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Human Kinetics
ORIGINAL INVESTIGATION

Optimizing Preseason Training Loads in Australian Football

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Purpose: To investigate whether preseason training plans for Australian football can be computer generated using current training-load guidelines to optimize injury-risk reduction and performance improvement. ***Methods:*** A constrained optimization problem was defined for daily total and sprint distance, using the preseason schedule of an elite Australian football team as a template. Maximizing total training volume and maximizing Banister-model-projected performance were both considered optimization objectives. Cumulative workload and acute:chronic workload-ratio constraints were placed on training programs to reflect current guidelines on relative and absolute training loads for injury-risk reduction. Optimization software was then used to generate preseason training plans. ***Results:*** The optimization framework was able to generate training plans that satisfied relative and absolute workload constraints. Increasing the off-season chronic training loads enabled the optimization algorithm to prescribe higher amounts of "safe" training and attain higher projected performance levels. Simulations showed that using a Banister-model objective led to plans that included a taper in training load prior to competition to minimize fatigue and maximize projected performance. In contrast, when the objective was to maximize total training volume, more frequent training was prescribed to accumulate as much load as possible. ***Conclusions:*** Feasible training plans that maximize projected performance and satisfy injury-risk constraints can be automatically generated by an optimization problem for Australian football. The optimization methods allow for individualized training-plan design and the ability to adapt to changing training objectives and different training-load metrics.

Keywords: AFL, injury, performance, workload ratio

Training-load prescription in team-sport athletes is a balance between performance improvement[1,2] and injury-risk reduction.[3–6] The manipulation of training intensity, duration, and frequency to induce improvements in athletic performance is a fundamental objective of training-plan prescription.[7] To inform this process, mathematical models of the relationship between training loads and performance have been proposed for multiple athletic populations.[1,7,8] Banister et al[1] modeled the response to a training dose using 2 time-decaying functions representing fitness and fatigue. This allowed performance to be projected at a later time by taking the difference between the modeled fitness and fatigue functions. While the accuracy of these models in predicting performance has been limited,[7,9] they provide a generalized basis for training prescription. Studies modeling team-sport performance are fewer, possibly due to difficulties in quantifying individual performance in a team environment and mixed training methods.

Training load has been identified as a risk factor for injury in recent reviews, with both absolute and relative loads needing to be considered when assessing injury risk.[4,6] The acute:chronic workload ratio quantifies an athlete's relative amount of short-term (acute) to long-term (chronic) training and is an injury-risk factor in a number of team sports.[4–6,10] In addition, there is evidence that cumulative absolute workloads can influence injury risk in Australian football.[3]

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Currently, physical-preparation staff are tasked with balancing the training guidelines associated with injury-risk reduction and performance improvement when prescribing training loads. Mathematical optimization is a method that may help in this process, particularly as more data on training-load monitoring become available.[5,6,10–12] Optimization is the task of finding a set of values (decision variables) that maximize an objective function (goal) and satisfy a set of constraints. Optimizing training loads has been explored in studies of tapering[8] and to generate training plans for performance improvement.[13] No study has explored optimization models that incorporate training guidelines for injury prevention based on cumulative loads and workload ratios in team-sport athletes.

This study aimed to determine the extent to which current training-load guidelines (for relative and absolute training loads) can be used to generate optimized preseason training plans in Australian football and to investigate the effects of varying optimization targets and load constraints on the computer-generated plans.

Methods

The task of planning preseason training loads was posed as an optimization problem. The decision variables were the amount of training prescribed each day, and constraints were defined based on recommended acute:chronic workload ratio and cumulative load limits for injury-risk reduction.

The fixture for an elite Australian football club was used as a template. Players were scheduled to play 3 practice matches 98, 104, and 112 days from the start of preseason and their first competitive match on day 125. Outside of these matches, training loads were able to be freely prescribed on each day.

Decision Variables

The goal of the optimization procedure was to generate a full preseason training plan by specifying the workload value (w) each day:

$$w_i = \text{training load on day } i; \quad i \in \{1, 2, \ldots, 125\}$$

In this study, total distance and sprint distance (SD) were explored since most of the research to date has examined the relationship between these variables and injury risk in team sport.[3,5,10] However, in general, the workload variable could be substituted for any method of training-load quantification.

For clarity, the following sections describe the complete optimization formulation for total session distance and then present the simple modifications needed to adapt the method to SD. This illustrates how the methodology can be generalized to different training-load representations.

