**The influence of different training load quantification methods on the fitness-fatigue model.**

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Abstract

*Purpose*

Numerous methods exist to quantify training load (TL). However, the relationship of these methods with performance is not yet fully understood. Therefore the purpose of this study was to investigate the influence of the existing TL quantification methods on performance modelling and the outcome parameters of the fitness fatigue model.

*Methods*

During a period of eight weeks, nine subjects performed three interval training sessions per week. Evolution of performance was monitored weekly by means of a 3-km time trial on a cycle ergometer. After this training period subjects stopped training but still performed a weekly time trial. For all training sessions, the Banister training impulse (bTRIMP), Lucia TRIMP (luTRIMP), Edwards’ TRIMP (eTRIMP), Training Stress Score (TSS) and TL based on the rating of perceived exertion (TLRPE) were calculated. The fitness fatigue model was fitted individually for all subjects and for all TL methods.

*Results*

The error, defined by the residual sum of squares (RSS), in relating TL to performance was similar for all methods (bTRIMP: 618 ± 422, luTRIMP: 625 ± 436, eTRIMP: 643 ± 465, TSS: 639 ± 448 and TLRPE: 558 ± 395). However, the TL methods evolved differently over time which was reflected in the differences between the methods in the calculation of the day before performance on which training has the biggest positive influence (range from 18.5 days).

*Conclusions*

We conclude that, although the differences in model output are limited, TL methods cannot be used interchangeably since they evolve in a different way.

*Key-words*

Performance modelling, impulse response model, performance prediction, training monitoring, influence curves

*Introduction*

Performance improvement is the response of the body to an appropriate combination of training load (TL) and recovery. In order to obtain maximal performance at the right moment, a precisely controlled training program is needed.1 Therefore, tracking and managing TL is a vital part of working with athletes. However, today there are numerous possible ways of quantifying TL, making it difficult for practitioners to choose the most appropriate method.2

In general the methods are described as either external TL (e.g., power, distance, speed) or as internal TL (e.g., heart rate (HR), rating of perceived exertion (RPE)). External TL is a given amount of work the athlete undertakes and internal TL can be defined as the psychophysiological effect that this external TL has on the athlete.3 Most TL quantification methods are a result of multiplying the duration of a training with the intensity of that session. It is the difference between the TL methods in quantifying the intensity of a session that is of greatest concern to coaches and scientists. Internal TL is often considered as more appropriate to monitor the training process since it is the internal stimulus that determines training adaptation.3 However, recent technological developments have made external TL measures increasingly popular. In this regard, the training stress score (TSS) is the most widely used TL measure in cycling.

It is suggested that the best TL method, is the method that is relatable to an outcome of importance (e.g., fitness, fatigue or performance).4 Several studies have related different TL methods to performance in a linear way. However, as recently discussed, this linear relationship should be questioned as the interplay between TL and recovery cannot be captured in a simple linear model.5 Mathematical models however, have previously shown promising results in relating TL and performance in athletes.6 Perhaps the most cited mathematical model, is the model of Banister.7 This model implies that every training session has both a positive (fitness) and a negative effect (fatigue). It is the difference between these two elements that reflects the performance of an athlete at any given time so that

Performance = Fitness – Fatigue

Although the model of Banister is most referred to, it are actually the refinements of the model by Morton et al.8 and later Busso et al.,9 that led to the formula in the form that is most frequently used

(eq. 1)

The model performance at day () is estimated from successive TLs with varying from 1 to -1. p\* is an additive term that represents the initial performance level of the subject. and are the exponential time constants, expressed in days, for respectively the fitness and the fatigue term and magnitude factors have been added to both fitness () and fatigue ().

