Training Simulation with Nothing but Training Data
Simulating Performance based on Training Data Without the Help of Performance Diagnostics in a Laboratory

Melanie Ludwig, David Schaefer and Alexander Asteroth
Computer Science Department, Bonn-Rhein-Sieg University o.A.S., Grantham-Allee 20, 53757 St. Augustin, Germany

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Abstract: Analyzing training performance in sport is usually based on standardized test protocols and needs laboratory equipment, e.g., for measuring blood lactate concentration or other physiological body parameters. Avoiding special equipment and standardized test protocols, we show that it is possible to reach a quality of performance simulation comparable to the results of laboratory studies using training models with nothing but training data. For this purpose, we introduce a fitting concept for a performance model that takes the peculiarities of using training data for the task of performance diagnostics into account. With a specific way of data preprocessing, accuracy of laboratory studies can be achieved for about 50% of the tested subjects, while lower correlation of the other 50% can be explained.

1 INTRODUCTION

It is widely accepted that the right dose of exercise is a very important factor in efficient training. However, the right dose strongly depends on each individual and may change during training periods. Professional athletes therefore have a coach, trainer, sport scientist, or are under doctoral maintenance and their exercise sessions are individually supervised and controlled by a professional.

Professional coaches make use of the athlete's physiological data, e.g., blood lactate concentration or $\dot{V}O_2max$, measured during standardized test protocols. Based on this data the current athlete's performance level is assessed and an appropriate training plan is generated. To put it the other way round, an appropriate training plan is mostly dependent on particular equipment and a specialist interpreting measured data and generating a plan.

But not only athletes and professionals are interested in appropriate and individual training plans. For amateur athletes and in leisure sports, the usage of activity tracking systems is increasing these days as cited in (Krebs and Duncan, 2015). With these applications they can track their activities and analyze past training sessions—with more or less accuracy (Yang et al., 2015; Lee et al., 2014). But so far they can not accurately predict the progress of training nor create a suitable training plan including next steps to do.

Regarding outdoor cycling performance, (Balmer et al., 2000) found peak power for a certain time to be a useful predictor. Furthermore, (Tan and Aziz, 2005) found that laboratory determined absolute peak power might predict cycling performance on a flat course, and that relative peak power seems to be a useful predictor of performance during uphill cycling. But here, too, laboratory tests are necessary beforehand in order to predict the outdoor cycling performance.

Therefore, the goal of this study was to examine the feasibility in simulating performance—which can be used for generating individual training plans—without invasive methods like blood lactate measuring, coaches, laboratory studies, or any other special equipment. As a first step towards this direction and to compare the results to the results of laboratory studies, the method was tested on ambitious (leisure) cyclists only.

Recently, (Schaefer et al., 2015) described a method for generating individual training plans based on the Fitness-Fatigue model (Calvert et al., 1976), a common antagonistic model for performance diagnostics.

Using the *traipor* concept, this paper presents a new possibility in preprocessing non-standardized data before fitting necessary model parameters to an individual without any laboratory measurements or invasive methods. Combined with generating training plans, ambitious sportsperson can easily figure out an

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individualized training plan following personal constraints and based on nothing but their own training data which they might already have collected.

2 STATE OF THE ART

The most common mathematical method to describe and analyze the physiological adaption of the human body to physical training was invented in the middle of the seventies and is known as Fitness-Fatigue model (Calvert et al., 1976). This approach in performance diagnostics is used and evaluated in several studies, which are usually based on standardized or at least controlled conditions and on a small amount of mostly well-trained athletes. In spite of many alternative models that have been proposed since then, the Fitness-Fatigue model is still one of the most important and fundamental models in training control. Basically, performance is made up of two antagonistic principles: training results in improved performance, but it also induces fatigue which diminishes performance. So the two-component model can be seen as difference between fitness and fatigue. A more feasible version is given by (Busso et al., 1994) as:

$$\hat{p}_n = p^* + k_1 \cdot \sum_{t=1}^{n-1} w_t \cdot e^{\frac{-(n-t)}{\tau_1}} - k_2 \cdot \sum_{t=1}^{n-1} w_t \cdot e^{\frac{-(n-t)}{\tau_2}},$$

where $\hat{p}_n$ describes performance at day n and p^* is the original performance level before workout. The input w (e.g., wattage) is considered for the past $n-1$ days of training. Here, $\tau_1 < \tau_2$ are time constants while $k_1 < k_2$ are multiplicative enhancement factors.