Constraints

The optimization model required training plans to satisfy 5 constraints:

- Daily training loads were constrained to be 0 to 50,000 m (a generous upper bound based on unpublished data from previous seasons).

$$0 \le w_i \le 50{,}000$$

- The acute:chronic workload ratio (r) was calculated on a daily basis, using a 6-day acute and 24-day chronic time window, found to be appropriate for this cohort.[10]

$$r_i = \sum_{j=i-6}^{i-1} \frac{w_j}{6} \Bigg/ \sum_{j=i-24}^{i-1} \frac{w_j}{24}$$

  Training plans were constrained to keep daily workload ratios in the previously described "safe zone" for injury-risk reduction ($0.6 < r_i < 1.3$).[5,10]

- Three-weekly cumulative distance loads of 73,721 to 86,662 m were reported to increase preseason injury risk in Australian footballers (odds ratio 5.49).[3] To account for this, a rolling 21-day cumulative load (C_i) was calculated and constrained to not exceed 73,721 m.

$$C_i = \sum_{j=i-21}^{i-1} w_j$$

$$C_i < 73{,}721$$

- Rest days ($w_i = 0$) need to be considered when planning training in professional team sport due to contractual entitlements. Rest days were included by replicating the proposed rest schedule at the football club. While it can be argued that the timing of rest may be a component of designing an optimal plan, considerations around public holidays, weekends, and player requests were considered beyond the scope of mathematical constraints.
- Match demands were taken from the 2015 AFL GPS Report[14] and incorporated by constraining the total match distance to be 13,200 m ($w_{125} = 13{,}200$). This is an average value and may not reflect the largest loads seen in matches or the differences between playing positions. By increasing the match-demand constraint the method can be adapted to prepare for higher match loads.

Preseason matches in the AFL are subject to altered rules that generally involve more interchange players and shorter match durations. Unpublished data collected in the participating club suggested that total distances covered were approximately 15% lower in preseason matches than in in-season matches ($w_{98,104,112} = 11{,}220$).

Calculating cumulative workloads and acute:chronic workload ratios at the beginning of preseason requires knowledge of off-season chronic loads. At the participating club, players are generally given, and expected to follow, an off-season training program but are not monitored with GPS devices due to league restrictions. As such there is an inherent assumption that players are completing their off-season training. Two levels of off-season chronic load were considered (representing typically prescribed loads): 14 km/wk and 21 km/wk.

Objective

Two objective functions (f_A, f_B) were considered. Objective A was to maximize the total amount of training distance in the preseason, representing the simple goal of allowing players to complete as much training as possible without violating injury-risk constraints (assumed desirable for team sports).

$$f_A(\boldsymbol{w}) = \sum_{i=1}^{125} w_i$$

Objective B was to maximize the Banister-model[1]-projected performance on match day. This objective was chosen as it included a consideration of the fatiguing effects of training, as well as a realistic goal of trying to maximize players' preparation before their first match. Banister-model parameters were adapted from a study of middle-distance runners,[15] as no such research has been undertaken in Australian football.

$$p_i = p_0 + k_1 \sum_{j=1}^{i-1} w_j e^{\frac{-(i-j)}{t_1}} - k_2 \sum_{j=1}^{i-1} w_j e^{\frac{-(i-j)}{t_2}}$$

$$k_1 = 1, \quad k_2 = 2, \quad t_1 = 45, \quad t_2 = 11$$

$$f_B(\boldsymbol{w}) = p_{125}$$

Modifications for Sprint Distance

Adapting the optimization problem outlined herein to SD (defined as the distance covered above 75% of an athlete's recorded top speed[3]) requires only a few parameter changes:

- The three-weekly cumulative load constraint was changed to $C_i < 1{,}453$ to reflect findings on increased injury risk by Colby et al.[3]
- Regular and preseason match demands were changed to 268 m and 200 m of SD, respectively.[3]
- Off-season chronic loads were considered at 150 m/wk and 225 m/wk of SD to reflect levels typically prescribed by the participating club.

These example values are taken from a study of 1 team and may not represent the demands of other athletes. It is recommended that constraints be tailored to suit team-specific demands when adapting this methodology.

Simulations

Training plans were initialized by random sampling from a normal distribution: mean (standard deviation) = 3 km (1 km) and 30 m (10 m) for distance and SD, respectively. Starting from the random training plan, the optimization software sought to find a solution that satisfied all the constraints and maximized the objective function (see supplemental movie available online with this article).

Optimization was performed using the MATLAB software package (MATLAB 8.1, The MathWorks Inc, 2013, Natick, MA), the nonlinear programming solver and the sequential quadratic programming algorithm. Default step and function convergence tolerances were used (10^{-6}). Twenty simulations were run for distance and SD under each combination of objective and off-season chronic load.