After individualizing the parameters, by fitting the model to measured performance, it is possible to calculate the influence curves.10 These curves give us the opportunity to calculate the moment at which training has the greatest influence on performance (tg) and the moment at which training results in a negative impact on performance (tn), thus the timeframe in which training should be avoided. On the basis of these parameters we can then individualize tapering strategies in order to obtain maximal performance on the moment required.10

Over the past decades the model has been used in various sports such as swimming1,11-12, running8,13, cycling14-16 and triathlon17. Nevertheless results are inconclusive, showing a high variability in the output parameters and an inability to predict real-world performances in several studies.18 This variability could be explained by methodological issues such as limited number of participants, variability in level of subjects and the fact that almost every study uses a different method to quantify TL. Next to this, most of the studies have not been performed in laboratory settings even though data of the highest quality are preferred in systems modelling.6

Therefore the purpose of this study was twofold. First, we tested if the systems model, as proposed in equation 1, is able to relate TL to performance in an experimental laboratory setting during a recreational cycling training program. Second, we investigated what the influence of different TL quantification methods is on the output parameters of the model, especially with regards to the parameters from which we can derive practical guidelines (i.e. tg and tn).

*Methods*

**Subjects**

Nine healthy physically active men (22.0 ± 1.6 yr., 177.5 ± 4.5 cm, 73.0 ± 9.3 kg) participated voluntarily for this study. Subjects had no previous structured training in cycling but were recreationally active in different sports. Participants were informed about the risks of the study and written informed consent was obtained before participation. Each participant underwent a medical examination and was declared to be in good health. This study was approved by the Ethical Committee of the Ghent University Hospital, Belgium.

**Experimental procedures**

*Overview*

A modelling longitudinal research design was used to analyze performance, fitness and fatigue over an 11-week period (Figure 1). An 8-week training period was implemented where subjects completed three interval training sessions and a 3-km time trial (TT) each week to monitor changes in performance. All tests and training sessions took place in the Sport Science Laboratory—Jacques Rogge (Ghent University, Belgium), under controlled environmental conditions (18-19°C, 50% relative humidity). During all sessions, HR (H7 Sensor; Polar, Kempele, Finland) and power output (Cyclus2 ergometer; RBM Electronics, Leipzig, Germany) were continuously monitored in order to quantify TL.

\*\*\* Insert Figure 1\*\*\*

*Exercise test*

Subjects performed a ramp incremental test to assess their fitness level and to individualize the training program. After a 3-min warm-up at 40 W, work rate increased continuously with 35 W.min-1. Participants were instructed to keep their cadence at 70-80 rpm. The protocol was terminated at voluntary exhaustion, i.e., the inability to maintain a minimal cadence of 70 rpm for more than 5 consecutive seconds despite strong verbal encouragements. Pulmonary gas exchange (O2, CO2) was measured breath-by-breath (Jaeger Oxycon Pro; Viasys Healthcare GmbH, Höchberg, Germany). Before the start of the test, the resting HR (HRREST) was defined as the lowest 5-s average HR when subjects lay in a supine position for 10 min in a quiet room.

*Time trials*

The week before the training period subjects were familiarized with the TT during two sessions. In those sessions they chose their preferred gear settings to perform the TTs and tested their pacing strategy. Before the start of the training period, subjects performed a TT in order to determine the initial performance level used for the study (p\*). TTs were preceded by a standard warm-up at 100 W for 5 min. Following the warm-up a 1-min seated rest was inserted before the start of the TT. Subjects were encouraged to complete the TT as fast as possible. The only feedback they received was cadence and remaining distance.

*Training period*

On Monday, Wednesday and Friday a 45-min aerobic interval training was performed consisting of five bouts of 4 min cycling at a power output equivalent to the respiratory compensation point (RCP) alternated with 3 min of recovery at a power output that was associated with the gas exchange threshold (GET). Each training session included a warm-up and cool-down of 5 min at the level of GET. On Friday the training was preceded by the TT, interspersed with a 10-min rest period. After the training period, there was a 3-week follow-up where subjects stopped training and only performed the TT so that the effect of dissipating fatigue and/or fitness could be monitored

**Data analysis**

*Ramp incremental test*

O2peak was defined as the highest 30-s average achieved during the test. GET and RCP were determined by three independent researchers as described elsewhere.19 The power output at the time points corresponding to GET and RCP were adjusted for the O2 mean response time in each individual to account for the kinetics of O2 and the delay between the muscles and the lungs inherent to a ramp incremental exercise test.20

