Modeling the Relationship between Training and Performance - A Comparison of Two Antagonistic Concepts

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Abstract

Few attempts have been made to apply systems theory to the description of human responses during physical training. Initially, Calvert, Banister, Savage & Bach (1976) proposed describing systems behavior with two antagonistic transfer functions ascribed to fitness as a positive and fatigue as a negative response to physical training. Performance, i.e. system output, was thus the balance between fitness and the fatigue effects calculated by a system of differential equations. This approach has been used in several studies to model the relationship between training and performance, but recently some authors have criticized the FF-Model for its methodical limitations and inconsistent empirical findings. Largely decoupled from this discussion another antagonistic model has been developed by Perl (2002). In order to analyze and optimize physiological adaptation processes, the so-called PerformancePotential-Model (PerPot) helps to simulate the interaction between training load and performance by using a dynamical state-event-model with adaptive delay in effect. To compare these two antagonistic models with regard to some critical considerations two training studies (untrained subjects) on a cycle ergometer were carried out. The results show, that in nine out of fifteen cases, better model fit to real performance data is achieved with PerPot. The prediction of the performance values for the final two weeks of the training experiment were, indeed, on average of higher quality for PerPot. But regarding to the individual cases with the FF-Model, prediction of values succeeds to a smaller middle percentage deviation in eight of the fifteen subjects. Furthermore, in both models a better model-fit and prediction accuracy was achieved by equidistant time interval between the training and testing sessions.

KEYWORDS: MODELING, TRAINING, ANTAGONISTIC TRAINING THEORY

Introduction

The analysis and understanding of training processes, i.e. the effect of training load on sports performance, are of extreme importance to training science and the practice of sport. In its research methodology, training-effect analysis has traditionally oriented itself, like other areas of science such as medicine, biology or psychology, on the prinicple of reductionism (cf. Gerok, 1989, etc). Here individual variables are isolated from the network of interactions, and interacting factors eliminated, as far as possible. Under these conditions, individual variables of a training process can be readily investigated and certain component phenomena scientifically grounded. Insodoing, training effects are typically evaluated using inferential statistical methods and models (eg. pre-post test-design). Increasingly in the recent past,

however, it has been shown that deterministic, linear models are inadequate in understanding and explaining simple biological mechanisms (Gerok, 1989) as well as complex forms of human behaviour (Tschacher & Brunner, 1997, Kriz, 1999). Nevertheless, the classical reductionistic approach to investigating individual component processes under simplified experimental conditions has not become superfluous as a consequence, to the contrary (Hughes & Franks, 2004; Balagué & Torrents, 2005). Indeed, to grasp the structure of the complex system of the training process, it is necessary to understand its essential building blocks. Despite this, deterministic, group statistical models are inappropriate for the understanding of complex training processes, if only because of their large number of various adaptive systems even down to the cellular level (Mester & Perl, 2000).
These problems more or less led to a paradigm shift in the approach to adaptation phenomena as complex dynamical systems and resulted in the abandonment of general, linear, structure-oriented models in favour of individual, non-linear, process-oriented models[1]. At present the most common theoretical approaches to physical adaptation processes in the field of sports are based on an antagonistic understanding of training effects. The basic assumption of an antagonistic concept used to model the interaction between physical training and performance is that the training (input) has two concurrent effects on performance (output) - a positive as well as a negative. Depending on the respective delays in the negative and positive effects, a training impulse can cause positive or negative results in the initial performance. This dynamics principle is “given by interactions of organs or components of an organism, which produce and transport substances with certain delays and so change the organism’s state” (Perl, 2005). The two currently most common antagonistic models are the Fitness-Fatigue-Model (FF-Model) and the Performance-Potential-Model (PerPot).

Fitness-Fatigue-Model (FF-Model)

In the middle of the seventies Banister and colleagues suggested a system theory founded model to describe and analyze physical adaptation due to physical training (Banister, Calvert, Savage & Bach, 1975, Calvert et al., 1976). In the so-called Fitness-Fatigue-Model the athlete is viewed as a system with training impulse as the input and performance as the output. The functional relationship between training impulse and the system’s response is described by two differential first-order equations ascribed to the antagonistic effects called fitness and fatigue. Thus fitness increased by physical training depicts a positive effect on performance as well as fatigue, which is affected negatively. For a general solution to these equations the convolution product of training impulse and time decay function has to be calculated. The final form of the FF-Model had two exponential functions that comprised fitness on the one hand and fatigue on the other (Calvert et al., 1976). Morton, Fitz-Clarke and Banister (1990) simplified the two-component FF-Model with three exponential functions to a form that had only one fitness and one fatigue function. In a further study Busso, Carasso & Lacour (1991) showed that adding up to four further components was not statistically supported. So in further studies a framework predominated, with two exponential functions which described the training-influenced change over the course of time in fitness ($\Delta g_i(t)$) and fatigue ($\Delta h_i(t)$) (for mathematical details see the “Methods” chapter of this paper). Finally, predicted performance ($p(t)$) was deduced by superposition of the contribution of training units (w) to fitness ($g(t)$) and fatigue ($h(t)$) (figure 1).

[1] The paradigm shift taking place in the understanding of sports performance is discussed by Balagué and Torrents (2005).

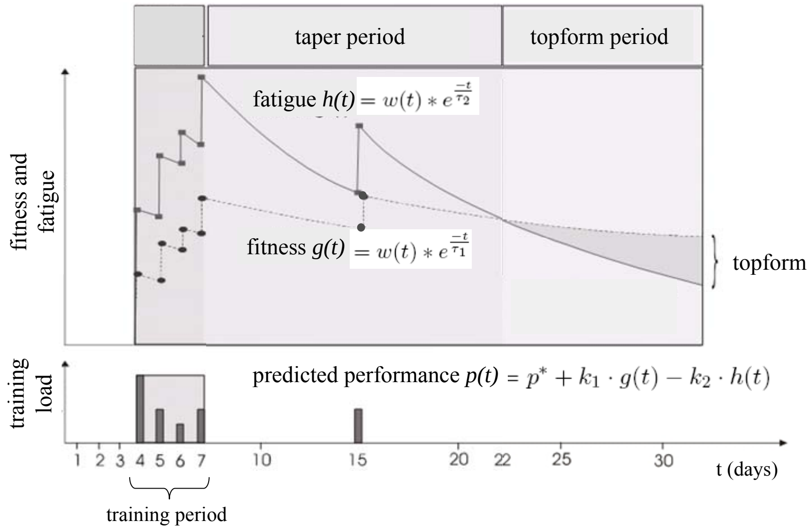

Figure 1. Principle example of the antagonism of the Fitness-Fatigue-Model including equations (reprinted from Banister & Hamilton, 1985).