Results

The optimization approach produced solutions that were able to satisfy both the acute:chronic workload ratio and cumulative workload constraints. Each simulated preseason training program converged to an optimal objective value within a similar number of iterations (Figure 1), suggesting that the optimization-problem formulation and the algorithms used were appropriate. Increasing the off-season chronic-load parameter resulted in higher total preseason training loads under optimization objective A (Figure 1[a] and 1[c]) and higher projected performance under objective B (Figure 1[b] and 1[d]).

The distribution of prescribed session distances and session SD loads for each objective is shown in Figure 2. Each simulation had slightly different distributions (ie, the lines in Figure 2 do not perfectly overlap), meaning it was possible for the optimization software to achieve the same objective value using slightly different training plans. Changing the objective of the optimization problem resulted in different load distributions in the generated training plans. In general, plans constructed with the objective of maximizing Banister-projected performance (objective B) prescribed more short sessions (distance <5000 m and SD <100 m), as well as more long sessions (distance ~7000–11,000 m and SD >100 m).

Sample preseason training plans (for distance and SD) generated by the optimization procedure are shown in Figure 3. Plans for total session distance (Figure 3[a] and 3[b]) were generally similar under the different objective functions. The longest prescribed sessions were ~15 km and scheduled approximately 30 days into preseason. A notable difference was observed near the end of the preseason before the first regular-season match. Plans aiming to maximize total distance (Figure 3[a]) prescribed frequent training up to and around matches, whereas those generated using the Banister model refrained from prescribing any training in the 2 to 3 days preceding the first competitive match (Figure 3[b]). This difference can likely by attributed to the fatigue component of the Banister-objective function used. Refraining from training before the first regular-season match allows for the fatigue component to decay toward zero and the projected performance level to be maximized.[1]

SD plans (Figure 3[c] and 3[d]) showed a different load progression than that of distance plans. A gradual increase in SD load was prescribed by the optimization software, with maximal loads not reached until around 90 days into preseason. Similar to distance plans, using the Banister model to guide training led to a reduction in SD load leading into the first match (Figure 3[d]).

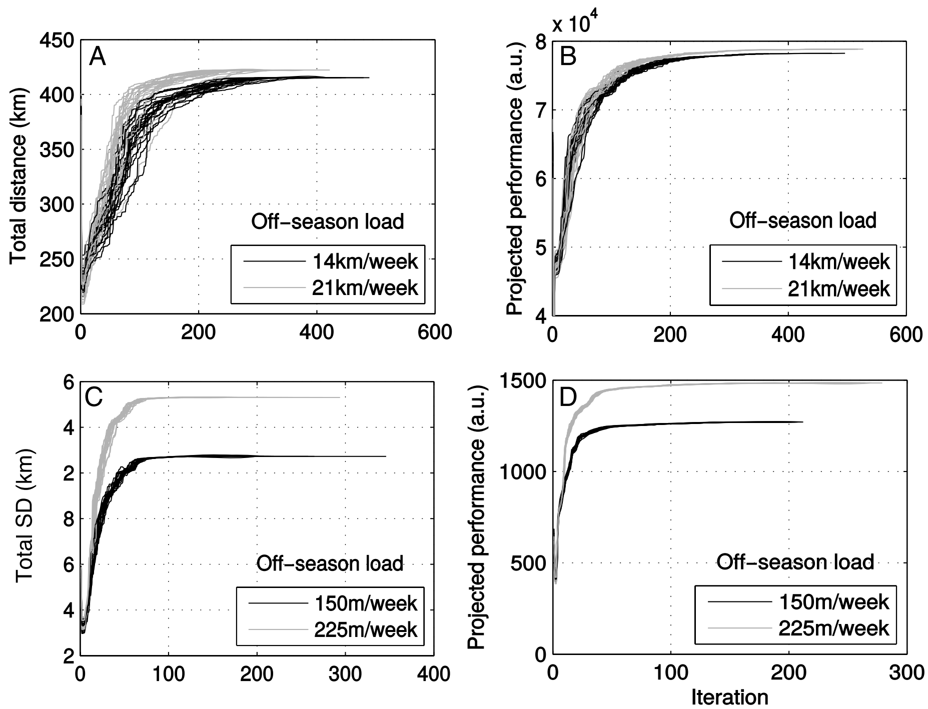

Figure 1 — Convergence of 20 simulated preseason training plans for (a) distance under objective A, (b) distance under objective B, (c) sprint distance (SD) under objective A, and (d) SD under objective B. Objective A is to maximize total preseason load; objective B is to maximize Banister-projected performance at round 1.