Furthermore, Busso et al. compared different modifications to the Fitness-Fatigue model in analyzing the training effect in hammer throwing and cycling on an ergometer (Busso et al., 1991; Busso et al., 1994; Busso et al., 1997). They came to know that the Fitness-Fatigue model with two components properly simulates training response, while a more complex version estimating time-varying parameter might improve results.

At about the same time, Mujika et al. analyzed the Fitness-Fatigue model relating to pre-competition preparation in swimming. Despite a high variance in parameters and regarding the correlation between modeled and measured performance, the model is appraised as useful for this purpose (Mujika et al., 1996).

In 2006, Hellard et al. tried to estimate the usefulness of the Fitness-Fatigue model in monitoring training for elite swimmers. In that regard, the model parameters variances are found too high and no physiological interpretation of these parameters can be motivated, such that the model is evaluated as not useful in monitoring this kind of training (Hellard et al., 2006).

In about 2000, Perl et al. invented a similar model for performance diagnostics, called Performance Potential Model (PerPot) (Perl, 2000). Pfeiffer et al. compared PerPot to the Fitness-Fatigue model within two cycling studies based on three college-aged students each. He confirmed the difficulties in interpreting parameters of the Fitness-Fatigue model and concluded a slightly better quality using PerPot (Pfeiffer, 2008). Despite its good simulation quality in the majority of subjects, in our studies the PerPot model exhibited instabilities in a significant number of cases making it less suitable for automatized generating training plans.

3 EXPERIMENTAL SETUP AND METHODS

An online training portal called *traipor* was developed and was used to obtain the training data utilized within the *traipor* concept. The portal offers the functionality to fit the Fitness-Fatigue model to the individual user based on the user provided training data. With the individual training parameters and the techniques described in (Schaefer et al., 2015) the portal is able to generate optimized training plans leading to the given goals of its user while supporting a variety of constraints, like a weekly training cycle or a maximum training load.

By using nothing but training data obtained from the users themselves, the setup of the described study is very different from laboratory based studies, especially since the training took place without any mandatory training schedule, standardized performance measurements or control of data quality.

3.1 Data Base

Among ambitious cyclists, measuring wattage and heart rate during training is quite common. A personal analysis is then widely done using the training analytic software *GoldenCheetah*[1] or similar softwares like Trainingpeaks™WKO+. To facilitate the usage of *traipor* for the potential target group of ambitious cyclists, data can be uploaded from a CSV-file exported directly from GoldenCheetah or similar software. These data exports contain various training and performance metrics, enabling *traipor* to run model fittings for the users. Metrics were evaluated

[1] http://www.goldencheetah.org/

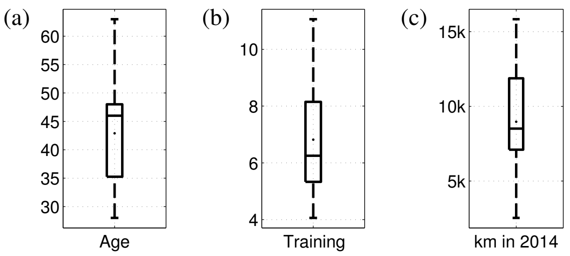


Figure 1: Subject's distribution concerning **(a)** age, **(b)** average weekly training time, and **(c)** overall cycling distance in 2014.

with respect to the attainable simulation quality using the presented experimental setting. Underlying measures here are 60 minutes Peak Power (PP60) for performance, and Training Stress Score (TSS) for strain. The PP60 is used because of the lack of physiological parameters like blood lactate concentration, $\dot{V}O_2max$ or similar conditioned by the data gathering, but is found a useful measure for outdoor cycling performance (Balmer et al., 2000; Tan and Aziz, 2005). Since solely values deduced from measured values were available, we compared the RMSE fitting quality of different TRIMP values, Skiba's bike score and TSS. Here, TSS reached best results, although all measures were located in a very similar range.

Out of 52 cyclists that registered only 20 supplied sufficient data for fitting, i.e., including both a value for the strain metric and for the performance metric and generating data using a power meter. Figure 1 shows the distribution of all 20 subjects concerning age, average weekly training time and performed cycling distance in 2014 per subject. All subjects had been familiarized with the utilization of their provided data for research purposes and have been acquaint about their self-responsibility in training and data elicitation. Data privacy is ensured by design and by pseudonymization.