*Training load*

TL was calculated using three different methods of HR-based training impulses (TRIMP). The Banister TRIMP (bTRIMP) was calculated using the training duration, average HR and an intensity factor (IF) using following equation:

bTRIMP = duration training (min) x HR x 0.64e1.92x

where HR = (HRMEAN – HRREST)/(HRMAX – HRREST), e is the base of the Napierian logarithms, 1.92 and 0.64 are generic constant for males, and x = HR.21 5 predefined zones (zone 1, 50-59% HRMAX, IF = 1; zone 2, 60-69% HRMAX, IF = 2; zone 3 70-79% HRMAX, IF = 3; zone 4, 80-89% HRMAX, IF = 4; zone 5, 90-100% HRMAX, IF = 5) were used to calculate Edwards’ TRIMP (eTRIMP). The time spent in each zone was multiplied by the respective IF and then summated in order to compute the total eTRIMP score22. For the calculation of the Lucia TRIMP (luTRIMP), 3 predefined HR zones were used. Zone 1 (IF = 1) was defined as below GET, zone 2 (IF = 2) between GET and RCP and zone 3 (IF = 3) above RCP. Again, the time in each zone was multiplied by its respective IF and then summed to provide a total luTRIMP.23

TL was also calculated according to the method of Foster, as a subjective measure of internal TL (TLRPE). After every session, subjects were asked to rate their RPE using the CR-10 scale. TLRPE was then calculated by multiplying this RPE with the session duration.24

TSS was selected as an external TL measure. TSS is calculated using the following formula:

TSS = [(t × NP × IF)/(FTP × 3600)] × 100

Where t is the time, NP is normalized power and IF is the intensity factor (=NP/FTP). FTP is an individual’s functional threshold power.25 For this study FTP was assumed to be equal to the determined RCP.

*Fitting the model*

The values of the model parameters (a vector , containing the values of , and ) of each subject were estimated by minimizing the error between the model prediction (Equation 1) and the experimental data. The model parameter values were estimated for each quantification method per subject.

The error between model prediction () and the measured subject performance () was calculated as the residual sum of squares ():

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which depicts the sum of the squared differences between the -th measured data point per subject () and the value of at the evaluated parameter values () and at the corresponding time point .

As several combinations of parameter values could result in a well-fitting model, a global minimization was applied, using an algorithm that scans a large part of the parameter space. This avoids only finding well-fitting parameter values that are close to the initially guessed values, a drawback that occurs in local minimizations.

The minimization algorithm that was used is called Particle Swarm Optimization (PSO).26 This global minimization technique entails that a number of particles searches the parameter space in parallel. Thus, every particle of the group, or swarm, evaluates the at each set of parameter values that it encounters. In each step of the algorithm, all particles of the swarm each evaluate a new location in the parameter space. Their searching direction is influenced by their inertia (how strongly they hold on to their original searching direction), their personal minimum and the lowest minimum found in the swarm. The PSO algorithm requires specification of the balance of these three search direction factors, for which in this study the three factors were all set at the same value of 0.5, opting for incorporating all three mechanisms equally.

The parameter space in which the minimization was conducted was 0 to 60 and 0 to 3 for the - and k-values respectively. This space was moreover constrained in order to avoid illogical model outcomes. These are the following:

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with the final restriction denoting that the predicted absolute change in performance over one time point cannot be larger than 10%.

Finally, for each case (i.e. each TL method per subject), eight global minimizations were carried out.

The timeframe wherein training will contribute more to fatigue than to fitness was calculated as:

The day on which training will have the greatest positive influence on performance was calculated as:

**Statistical analysis**

Data are presented as mean ± SD. A Repeated Measures Anova (RMA) was used to check the performance progression over time. The evolution of the different TL methods over time was checked with a RMA with the different TL methods as a within subject factor. For every model fit, the RSS was calculated and a third RMA was used to compare the effect of the five different TL methods on the outcome parameters of the model (, k1, , k2, tn, tg and RSS). All statistical analyses were performed with SPSS Statistics 24 (IBM Corp., Armonk, NY, USA) and statistical significance was set at P < 0.05.