The constants τ_1 and τ_2 are the decay time constants of fitness and fatigue, however the factors κ_1 and κ_2 weighting the training magnitude to fitness and fatigue expressed in arbitrary units. Whereas the time constants (t) describe the decay in the course of time expressed in days, the magnitude factors (κ) depend on the units used to measure the training load and performance and have no direct physiological basis. The time constants and the magnitude factors have to be determined for the individual through the use of an iterative process repeated for each subject. To obtain the best model-fit parameters, the non-linear least squares iterative method is used, by minimizing the residual sum squares between modelled and actual performance (Hellard, Avalos, Lacoste, Barale, Chatard & Millet, 2006). By calculating individual specific model parameters, the effect of known training response determinants such as past activity, initial fitness and genetic predisposition may be incorporated (Taha & Thomas, 2003).

Busso et al. (1991) investigated whether a better model-fit could be achieved by using a one- or a two-component FF-Model. The values determined by the two-component model were higher without exception than those for the one-component solution, but the result was not statistically significant. Nevertheless the authors conclude that a system model composed of two antagonistic first-order transfer functions will provide a proper representation of the training responses.

Referring to different time parameters reported in further studies Busso, Denis, Bonnefoy, Geyssant and Lacour (1997) infer that this was indicative of changing model parameters throughout the course of the training period causally founded in variable training intensity. As a result, they proposed using a model with time-varying parameters in which a recursive least square method was employed to recalculate the parameters stepwise each time data are collected. In the research presented here, two recreational cyclists were studied during two periods of intensive training (14 weeks). Unsurprisingly, better model-fit was obtained for the time-varying model for both subjects. The authors suggest that variations in model parameters reflect changes in training responsiveness, but restrictively these variations cannot be directly interpreted as modifications in the underlying physiological structures. However the time-varying model can be a useful tool to learn more about the chronological progression of adaptation to physical training (Busso et al., 1997).

The FF-Model has been used time and again to analyse training processes in competitive sports as well as in training studies with recreational athletes or untrained subjects. In several studies, attempts have been made to relate the model components of fitness and fatigue to physiological responses (Banister, Morton & Fitz-Clarke, 1992) (Tab. 1).

Table 1. Overview of existing approaches used the FF-Model.

Reference	*Year*	*Sport*[1]	*N*	*Duration*	*Physiological Parameters*	*Model-fit*[2]	*Model*
Banister & Hamilton	1985	Distance Running (C)	5 (♀)	43 wks	Iron status variables, Ferritin	-	time-invariant
Banister et al.	1986	Running (C)	? (♂)	52 wks	-	-	time-invariant
		Soccer (C)	1 (♂)	22 wks	VO_{2max}	-	time-invariant
		Swimming (C)	1 (♂)	18 wks	-	-	time-invariant
		Distance Running (C)	5 (♀)	43 wks	Iron status variables	-	time-invariant
Busso et al.	1990	Weight Lifting (C)	6 (♂)	52 wks	Hormones: Testosterone concentration, Cortisol ratio	R^2=.50 - .97	time-invariant
Morton et al.	1990	Running (R)	2 (♂)	4 wks	-	R^2=.71; .96	time-invariant
Busso et.al.	1991	Cycling (U)	8 (♂)	14 wks	-	R^2=.764 - .938	time-invariant
Banister et al.	1992	Running (R)	2 (♂)	4 wks	LDH, CK, AST	R^2=.71; .96	time-invariant
Busso et al.	1992	Weight Lifting (C)	6 (♂)	52 wks	Hormones: Testosterone concentration, Cortisol ratio, LH	R^2=.29-.85	time-invariant
Candau et al.	1992	Cross-Country-Skiing (C)	3 (1♀/2♂)	33 wks	Iron status indices	-	
Busso et.al.	1994	Hammer throw (C)	1 (♂)	37 wks		R^2=.91	time-invariant
Mujika et al.	1996	Swimming (C)	18 (8♀/10♂)	50 wks	-	R^2=.45 - .85	time-invariant
Busso et.al.	1997	Cycling (R)	2 (♂)	14 wks	VO_{2max}	R^2=.879 - .875	time-varying
						R^2=.666 - .682	time-invariant
Banister et al.	1999	Triathlon (C)	11 (♂)	14 wks	VO_{2max}	-	time-invariant
Busso et al.	2002	Cycling (U)	6 (♂)	15 wks	VO_{2max}	R^2=.957 - .982	time-varying
Millet et al.	2002	Triathlon (C)	4 (3♀/1♂)	40 wks	Heart Rate	r=.37 - .74	time-invariant
Busso	2003	Cycling (U)	6 (♂)	15 wks	VO_{2max}	Adj. R^2=.857; .944 (Mean)	time-invariant
Millet et al.	2004	Triathlon (C)	4 (3♀/1♂)	40 wks	Heart Rate,	r=.32; r=.30	time-invariant
Wood et al.	2005	Running (R)	1 (♂)	12 wks	VO_{2max}, VTRS, POMS	R^2=.92	time-invariant
Hellard	2006	Swimming (C)	9 (5♀/4♂)	60 wks	Blood lactate	R^2=.79	time-invariant

[1] C = Competitive (Elite) Sport; R = Recreational Sport; U = Untrained Subjects
[2] R^2 = coefficient of determination; Adj. R^2 = adjusted coefficient of determination; r = correlation coefficient

Recently some authors criticized the FF-Model concerning (1) its inability to predict future performance with accuracy, (2) differences between the estimated time course of change in performance and experimental observations, (3) the ill-conditioning of model parameters and

(4) the model was poorly corroborated by physiological mechanisms (Taha & Thomas, 2003; Hellard et al., 2006).

Performance-Potential-Model (PerPot)

In the recent past another model to investigate adaptive physiologic processes by means of antagonistic dynamics has been developed by Perl (Perl, 2001; Perl, 2002; Perl, 2004). In order to analyze and optimize physiological adaptation processes, the so-called Performance-Potential meta-model (PerPot) helps to simulate the interaction between training load and performance.

The starting point of the new model was the fact that adaptation to physical training is mainly (1) dominated by the individual conditions, (2) an extremely complex process and (3) characterised by diversity of parameters and their interrelation (Mester & Perl, 2000). Starting from these aspects, the primary aim of the research work was to model adaptation phenomena such as super-compensation, collapsing effect and the so-called U-function of protein metabolism (Mader, 1988, 1994). In addition the phenomenon of constant and moderate training leading to performance asymptotically tending to an upper limit was to be be modelled.