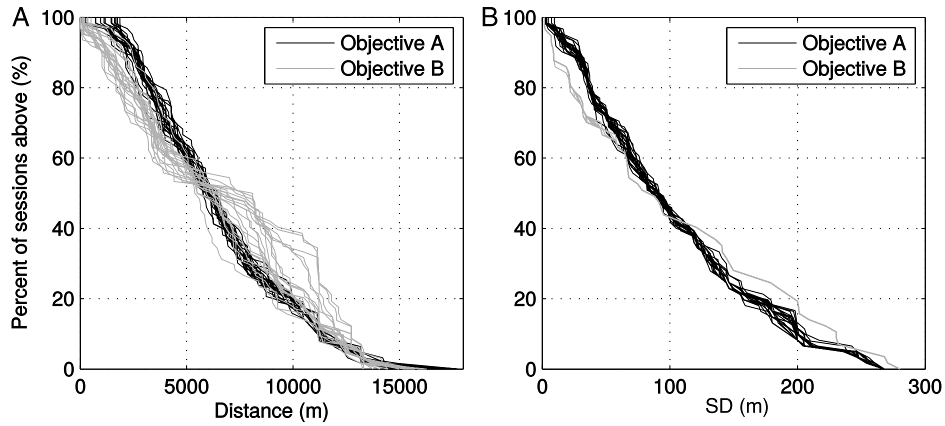

Figure 2 — Distribution of session loads in optimal preseason plans for (a) distance and (b) sprint distance (SD). Objective A is to maximize total preseason load; objective B is to maximize Banister-projected performance at round 1 (off-season chronic loads: 14 km/wk distance and 150 m/wk SD).

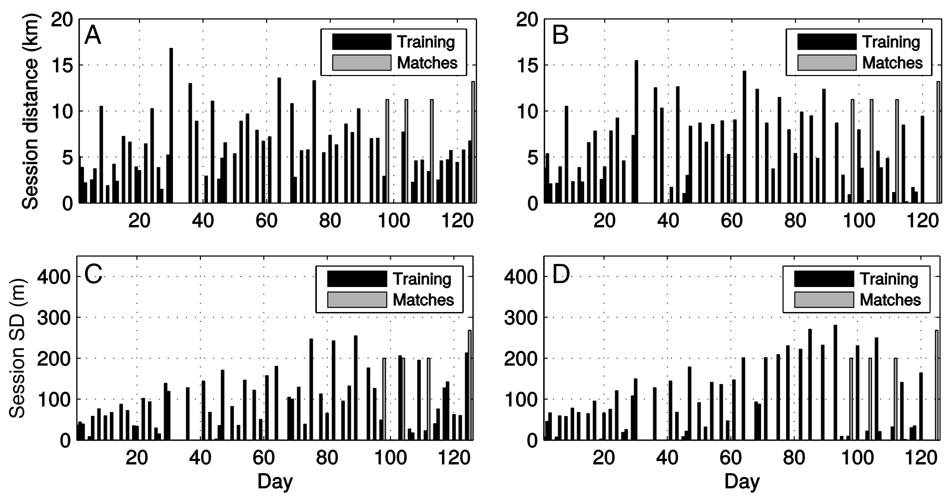

Figure 3 — Computer-generated optimal preseason training plans for (a) distance under objective A, (b) distance under objective B, (c) sprint distance (SD) under objective A, and (d) SD under objective B. Objective A is to maximize total preseason load; Objective B is to maximize Banister-projected performance at round 1 (off-season chronic loads: 14 km/wk distance and 150 m/wk SD).

Discussion

This study aimed to determine whether training-load guidelines could be used to generate optimized preseason training plans in Australian football and how varying optimization targets and load constraints influenced the computer-generated plans. The results demonstrated that the total and SD distances across preseason training programs could be generated using an optimization approach. Cumulative load and acute:chronic workload-ratio guidelines for injury-risk reduction[3–5,10] were able to be satisfied on each day of the preseason plan when they were defined as mathematical constraints. The theoretical approach taken, based on match demands and workload constraints, generated preseason plans (Figures 1 and 3) comparable to those previously reported in professional Australian football teams (mean total distance = 314–411 km, mean total SD = 2.7–8.9 km).[3] This research extends the approach of Schaefer et al[13] by including constraints based on injury-risk factors and putting the approach in a sport-specific context.

