 displays the second outcome measure $P_{\Delta v}$.

Please Insert Figure 2 Here

Please Insert Figure 3 Here

Please Insert Figure 4 Here

4. Discussion

In agreement with the authors' hypothesis, the results demonstrate that an IC was superior to both an RC and an PC when applied to the task of prescribing and adapting training loads to realise a higher-level training plan policy goal. To the best of our knowledge, this is the first objective method introduced to adjust future training loads when subjected to real world unplanned deviations and disturbances, thereby minimizing the difference between a realised training plan and a specified or optimal plan. The novel method which we have introduced utilizes established theory from the fields of intelligent control and artificial intelligence to provide an initial solution to an important problem in sport and exercise science. The results of our simulation experiment have shown that feeding back and intelligently adapting training plan variables, can reduce future deviations from an optimal planning policy caused by unplanned disturbances. We have also highlighted the relatively poor performance of the naive control strategies such as randomly prescribing future loads or adapting future loads by adding or subtracting load values proportional to previous deviations. These findings make an important contribution to the current body of research concerning the planning and realization of athletic training. We have shown that even small training session deviations can accumulate over the length of a training plan and cause an overall significant deviation away from an initial optimal planning policy or higher level goal. This research has demonstrated that even for a simple planning policy with linear goals, deviations can accumulate which require some form of intelligent correction. Previous research has established the positive physiological adaptions that can be achieved from appropriately planned or 'periodized' training.[22,23] Therefore the rationale for adhering to a training plan is well understood, however to date no method has been purposed to reduce the impact of deviations away from a training plan. In this work, we have demonstrated that an intelligent feedback controller is a feasible and effective method for adapting training plans to achieve higher level linear or non-linear training goals.

The results of this experiment have demonstrated that the intelligent adaptive control of training load variables can reduce the overall deviation from a desired or optimal training plan policy quantified using the RMSE outcome measure. The significant differences and moderate to very large effect sizes found between the three control strategies for the $P_{\Delta v}$ outcome measure suggest that the magnitude of the control signal may be a strong discriminating factor when evaluating the quality of an adaptive planning method, e.g. if a large unplanned deviation occurs it can not simply be corrected by a large deviation of an equal and opposite magnitude. The significant RMSE and $P_{\Delta v}$ differences found between the performance of control strategies adds further support to this argument. The RC has shown to perform worse than the IC whilst demonstrating similar magnitudes of corrective action. This would suggest that an optimal set of training load variables exists which when realised results in the achievement of a higher level hierarchical goal and that to achieve that goal subject to forced/unforced deviations from the optimal policy an intelligent search of the solution space needs to be conducted to update future training plan variables, such that the residual negative effects of any distributive deviations are minimized reducing the risk of potential illnesses, injuries and or performance reductions. This work is the first of its kind to be applied to the problem of training plan design and control in the field of sport and exercise science. A limitation of this study is the lack of comparison between the corrective action which would have been implemented by a human coach both with and without the support of this system to make a decision. Ultimately this system is intended to support decision makers in their choice of corrective action. The authors recognise that constructing an optimal or effective training plan goal is also currently an open area of research and comprises of several complex considerations which need to be specified as inputs to this system. However, we feel that the design of the system is such that it allows the user to leverage their own knowledge and experience to devise goals which are specific and sufficient for them, or which incorporate other techniques previously reported in the literature.[7,8]

Future work will seek to advance the initial work presented in this study to develop the capabilities of the feedback controller to consider multiple inputs in the control process and be guided by model based predictions. We will seek to address other considerations such as the relationship between deviations from a training plan and the subsequent effect on measured performance at various time points using intelligent model-based control strategies. Finally, we will seek to robustly test the performance of this system and its iterations using from real world environments.

The practical applications of this work are numerous, the importance of refined control in the training process is heightened during the rehabilitation and return to play process.[24] Athletes exhibit extremely non-linear responses to, and deviations from, training activities during rehab but are required to follow training plans stringently in order to make a timely return to competition. Practitioners can use the novel control system presented in this study to support the planning and adaption of training during the rehabilitation process to achieve their goals in the most time efficient way. Similarly, the application of this system can be extended to any type of higher level goal or planning policy which can be quantified and controlled by a set of training load variables. Another strength of the control system which we have designed is its flexibility, the system is training variable agnostic and the training variable inputs that represent a higher level goal or sub-goal can be in any unit (e.g., RPE, TRIMP and Distance). The systems' flexibility allows it to be highly versatile, a user can make trivial adjustments adapting it to different goals, and training scenarios, such as gym based resistance training or field based conditioning.