PerPot is based on a meta-model, where an output potential (the performance potential) is influenced by input load (training) – itself dynamically controlled by two internal buffer potentials, the strain potential and the response potential. Both potentials are influenced by each training impulse in equal measure and affect performance in an antagonistic way. Whereas the response potential raises the performance potential delayed by a numeric factor (DR), the strain potential reduces the performance potential also delayed by a factor (DS) (figure 2). The effect on performance is basically dependant on the course of time (t). For the mathematical calculation of the model potentials, differential equations are used in discrete steps. This means that the actual potential level results out of the prior potential level and the corresponding flow between the relevant potentials. Contrary to the FF-Model the chronological interval (time scale for Δt) can be chosen freely[2]. Because of an internal normalization of the potentials (values from 0 to 1), PerPot is independent of the scales of load and performance. Also, the time-scale does not play any role because the time units are embedded in the delays. Therefore, PerPot can be used for modelling arbitrary types of load–performance interaction (Perl, 2004).

The basic structure of PerPot was added to by an overflow pathway, which allows modelling of a collapse effect (Perl, 2003; Perl, 2004). That means, if the load integral over a period of time becomes too high, the performance breaks down spontaneously. This collapsing effect, known as the “overtraining” phenomenon, can be described by PerPot because the potential capacities are limited. If in particular the strain potential reaches beyond its upper limit, an overflow is produced, which reduces the performance potential with only small delay (DSO) (figure 2).

[2] the mathematical details are explained in the chapter “Methods” of the present contribution

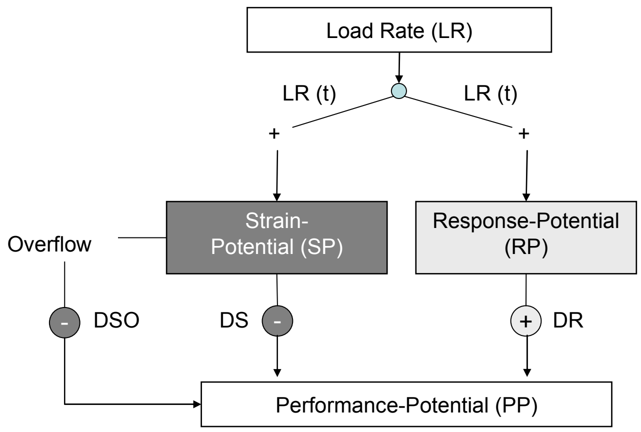

Figure 2. Basic antagonistic structure of the Performance-Potential meta-model (PerPot) containing strain overflow (reprinted from Perl, 2001).

In the manner described for the FF-Model, it is necessary to adapt the PerPot parameters to the individual conditions based on empirical data. The delay values and the capacity parameters of the potentials (maximum and start-capacity) have to be determined using a simulation-based calibration to achieve the best approximation to the real performance data. As a calibration criterion, the method of minimizing the residual sum squares between predicted and actual performance (model-fit) is applied. After an appropriate calibration, the two flow delays, DS and DR, determine the characteristic behaviour of the model and so, like a fingerprint, encode the characteristics of the modelled systems. The manner in which internal potentials control each other in order to take joint control of the input-output-behaviour is reminiscent of several examples of physiological antagonism (Perl, 2004). Upon obtaining good results from the theory based simulation and validation, PerPot was successfully applied to empirical data (Perl & Mester, 2001).

Due to the fact that training in general as well as training intensity changes the physiological status of an athlete, which in turn influences the delay values, PerPot allows the determination of model parameters by two procedures: constant delay values over the whole process (global) or varying delay values step by step in time (local). The latter is comparable to the time-varying FF-Model (see above) and reflects physiological phenomena of training like the improving adaptability of organic components. The change in physiological conditions in long term training prompted the development of a two-level PerPot with changing delay values. The dynamics of these long-term effects can be modelled using two exemplars of PerPot, where the performance output of the internal long-term model modifies the delay values of the external short-term model (Perl, Dauscher & Hawlitzky, 2003).

In previous applications with empirical data, PerPot was mainly used to study the interrelation between running speed and heart rate during a running race (Perl & Endler, 2006), to analyse the dynamic interaction between teams in games (handball) (Perl, 2006) or to get information about the effect of training on protein metabolism (Perl & Mester, 2001). Scientifically and statistically proven studies to validate PerPot with regard to simulating the training-performance relationship are quite rare. In order to compare the FF-Model and PerPot, Ganter, Witte and Edelmann-Nusser (2006) modelled the relationship between training and performance over an eight week cycling training program, with a prediction of the performances - measured in a 30-seconds-all-out test (Wingate-Test) - in the last week (two values). The model-fit obtained for PerPot provides an inconsistent result, with coefficients of determination ranged between r^2=.134 and r^2=.928. In the same way the quality of prediction, measured by the mean relative difference between the predicted and

actual performances of the last week of training, varied between 1.66 and 8.29 percentage (further aspects of this study are described in chapter "discussion").
The aim of the study conducted by Torrents, Balagué, Perl and Schöllhorn (2007) was to observe the differences of a linear tool (cross correlation) and PerPot in analysing the interaction between training and different parameters of strength performance in aerobic gymnastics (two subjects). As for PerPot, the scientific interest was to study the differences in delay characteristics of strain and response by using two kinds of training impulses (quantitative and qualitative). Thus, the approximation quality of the PerPot simulation was only specified in the value of average relative deviation between modelled and real performances (5.06% to 10.62%). The interpretation of and comparison to reported findings of this parameter is rather difficult and can only be done with regard to the semantic background. The average relative deviation has no mathematical limits, so that no general statistical convention exists. The authors fail to discuss the quality of the determined model-fit. Nevertheless, the calculated delay values were interpreted.
Altogether there are hardly any empirical findings - in contrast to the FF-Model – suitable for validating PerPot for modelling short- and long-term training adaptation. Moreover, PerPot has scarcely been recognized in the international community of training science or in sports medicine.