Choice of Optimization Objective

The choice of optimization objective influenced the distribution of training sessions prescribed by the model (Figure 2). The generated plans were generally similar in how they progressed loads until the latter stages of the preseason, prior to the first competitive match (Figure 3; days 112–125). Maximization of projected performance with a Banister model (objective B) was achieved by reducing training frequency leading into competitive matches. This reduction allows for the fatigue component of the Banister model to decay toward zero,[1] maximizing the projected fitness level. This aligns with previous theoretical results from Fitz-Clarke et al,[8] where a taper before competition maximized projected performance. Maximizing total preseason volume (objective A) was accomplished by prescribing more frequent moderately sized sessions. More frequent training is a way to accumulate more load (the goal of objective A) without breaking acute:chronic workload constraints. No taper is included since objective A does not include consideration for fatigue accumulation, suggesting that a Banister-model objective may be more appropriate.

Effect of Off-Season Chronic Load

Modifying the off-season chronic-load parameter changed the amounts of prescribed training and projected performance in the generated plans (Figure 1). A higher off-season chronic load (21 km/wk for distance or 225 m/wk for SD) enabled the optimizer to prescribe larger "safe" training volumes (Figure 1[a] and 1[c]) and achieve higher projected performance (Figure 1[b] and 1[d]). These findings highlight the potential benefit of prescribing and adhering to training plans during off-season periods to promote follow-on positive effects. The importance of high chronic workloads aligns with the findings of Malone et al[11] that they may be protective against injury in Gaelic football.

Ability to Customize Plans

The methodological framework outlined in this study allows for customization and individualization of training plans depending on the preferences of the practitioner and needs of the athlete and team. For example, more aggressive or conservative training plans could be generated by simply modifying the workload-ratio constraint, lowering it to 1.1 for a safer plan or raising it to 1.5 if the user is willing to accept higher injury risk.[5] Individualized planning could be incorporated by changing the off-season chronic-load parameter or cumulative-load constraint. For example, first-year players or athletes returning from injury could be assigned a lower off-season chronic load or a lower acceptable cumulative load—and have their plans represent this lower load capacity.

The framework also allows for customization to suit different team objectives. For example, a team may want to employ a game style that requires a higher amount of SD. This could be incorporated into plans by increasing the match-demand constraint for SD from 268 to 350 m (or whatever the desired level may be). The time frames used in this study (125-d preseason with practice matches on days 98, 104, and 112) can be modified for teams or sports with different schedules. This could be accomplished by moving the timing of the match-demand constraints (eg, for a 30-d-shorter preseason: $w_{95} = 13{,}200$ and $w_{68,74,82} = 11{,}220$).

The optimization objective can also be adapted to suit different goals. Instead of maximizing projected performance (peaking) at round 1, the user may prefer to have athletes peaking for each preseason practice match, as well, or a match later in the season. A plan with this goal could be generated by changing the objective function to be the sum of Banister-projected performance on each practice-match day or on a day later in the season.

In general, the optimization approach described can be used to generate training plans that consider a number of combinations of the modifications described herein, allowing for rapid troubleshooting of different training strategies.

Limitations

This study presented a method for optimized training-plan generation in the context of a standard Australian football preseason. As such, the parameters considered were specific to the cohort of interest. A full evaluation of the effects of varying model parameters to reflect different possible training philosophies and timelines was considered beyond the scope of this study. The intent of the study was to determine if training plans could be generated using an optimization approach. As such, there were no data available on the implementation of a generated plan to allow for comparison between planned and actual loads. Future studies are needed to evaluate the effects of an optimization approach on injury occurrence and performance.

A Banister impulse-response model was used to model athlete responses to training loads.[1] A discussion of the merits of using a Banister model for team-sport athletes was considered beyond the scope of this study, and it is possible that other models may be more appropriate.

Practical Applications

The methodology outlined in this report provides an adaptable framework for physical-preparation staff to quickly create athletic-training plans that objectively optimize training goals while satisfying injury-risk and life-balance constraints (ie, days off) without exposing their plans to subjective bias. Practical applications include individualized training-plan design and adaptability to changing training objectives. The framework described also provides theoretical scope for testing different training strategies and assumptions (eg, how much more total training volume could athletes attain if acute:chronic workload-ratio limits are increased to 1.5, or are athletes able to reach match fitness levels if their off-season chronic loads are reduced by 50%?).

Conclusion

Feasible preseason training plans for Australian football can be automatically generated using an optimization approach that maximizes performance while being constrained by injury-risk guidelines. Training plans generated for athletes who enter preseason with higher off-season chronic loads prescribed larger total training volumes. This allowed larger projected performance improvements while theoretically avoiding exposure to high-risk training patterns. The methodology described allows for individualized training-plan design and the ability to adapt to changing training objectives.

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