*Results*

**Performance**

The results of the ramp test are given in table 1. Figure 2 shows the evolution of performance during the TTs. At the end of the 8 week training period the mean performance improvement was 15.2 ± 4% (pre: 300 ± 58 W, week 8: 345 ± 62 W, p < 0.001, ES: 0.74). Maximal performance improvement was found one week after training cessation with an improvement of 16.6 ± 3% in week 9 (pre: 300 ± 58 W, week 9: 349 ± 66 W, p < 0.001, ES: 0.79).

\*\*\* Insert Table 1\*\*\*

\*\*\*Insert Figure 2\*\*\*

**Training load**

A visual representation of the weekly mean TL is given in Figure 3. This figure shows that there is a drop in weekly TL. It is clear that this drop is more pronounced in the first (week 1 to week 4) compared to the second training phase (Week 4 to week 8) (-15.4 ± 12.8% vs. -0.039 ± 12.1% respectively, p < 0.001). Based on this observation, the difference was further investigated in Table 2. For all HR methods the drop in TL was more pronounced in the first than the second period. However, TLRPE did not show a significant difference between the periods (p = 0.139). Also, within the first period bTRIMP decreased more than the other HR methods (p < 0.001 for eTRIMP, p = 0.01 for luTRIMP). In the second period, all methods evolved in a similar way. TSS was not included in the analysis since this TL metric was only calculated based on the results of the pre-test and thus could not change over time.

\*\*\*Insert Figure 3\*\*\*

\*\*\*Insert Table 2\*\*\*

**Fitness Fatigue Model**

An overview of the model parameters for each TL method is given in Table 3. The mean values of the output parameters across all methods for 1, 2, k1 and k2 were 30.0 ± 15.5 days, 4.2 ± 3.9 days, 0.14 ± 0.23 and 0.26 ± 0.28 respectively.

\*\*\*Insert Table 3\*\*\*

The RSS was similar for all TL-methods. There was also no difference found for 2 and tn. 1 was greater for bTRIMP than for all other methods, except for luTRIMP (p = 0.056) with 1 for luTRIMP also being higher than for TSS (p = 0.015).

TLRPE and eTRIMP differed for k2 (p = 0.017). k1 and k2 for TSS were higher than for all other methods, with the exception of luTRIMP (p = 0.844, p = 0.172 respectively).

The tg output for TLRPE was similar to all other methods. For bTRIMP tg was higher than for luTRIMP (p = 0.026) and TSS (p = 0.014), with tg for TSS being smaller than for eTRIMP (p = 0.019). The individual variability, according to the TL-method used, for tg and tn is shown in Figure 4.

\*\*\*Insert Figure 4\*\*\*

*Discussion*

The TT improved with 16.6 ± 3.0%, with a considerably high variability in the timing and magnitude of improvement despite the theoretical equal TL for the subjects. Four subjects showed a small to large decrease in performance in the first week of the training period, with five subjects showing a small to large increase during that same period (Figure 2). This individuality in training response is also reflected in the parameters of the fitness-fatigue model, contributing to the idea that the application of such a model is only effective when these parameters are individualized. The authors acknowledge the fact that there is no overload during the training period (i.e. a constant external TL in each session), which leads to a non-optimal improvement. However, this approach was chosen in order to isolate the effect of the different TL methods on the output of the model.