Discussion of the current research

In a review article by Taha and Thomas (2003) the current status of research on systems modelling the relationship between training and performance were discussed with regard to different models stemming from the original Banister FF-Model. The authors criticized the applied models concerning:
(1) Descriptive ability: The ability of the model to describe actual or future performance varies in the different studies, depending on the degree of external influences on the athlete's life, the precise quantification of training load and the changes in model parameters over a longer period of time. Nevertheless, the time-varying model (recalculating model parameters each time data are collected) of Busso et al. (1997) did obtain better results in describing the actual performance than the standard time-invariant model (using only one initial set of model parameters). However, unless it is possible to predict the change of the parameters themselves, this approach makes it impossible to use the model and its parameters to predict the response to future training.
(2) Quantification of training inputs: The existing concepts of quantifying training do not consider the specific effects of training, resulting in equally modelled effects from long, low intensity training sessions and short, high intensity training sessions.
(3) Relationship to underlying structures: Most studies were unable to identify significant relations between calculated fitness and fatigue components of the model and physiological parameters. Observed physiological variables such as resting heart rate or blood volume showed no fatiguing or negative effect with training, while not necessarily reflecting the athletic performance either. Other physiological parameters such as serum testosterone were positively related to both modelled fitness and modelled fatigue.
(4) Several modelling studies with various groups of study participants showed differences between the estimated time course of change in fitness and performance and their experimental observations, especially in response to short-term training.
Hellard et al. (2006) pick up several of these critical aspects and add the problem of ill-conditioning of model parameters. The authors advise carrying out further studies to determine whether the parameter estimation of the FF-Model would be more accurate under standardized experimental conditions. In point of alternative methods, the authors refer to the

PerPot meta model, which "seems conceptually very rich, because it takes into account the collapse effect in the wake of an overload training period, atrophy following a period of detraining, and the long-term behaviour of the training-performance relationship" (Hellard et al., 2006, 519).
The critical overview to investigations using the FF-Model up to now and the rare and inconsistent findings on PerPot prompted us to compare these antagonistic models with regard to (1) model-fit and (2) prognostic accuracy. To this end, two quasi-experimental studies were conducted.

Methods

Experimental methods

Subjects: The participants for two studies included three female and three male, college-aged students, with no known cardiovascular/pulmonary disease, medication or tobacco consumption or other medical contraindications, exercising as determined by self-response. The active but not endurance-trained, subjects volunteered for an endurance training program on a cycle ergometer. Subjects were encouraged not to participate in any other specific training during the study period. The experimental procedure and possible risks of the study were explained to each subject who gave their written informed consent before participation. The studies were conducted in laboratories at the Institute of Sport Sciences of the University of Bayreuth and approved by the Ethics Committee. All subjects were familiarised with the testing procedures by completing three performance tests (see below) one week prior to the commencement of the training experiment.
Training protocol: The protocol involved in Study 1 seven weeks (wks) and in Study 2 ten wks of bicycle ergometer (Cyclus 2, RBM GmbH, Leipzig, Germany) exercise, carried out in Study 1 three times weekly (Monday, Wednesday, Friday) and in Study 2 twice weekly (one and four days rest between training sessions), each session lasting 45 minutes. A previously determined and constant over the whole session (continuous method) resistance load was used. Each of the subjects completed various endurance training programs (TP) at cadences between 70 to 90 revolutions per minute (rpm), which was displayed in full view of the subject. The training load was quantified for each session in watts. Whereas in Study 1 the training and testing period was six wks followed by one wk testing only (once-weekly), in Study 2 this relation was nine wks and one wk (twice-weekly).
TP-A: Training was scheduled progressive-regressive to obtain an adaptation characteristic in the manner of tapering concepts. During the first four wks (Study 1) and six wks respectively (Study 2) workload was progressively boosted from 35% to 50% of power workload (watt) at VO2max[3] (pVO2max) of each subject, followed by two wks regressive reduction (50-30% of pVO2max).
TP-B: In Study 1 the resistance load was freshly determined for each training session at random within the range of 25-50% of pVO2max. The same procedure was used in Study 2, but within a range of 30-50% of pVO2max in wk 1-4 and 40-60% of pVO2max in wk 5-10. This training concept of varying loads was inspired by the differential training concept (Torrents, Ballagué, Perl & Schöllhorn, 2007) theoretically provoking a fluctuating increase in performance.
TP-C: Constant and moderate training (45% of pVO2max) to allow the performance asymptotically to tend to an upper limit.

[3] All values consecutively reported in percentage of VO_{2max} refer to the maximal workload (watt) measured in a maximal aerobic power test (VO_{2max}) until exhaustion with a continuous incremental testing protocol conducted one week before beginning the training experiment.

Performance testing: On each training day performance was tested on a cycle ergometer (Cyclus 2, RBM GmbH, Leipzig, Germany) prior the exercise in an all-out test. The all-out test should be able to be performed, as far as possible, without prolonged damage to physiological structures or functions, and not represent an additional training intervention. In various bicycle ergometer studies, it has been shown that endurance-oriented training additionally leads to a significant improvement in maximal performance output or maximal work performed (Izquierdo, Ibanez, K, Kraemer, Larrion & Gorostiaga, 2004). Moreover, the literature relates a relationship between aerobic and anaerobic performance components. Balmer, Davison and Bird (2000) were able to prove that the peak power output of a short all-out test represents a satisfactory predictor for mean power output of an individual time trial (16.1km). Similar findings are to be found in Baron (2004) and Stapelfeldt, Lohmüller, Schmid, Röcker, Schumacher and Gollhofer (2006).
Procedure: The cycle ergometer was calibrated to the individual conditions before data collection, which included adjusting the saddle height to accommodate partial knee flexion of 170-175° during the down stroke. Afterwards each subject began a 5-minute warm-up phase pedalling at 30% of pVO2max comprising three 8-second sprints at 100% of pVO2max. Closing the warm-up the subjects pedalled against no resistance at 60 rpm for 2 minutes. Following completion of the warm-up the testing procedure started as follows.
Study 1: The subjects completed an 8-s maximal cycling sprint test (isokinetic) limited to 100 rpm (cf. Baron, Bachl, Petschnig, Tschan, Smekal & Pokan, 1999; Baron, 2004; Stapelfeldt et al., 2006). The test was started by pedalling 20 seconds against a resistance of 30N. After a short countdown (tree - two - one - go), the subject maximally accelerate for 9 seconds against an automatically controlled resistance, so that the subject could not exceed the limit of 100 rmp. To minimize any possible effect of a subject's anticipation of the end of the test exercise, the last second was ignored for purposes of performance measurement. Peak Performance (PP), the highest power output (average of 1 second) and Mean Performance (MP), the average power output within the 8 seconds were calculated to quantify the performance.
Study 2: According to Williams, Barnes and Signorile (1988) a 15-s-Wingate-Test was adapted to measure the subject's performance. The starting procedure was as like in study 1 (see above). Subjects were verbally encouraged to maximally accelerate and maintain maximal pedalling velocity for 15 seconds against a preselected load, which was calculated as follows:

$$\text{resistance} = \frac{\text{body mass} \times \text{F} \times 52}{12}$$

where F is a weighting factor of 1,4 N per kg body weight for men and 1,2 N per kg for female. To characterize the temporal changes in performance, the following mechanical parameters were computed: Peak Power (PP), the highest power output value (average of 0,33 seconds); Mean Power (MP), the average power generated during the 15 seconds; Fatigue-Index (FI), the relative decline in power output from peak power to that produced at the end of the test. Williams, Barnes and Signorile (1988) identified a high correlation between PP and MP, while in comparison these mechanical parameters were not correlated with FI.
Table 2 gives an overview of the main experimental information of the conducted studies.