5. Conclusion

This study has shown that an intelligent closed-loop feedback controller consistently outperforms a random controller and proportional controller when adapting the future training loads of athletes when subjected to real world disturbances and deviations from a non-linear higher level training plan goal. This work is the first of its kind to apply techniques from the fields of control systems theory and artificial intelligence to the problem of training plan design and adaption in athletic populations.

The system proposed in this study can be used to support coaches and practitioners to realise higher level training plan goals when subject to forced/unforced deviations away from a desired or optimal planning policy. Therefore this system has numerous practical applications in various areas considered important for the effective planning, maintenance and control of athletic training.

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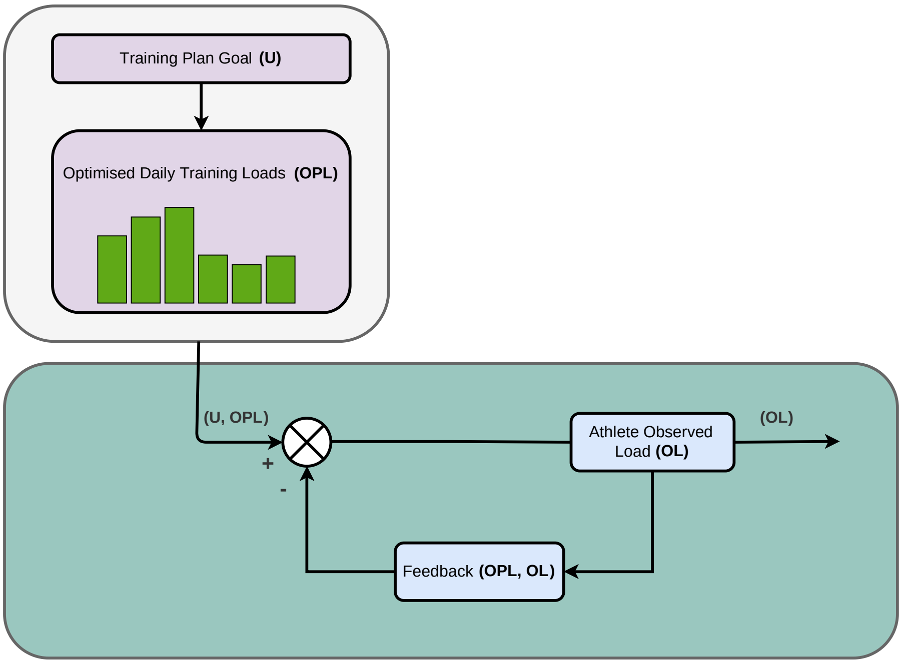

Figure 1. Adaptive training load control model.

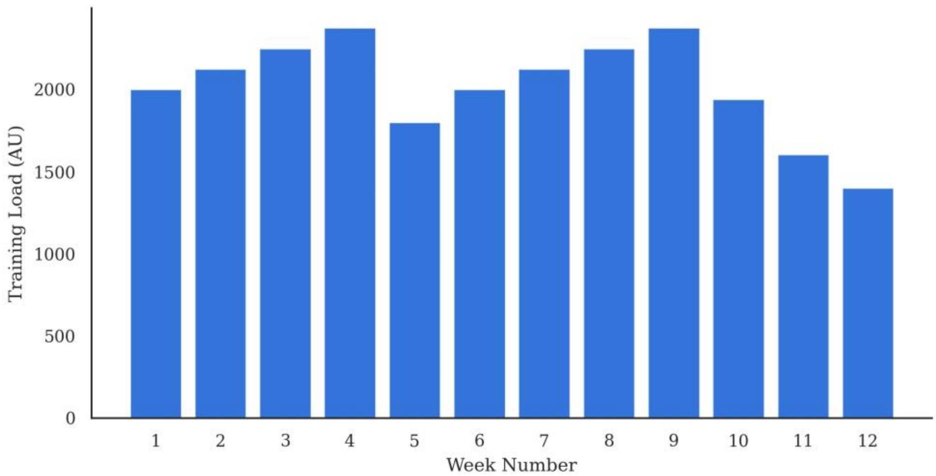

Figure 2. Training plan policy.