Despite keeping the external TL constant throughout the training period, the internal TL showed a clear drop over the course of the study. This drop was more pronounced during the first few weeks of the training period, which could be explained by an increase in blood volume during the first weeks of the study. An increase in blood volume is generally one of the first adaptations to a training program and in turn leads to a greater stroke volume. Given that a constant cardiac output is required for a given power output, the HR at this power output will decrease.27 But even within the HR methods there is a clear difference, with bTRIMP decreasing more than luTRIMP and eTRIMP during the first 4 weeks. This difference originates from a more methodological nature. bTRIMP uses the HRMEAN of a training and an exponential factor, which means that a small decrease in HRMEAN will lead to an associated exponential drop in TL. However, both luTRIMP and eTRIMP use training zones, implying that the HR will have to decrease enough and drop into a lower HR zone to be noticeable in the total TL. Although previous studies have shown strong correlations between TL methods,5,28 this study shows that the TL methods evolve differently over time, suggesting a different sensitivity of the methods to adaptations caused by training.

Irrespective of the TL method used, the fitness fatigue model accurately related TL to performance with an average error of 1.73 ± 0.52%, which seems an acceptable error to work with in the field. Previous studies,29,30 also found no difference in the quality of the model in relating TL to performance when different TL measures were used. However, these studies did not investigate the influence of the different TL methods as input on the outcome parameters of the model.

Despite the small error margin for all TL methods, using a different TL as input for the model, leads to differences in the output parameters within a subject (table 3). Most interesting is the intra-subject variability in tg caused by a different input for the model. The mean range across the TL-methods in tg is 1.8 ± 1.2 days within an individual, although in some subjects the difference in tg across the TL-methods goes as high as 5 days (e.g., subject 8). This difference would lead to a different timing of the tapering period, despite the fact that the training sessions and the resulting performance are exactly the same. Thus it is clear that understanding the influence of the input used for the model on these parameters is crucial in interpreting the results derived from the modelling.

Also interesting is the intersubject variability in the model parameters with tg ranging from 0.5 to 19.0 days and tn from 0.0 to 6.1 days, showing the ability of the fitness fatigue model in capturing the individual responses to training. So, the use of generic constants, as is typically done in online training platforms, is not warranted in guiding athletes to optimal performance. Moreover, the values found for both variables are lower than wat is mostly found in previous studies ( ± 40 days for tg and 15 days for tn), which are commonly used to advize taper periods.1,10,11 However, some studies using similar training modalities as the present study, also reported values that are in the same range.13,14 This leads the authors to conclude that the commonly used duration of a taper period (i.e. 2 weeks) is excessive for recreational cyclists typically training 3 times a week and that a taper period of 1 week should be sufficient in order to obtain maximal performance.

*Practical applications*

Coaches in the field should choose a TL method that is, depending on the situation and regulations of the sport, most likely to register the required data. If possible, the combination of an external and internal TL method is preferred. Next to this, it is important when using TL in a model as presented above, that the same TL measure is used over the whole period since the methods have a different order of magnitude and evolve differently over time. So when data is missing from a training session, it is preferred to make an estimated guess based on previous training data, than to use a different TL method within the same model, as is now frequently being done in the field (e.g. Performance Management Chart).

*Conclusions*

This study is the first to investigate the influence of using different TL methods during a cycling training program on the outcome parameters of the fitness-fatigue model. The main findings of this study were that, although the TL methods evolve differently over time, they produce a similar error margin when relating TL to performance and that despite this small error margin, the choice of TL-input does lead to a different timing with regard to the moment when training has the greatest positive influence and the timeframe wherein training should be avoided within an individual.

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*Figure captions*

Figure 1

Overview of the experimental procedure. ET is the exercise test, TTf is a familiarization time trial, p\* is the time trial to determine the initial performance level and IT stands for the interval training session.

Figure 2

Evolution of performance on the 3km TT. The full black line represents the mean performance progression. The grey dashed lines represent the individual evolution in performance. The vertical dotted lines demarcate the two periods of the study.

Figure 3

Visual representation of the mean weekly training load during the study period according to the different methods. Bars (+ SD) represent the absolute training load scores (AU), where the lines represent the training load scores relative to the training load of the first week.

Figure 4

Overview of the influence curves of the subjects according to the TL-method used. On the y-axis the netto influence of a training on the day of performance is given (AU). On the x-axis the days preceding the day of performance are plotted. Vertical dotted lines and dashed lines represent the range of respectively tg and tn calculated for the different TL-methods.