Table 2. Overview of the main methodical variables of both experimental studies

	Study 1	Study 2
Subjects (TP/gender)	3 (A ♂, B ♂, C ♀)	3 (A ♂, B♀, C ♀)
Length of study	6 wk (5 wks training & testing; 1wk testing only)	9 wks (8 wks training and testing; 1 wk testing only)
Training sessions per week	3	2
Training unit (input)	Watt	Watt
Performance Test	8s-All-Out-Test (isokinetic, 100 rpm)	15s-Wingate-Test (Williams, Barnes & Signorile, 1988)
Performance units (output)	• Peak Power (PP) • Mean Power (MP)	• Peak Power (PP), • Mean Power (MP) • Fatigue-Index (FI)

Modeling training effects on performance

The FF-Model and PerPot was used to simulate the training effects on performance data in both studies. Having given a detailed explanation of the fundamental ideas and developments of the two antagonistic models in the introduction above, in the following only the mathematical specifications used in the presented research are explained.

FF-Model: The two-component FF-Model relates to the basic framework by Morton et al. (1990) as described above. The following functional relation between the training load w(t) and an output of the physiological system g(t) and h(t) respectively is assumed:

$$\frac{\partial g(t)}{\partial t} + \frac{1}{\tau_1} \cdot g(t) = w(t) \qquad (1)$$

$$\frac{\partial h(t)}{\partial t} + \frac{1}{\tau_2} \cdot h(t) = w(t)$$

By using the convolution product the differential equations can be solved by the functions of fitness g(t) and fatigue h(t).

$$g(t) = w(t) * e^{\frac{-t}{\tau_1}} = \int_0^t w(t') \cdot e^{\frac{-(t-t')}{\tau_1}} dt' \qquad (2)$$

$$h(t) = w(t) * e^{\frac{-t}{\tau_2}} = \int_0^t w(t') \cdot e^{\frac{-(t-t')}{\tau_2}} dt'$$

Hence, the FF-Model is re-oriented daily, for which the following discretization holds.

$$g(n) = \sum_{i=1}^{n-1} w(i) \cdot e^{\frac{-(n-i)}{\tau_1}} \qquad (3)$$

$$h(n) = \sum_{i=1}^{n-1} w(i) \cdot e^{\frac{-(n-i)}{\tau_2}}$$

For the time continuous performance-output an antagonistic of fitness and fatigue is proposed. Furthermore it assumes an initial value p* of performance.

$$p(t) = p^* + k_1 \cdot g(t) - k_2 \cdot h(t) \qquad (4)$$

Thus, the discretizised model provides:

$$p(n) = p^* + k_1 \cdot \sum_{i=1}^{n-1} w(i) \cdot e^{\frac{-(n-i)}{\tau_1}} - k_2 \cdot \sum_{i=1}^{n-1} w(i) \cdot e^{\frac{-(n-i)}{\tau_2}} \tag{5}$$

The set of model parameters (τ1, τ2, κ1 and κ2) was determined by minimizing residual sum squares (RSS) between predicted and real performances. Computations were completed using MatLab 2008 (version R2008a, The MathWorks™).

PerPot: The subsequent formal description refers to the basic PerPot version drafted in figure 2 with the following definition of variables and parameters (Perl, 2001).

LR	(external) Load Rate
SP, *RP*, *PP*	Strain, Response and Performance Potential
SR, *RR*, *OR*	Strain, Response and Overflow Rate
DS, *DR*, *DSO*	Delay of Strain Rate, Response Rate and Strain Overflow Rate

The main equations of the complete PerPot meta-model are as follows, where all upper limits (i.e. potential capacities) are normalised to "1" and all lower limits are normalised to "0":

Raising Potentials *SP* and *RP*

$$\begin{aligned} SP &:= SP + LR \\ RP &:= RP + LR \end{aligned} \tag{6}$$

Computing rates

$$\begin{aligned} SR &:= \frac{min(min(1, SP), max(0, PP))}{DS} \\ RR &:= \frac{min(min(1, RP), min(1, 1 - PP))}{DR} \\ OR &:= \frac{max(0, SP - 1)}{DSO} \end{aligned} \tag{7}$$

Updating potentials *SP*, *RP* and *PP*

$$\begin{aligned} SP &:= SP - SR - OR \\ RP &:= RP - RR \\ PP &:= PP + RR - SR - OR \end{aligned} \tag{8}$$

The PerPot model parameters (starting capacity of SP and RP as well as DS, DR, DSO) were estimated from the pool of real performances by minimizing residual sum squares (RSS) between predicted and real performances. In the present analysis the PerPot software version 10-4 was used. For both studies, a time scale of approximately equidistant intervals of 1 or 2 days between the sessions (training and testing) was chosen.

Statistical analysis

The statistical parameter mostly used to determine the model-fit is the "Coefficient of Determination" (R^2) as described above. The problem is that there is no consensus on the exact definition of R^2. Only in the case of linear regression - were R^2 is simply the square of a correlation coefficient - are all definitions equivalent. By reason that in most contributions no detailed explanation of the applied equations can be found and the coefficient of correlation comprised no information about the level of the analysed variables, we determined two different values to test the models´ validity.

The mean relative deviation (rel.dev.) between the modelled and actual performances (PP, MP and FI) gives practical information about how accurately and close to the real data the model is able to describe the value series. Complementary to this, the Intraclass Correlation Coefficient (ICC; one-way random, single measure) was calculated to test the basal course.
Based on the individual model parameters and the real training loads, the performances of the last two weeks (one wk training and testing, one wk testing only) were estimated by extrapolation. The quality of the prediction was determined by the relative deviation (rel.dev.) between predicted and real performances.

Results

First it had to be determined, to what extent the two studies succeeded in provoking development in mechanical performance output, conforming to the theory, with their varying endurance-oriented training programmes. With Study 1, it can be shown that with TP-A (M1), after an initial improvement in performance, a progressive increase in intensity led to a reduction in performance. In the regressive training phase, and especially one week after the end of training, a gain in performance beyond the starting level could be observed (Fig.3, upper diagram). For subject M2 (TP-B), a clear though irregular gain in performance in the period of study was shown as predicted (see above). Subject F1 (TP-C) was able to improve her performance over the first 12 days, and plateaued at this level for the remainder of the programme. The collapse in performance on day 38 can be attributed to minor health complaints, which were reported by the subject in advance of the test (Fig.3, upper diagram).
In Study 2 for subject M3 (TP-A) a similar picture to that of M1 (TP-A) developed with regard to the progress of PP and MP (Fig.4, upper diagram). Contradicting this is the curve of the Fatigue-Index (FI) (Fig.4, lower diagram, top). The theoretically assumed progress for the TP-B of subject F2 can only be observed for the MP. In contrast, the TP-C of subject F3 leads in FI to a predicted continual increase in performance up to a limit value (Fig.4, lower diagram, top).