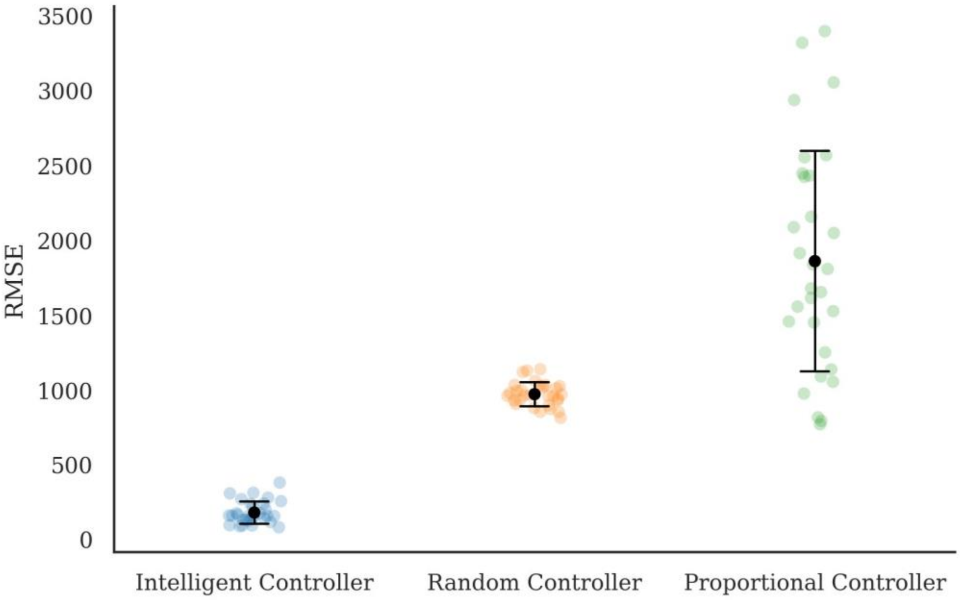

Figure 3. RMSE controller values over thirty experimental simulations.

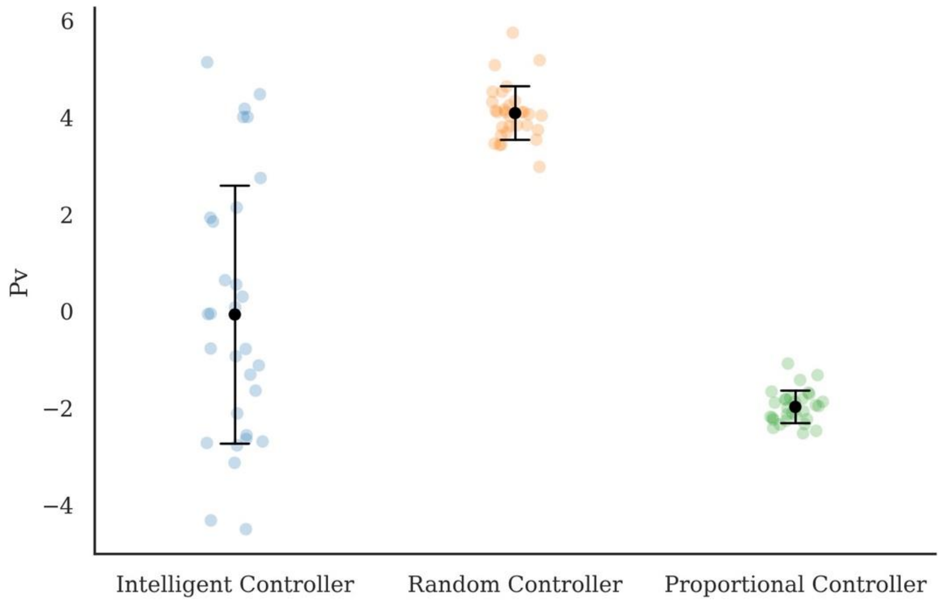

Figure 4. $P_{\Delta v}$ controller values over thirty experimental simulations.

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Conflict of interest
All authors declare no potential conflicts of interests.

Ethics
Due to the computational nature of this research and the absence of human subjects in the experimental procedures, ethics was not sought.