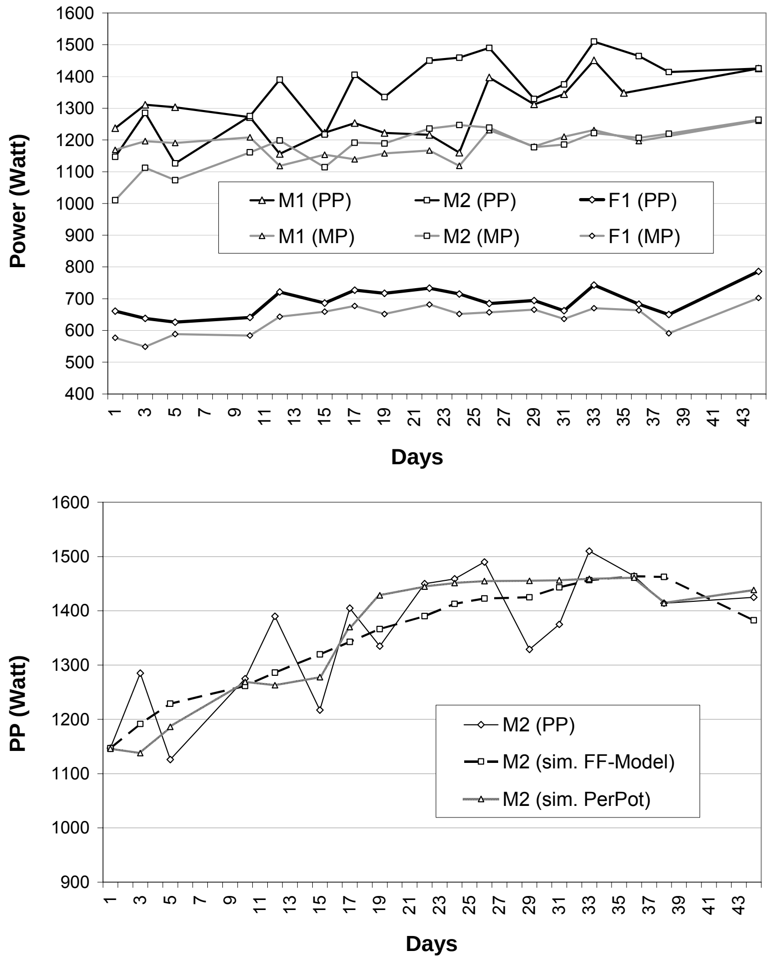

Figure 3. Progression of performances of the mechanical parameters Peak Performance (PP) and Mean Performance (MP) of all subjects of Study 1 (left); comparison to demonstrate the differences in dynamic between the FF-Model and PerPot simulation using subject M2 as example.

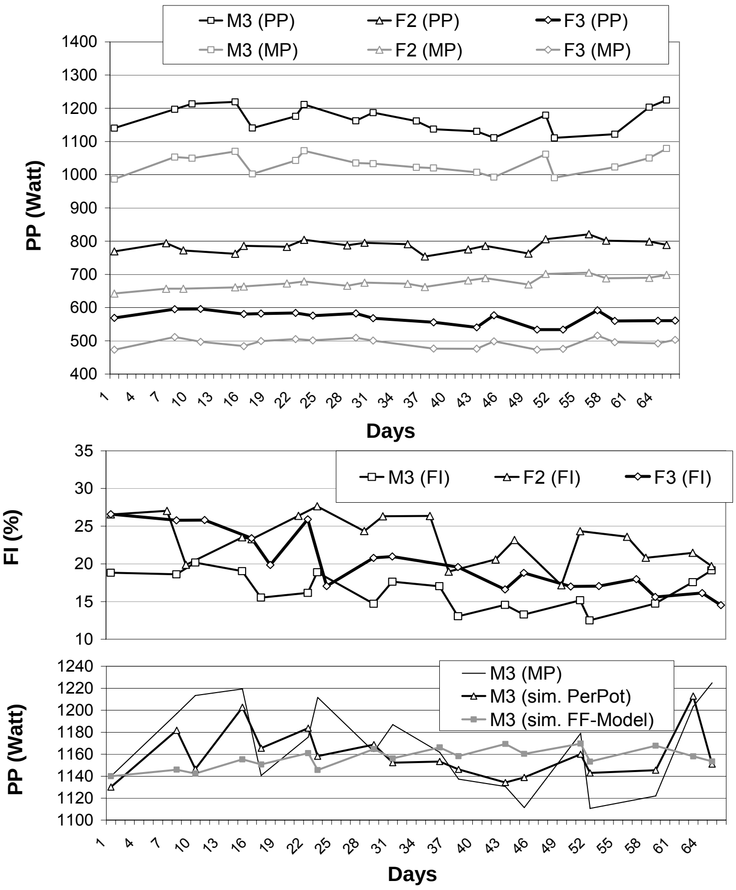

Figure 4. Progression of performances of the mechanical parameters Peak Performance (PP), Mean Performance (MP) and Fatigue-Index (FI) of all subjects of Study 2 (left and right top); comparison to demonstrate the differences in dynamic between the FF-Model and PerPot simulation using subject M3 as example (below bottom).

With the two antagonistic models, the real performance values can be simulated on average to a mean relative deviation of 2.78% (FF-Model) and 2.48% (PerPot) respectively (Table 2). The differences between the two studies (FF-Model 3.52% and 2.04%, and PerPot 2.9% and 1.98% respectively) can be explained by the lesser dynamics in performance progression in Study 2. The twice-weekly training led to a lesser performance adaptation. Model fit is evident to varying degrees according to the study, subject and training programme. Whereas in Study 1, satisfactory model fit could be achieved for both models, with r_{ICC} values exceeding .60 (with one exception), this was not achieved in Study 2, except for the parameters with performance adaptation conforming to theory, as described above (Table 2).
A comparison of the two models shows that in nine out of fifteen cases, better model fit to real performance data is achieved with PerPot, which can be attributed to the more adaptive internal model dynamics of that model (see Fig.3, lower diagram and Fig.4, lower diagram, bottom). The prediction of the performance values for the final two weeks of the training experiment were, indeed, on average of higher quality for PerPot, i.e. showing smaller deviation from the original values. However, it also became evident here, that measured against rel.dev., a satisfactory prediction could only be achieved with sufficient model fit (r_{ICC}). As demonstrated by the individual values, the simulated values in the week without training deviate clearly from the original values, especially with PerPot. With the FF-Model, prediction of values succeeds to a smaller middle percentage deviation in eight of the fifteen subjects.

Table 2. Model parameters for the test data of all subjects of both studies (rel.dev.: mean relative deviation between the modeled and actual performances; r_{ICC}: Intraclass Correlation Coefficient; τ_1 and τ_2: decay time constants of fitness and fatigue; κ_1 and κ_2: magnitude factors of fitness and fatigue; DS and DR: delay values of strain and response; Pred.: relative differences between the performances of the last two weeks (one wk training and testing, one wk testing only).

Study 1		**FF-Model**								**PerPot**					
Subj. (TP)	Perf.	rel. dev.	r_{ICC}	τ_1	τ_2	κ_1	κ_2	κ_1/κ_2 ratio	Pred.	rel. dev.	r_{ICC}	DS	DR	DS/ DR	Pred.
M1	PP	3,90	.642	45,2	11,3	0,242	0,372	0,65	3,12	3,36	.770	6,8	6,3	1,08	4,33
(A)	MP	2,12	.603	31,0	11,2	0,166	0,269	0,62	1,62	2,11	.360	1,5	1,5	1,00	4,16
M2	PP	4,36	.804	10,0	6,0	0,150	0,130	1,15	3,32	3,78	.824	3,0	2,5	1,20	3,50
(B)	MP	3,04	.803	9,0	4,0	0,090	0,070	1,29	7,06	2,31	.848	2,4	1,9	1,26	2,03
F1	PP	3,99	.560	9,0	5,0	0,834	1,291	0,65	8,14	3,72	.600	2,0	2,0	1,00	3,08
(C)	MP	3,70	.688	6,0	3,5	1,286	1,780	0,72	8,43	2,66	.793	2,5	2,0	1,25	4,12
	Mean	*3,52*	*.715**	*18,4*	*6,8*	*0,461*	*0,652*	*0,85*	*5,28*	*2,99*	*.730**	*3,0*	*2,7*	*1,13*	*3,54*
Study 2															
M3	PP	3,00	-.160	4,0	3,0	0,090	0,110	0,82	11,65	2,08	.491	1,6	1,1	1,45	2,69
(A)	MP	2,82	-.085	5,0	4,0	0,170	0,190	0,89	12,35	1,85	.511	1,9	1,2	1,58	2,79
	FI	1,54	.653	10,0	1,0	0,000	0,000	1,29	3,84	1,43	.798	2,0	2,0	1,00	4,20
F2	PP	1,42	.445	13,0	13,0	0,092	0,033	2,82	5,47	1,55	.219	4,3	3,7	1,16	11,03
(B)	MP	1,06	.921	29,0	27,0	0,070	0,008	8,95	3,00	1,28	.714	4,3	3,8	1,13	5,00
	FI	2,68	.610	41,0	41,0	0,000	0,000	2,78	6,21	2,83	.382	2,0	2,0	1,00	3,97
F3	PP	2,12	.545	10,7	20,8	0,476	0,275	1,73	3,56	2,36	.257	2,5	1,1	2,27	3,72
(C)	MP	2,00	.354	9,6	22,7	0,320	0,092	3,46	3,26	1,89	.490	3,3	2,8	1,18	2,44
	FI	1,67	.894	45,0	1,0	0,000	0,00	0,27	0,99	2,52	.748	2,0	1,5	1,33	6,35
	Mean	*2,04*	*.600**	*18,6*	*14,8*	*0,135*	*0,079*	*2,50*	*5,59*	*1,98*	*.550**	*2,7*	*2,1*	*1,35*	*4,69*
Total	Mean	**2,78**		**18,5**	**10,8**			**1,67**	**5,44**	**2,48**		**2,8**	**2,4**	**1,24**	**4,11**

* Before calculating the average correlation coefficients the values were transformed into Fishers Z-Values (Bortz & Döring, 1995).

The model parameters (τ_1, τ_2, κ_1, κ_2, DS and DR) display a broad distribution in both studies, meaning a physiological interpretation of the parameters is only possible to a limited degree (Table 2).

A further evaluatory step investigated whether the criticism of ill-conditioning made by Hellard et al. (2006) applied to our data. To this end the determined model parameters were correlated to one another (Table 3).

Table 3. Correlation between estimated model parameters.

Model parameter	**N**	**Model**	**Correlation coefficient**
τ_1 - τ_2	15	FF-Model	.388
τ_1 - κ_1	15	FF-Model	-.362
τ_1 - κ_2	15	FF-Model	-.274
τ_1 - κ_1/κ_2	15	FF-Model	.091
τ_2 - κ_1	15	FF-Model	-.185
τ_2 - κ_2	15	FF-Model	-.278
τ_2 - κ_1/κ_2	15	FF-Model	.633*
κ_1 - κ_2	15	FF-Model	.964**
DR - DS	15	PerPot	.967**
DR - DS/DR	15	PerPot	-.400
DS - DS/DR	15	PerPot	-.161

The only significant relationships arising for the FF model were between the two magnitude factors of fitness and fatigue, as well as the decay time constant for fatigue (τ_2) and the magnitude factors ratio (Table 3). In PerPot, there was statistical interdependence between the two flow delays DS and DR.

Discussion

FF-Model

Comparing the parameters determined by the FF model with the details of previous studies, the large distribution of the decay time constants (τ_1, τ_2) as well as that of the magnitude factors (κ_1, κ_2) is immediately obvious. Busso et al. (1991) reports τ_1 values for eight untrained men of between 5 and 30 days (mean = 38; SD = 9) and τ_2 values of 1 to 5 days (mean = 1.9; SD = 1.5). Reviewing all the previous experiences with the FF model, one finds values, with τ_1 = 38 - 60 and τ_2 = 4 - 15 (Taha & Thomas, 2003). In reference to this critical overview Hellard et al. (2006) were interested in (1) assessing the appropriateness of fit, (2) the accuracy of the model, (3) ill-conditioning and (4) the stability of the Banister model. Over and above that, a review and suggestion of alternative methods to model the training-performance relationship is given. They conclude that the FF-Model showed substantial variability in the determined parameters (decay time constants, magnitude factors and time to peak performance after the end of the training period), making it imprecise. Furthermore, fitness decay time constants up to 65 days (range = 13 - 65; mean = 38; SD = 16) do not confirm training experience and are undesirable from a practical point of view. Nevertheless, it could be demonstrated that “the variability in modelled performances was reasonably small and the Banister model was stable” (Hellard et al., 2006, 519). So the disappointing results could be ascribed to the improper parameters used to indicate training strain and performance.

The here presented values for τ_1 (range = 4 - 45.2; mean = 18.5; SD = 15.2) and τ_2 (range = 3 - 41; mean = 10.8; SD = 11.5) deviate considerably from those previously published. Especially in comparison to Busso et al. (1991), where endurance training in untrained subjects was also investigated, we arrive at considerably larger τ_2 values. The broad spread, even within similar performance levels among the subjects and under similar training methods (eg. endurance training), lead to the assumption that the delay parameters are intrinsically dependent on study design and on the quantification of the training as well as that of performance. In summary, it must be supposed that the original physiological interpretation of the decay time constants, with a range of up to 39 days for τ_1 and 38 days for τ_2 must be judged critically (Taha & Thomas, 203; Hellard et al., 2006).

As already detailed in the introduction, the absolute values for the factors κ_1 and κ_2 are exclusively dependent on training load unit, and do not admit any other physiological interpretation. Only the relationship of both values to one another, the κ_1/κ_2 ratio, can be compared to other studies (Busso et al, 1997). In a study of elite swimmers by Mujika, Busso, Lacoste, Barale, Geyssant and Chatard (1996), the κ_1/κ_2 ratio ranged from 0 to 13.34, while Ganter et al. (2006) derived significantly lower values between 0 and 2.43 in a bicycle study with untrained subjects. The findings made here, as well as the data referred to in the literature, point to an enormous distribution of the κ_1/κ_2 ratio parameter. The ratio of 1(κ_1) to 2 (κ_2) propagated in earlier work can thus not be assumed in general (Morton et al., 1990; Fitz-Clarke et al., 1991).

PerPot

For the parameters of PerPot, comparable data is only available from the field of weight training (gymnastics) (Torrents et al., 2006) and endurance training (cycling) (Ganter et al., 2006). By means of multiplying the delay values DS and DR by factor 3, as well as a subsequent adaptation to the chosen time-scale, the decay time of the positive and negative training effect for PerPot can be expressed in days, analagous to the parameters τ_1 and τ_2 in the FF-Model. According to this, temporal delay values for DS resulted of between 10 and 47 days (mean = 16.9; SD = 9.8) and for DR of between 8 and 44 days (mean = 19.9; SD = 9.6). While Ganter et al. (2006) came up with similar values, which because of identical time scales are directly comparable, in Torrents et al. (2007) (weekly performance measurement), DR values lay above those of DS, ie. while the negative influence decays in comparison to the positive during endurance training with untrained subjects, in weight-lifting with female gymnasts of national standard, the opposite effect is in evidence.

Comparison of FF-Model and PerPot

Although the FF-Model (mathematics) and PerPot (informatics) differ intrinsically in their model structures, both claim to represent the interaction between training and performance. Moreover, in both models a time-delayed, positive and negative influence of training on performance (antagonistic concept) is pre-supposed. Hence, the two models can be compared in terms of their model fit, ie. how well they can be aligned to actual data, and of their prognostic accuracy. Furthermore, the temporal delay in the decay of the positive and negative training effect can be represented in days in both models, meaning the temporal parameters are also formally comparable. Interpretation, nonetheless, requires reference to the respective model structure.

In the comparative study by Ganter, Witte & Edelmann-Nusser (2006) both, the FF-Model and PerPot were used to model the performance responses to training in cycling. The coefficients of determination ranged between r^2=.000 and r^2=.833 for the FF-Model and r^2=.134 and r^2=.928 for the PerPot, but the differences were not statistical tested. For the majority of the subjects at least one of the constants of the FF-Model is equal to the upper or lower limit used according to Busso et al. (1997). Hence, the interpretation of the model parameter values is questionable. Even though the FF-Model offers a higher quality of prediction on average, it is assumed that the FF-Model "will not be preferred" because of the inexplicable values of the decay time (Ganter, Witte & Edelmann-Nusser (2006, 59). Also the general applicability of PerPot can not be supported by the authors. The dissatisfying results are due to unstable performance levels of the athletes, a too short training period and the variability in the measured performance. Another reason for the inconsistent findings could be assumed in the research method (field study), or more precisely in the uncontrolled training on personal bicycles on the road (field study). Furthermore results in the 30-seconds-all-out test are largely determined by the motivation of the subjects, particularly in light of the three testing sessions per week.

Comparing the two models in regard to the results of our studies, it becomes clear that a better model fit as well as the average of prediction accuracy was able to be achieved with PerPot. But with the FF-Model, prediction of values succeeds to a smaller middle percentage deviation in eight of the fifteen subjects.

Comparing the time constants (τ_1, τ_2 and DS, DR) determined by the two models, the inverse relationship of the value pairs becomes obvious. While in the FF-Model the negative influence decas more quickly than the positive, PerPot produces the opposite relationship. It is necessary, however, to consider the strengthening factors κ_1 and κ_2 in the FF-Model, whose relationship indirectly influences the temporal effect delay. In seven of eleven cases

with $\tau_1 > \tau_2$, κ_2 was also $> \kappa_1$. The results indicate that time parameters merely represent inner-model factors, and that any interpretation with regard to phsiological mechanisms is misplaced given the current state of understanding.
Finally, the ill-conditioning problem, which means any model parameters were highly correlated, has to be discussed. Our findings were not in line with Hellard et al. (2006), who estimated high correlations within the two decay time constants (τ_1 - τ_2 = .99 ± .01) and the two magnitude factors (κ_1 - κ_2 = .91 ± .13) just as between these parameters (κ_1 - τ_1 = .69 ± .26; κ_1 - τ_2 = .69 ± .26; κ_2 - τ_1 = .75 ± .30; κ_2 - τ_2 = .76 ± .27;). In the present research only the magnitude factors of fitness (κ_1) and fatigue (κ_2) were excessively highly correlated, what however is caused in the mathematical framework of the FF-Model. That applies to the high correlation of the PerPot parameters DS and DR.
Comparing the results of the two studies regarding to the used research method and design, it could be assesses, that endurance training of 45 minutes twice weekly is not enough to provoke sufficient changes in performances over a period of eight weeks. Furthermore, in both models a better model-fit and prediction accuracy was achieved by equidistant time interval between the training and testing sessions as arranged in Study 1. On the other hand the 15-s-Wingate-Test in Study 2 offers a more differentiated analysis of the progression of anaerobic power output. On the basis of two none correlated performance factors (PP/MP and FI) individual differences in the adaptation characteristic founded in different training programs could be measured and simulated.

Conclusion

The aim of the two studies was to compare the FF-Model and the PerPot regarding to model the relationship between training and performance. In detail the model-fit and the accuracy to predict future performances were analysed. Both models showed substantial variability in the estimated model parameters, so that a physiological interpretation of theses parameters is critical. Further research should be conducted to determine substantial differences between both models in the quality of modelling the effect of training on performance. Therefore long term studies with standardized conditions have to be carried out.

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