3.2 Fitting Concept

In terms of adapting a performance model to a subject, the model's parameter set has to be figured out. A least squares approach is used to fit parameters to given data as widely suggested, e.g., by (Busso et al., 1997). In preliminary comparative studies we found any state of the art Quasi-Newton method to show similar or better performance than stochastic search methods while being computationally less expensive.

One of the model parameters describes the concept of an initial performance level which is modeled by p^* in the Fitness-Fatigue model, while the other parameters are time constants describing how fast a subject adapts to strain. p^* represents the performance level without any specific training. It is also the level an athlete returns to after stopping training.

Usually, laboratory studies make a specified training plan compulsory for each subject and often last between 4 to 60 weeks, cf. (Pfeiffer, 2008). Performance is often tested every three to five weeks (cf. (Hellard et al., 2006; Busso et al., 1991)). In these plans, fluctuating strain is provided in order to fit model parameters to the subject's adaptability. Furthermore, subjects are aware of their responsibility and controlled by some training supervisor. Since the idea of the *traipor* concept was to simulate or predict performance process without laboratory studies and fixed training plans, such data can not be taken as assured here. To deal with training data from non-predefined workout and without a certain quality, a special fitting concept is elaborated.

The therefore designed *traipor* concept for fitting can be subdivided in two parts: 1. data cleansing, and 2. data grouping. After this concept of preparing data, subject's individual parameters are determined using a least squares approach evaluated on training days only. Following parameter fitting, a training plan can be generated as described in (Schaefer et al., 2015) regarding individual constraints.

3.2.1 Data Cleansing

Restricting the duration of training data to the current and last year: As stated before, laboratory studies usually fit their models over a one to few month period of time. These studies predefine a training plan for subjects and can control the execution. Usually, subjects can perform a variety of different load and performance levels, whereby performance limits were tested regularly. Since there is no supervision or control in this study, any performance development has to be extracted from training data itself. A longer period for fitting therefore is beneficial, since adaptability of the human body to training can be mapped to the set of system inherent variables. This is stated as general adaptability to *fitness* and *fatigue* within the parameter set. But if the fitting period is too long, body might have changed this adaptability over years and react different to training.

Rejecting data which do not include both a value for the strain metric and for the performance metric: This step is necessary to avoid unusable data since both values are inalienable.

3.2.2 Data Grouping

Group data sets according to the subjects specification: Within each group, the highest performance

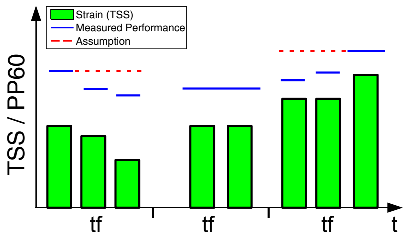


Figure 2: Grouping of data. The highest performance value of each group *tf* is chosen to replace other performance values within this time frame (dotted line).

value replaces all values inside this group. Considering that even ambitious sportsperson do not reach their personal performance limit within each training, using every single performance value in fitting might lead to highly fluctuating performance in a short time. Therefore, information is needed about the approximate time frame in which the subject does usually reach its performance limit, e.g., weekly, biweekly, or monthly. This information was provided by the subject itself. The highest performance in this specific time frame approximate the real performance limit more accurate and therefore is chosen for all performances within this period. An example is illustrated in Figure 2. For the specified length of the time frame *tf*, given data set excerpt is divided into three groups. Strain performed within a training session is represented by rectangles. After identifying the highest performance value, all other performance values are substituted with the very same and depicted as dotted lines.

Accumulate all strain data performed on one day: To use just one single value of strain and performance for each day, strain is accumulated if training was performed on several occasions same-day. Performance value remains at the maximum performance value determined beforehand during grouping of data.

3.3 Experiments

We divided our experiments into three main parts:

1. Ability of the presented concept to improve fitting quality for outdoor training data in general.
2. Comparison of results between this concept and laboratory studies to prove usability.
3. Analysis of the underlying data in cases where fitting does not reach a reliable accuracy.

When comparing our results to laboratory studies, fitting correlation serves as reference value: In (Pfeiffer, 2008), results are evaluated using the *intraclass correlation coefficient* r_{ICC} in version of $r_{ICC}(1,1)$ (one-way random, single measure) regarding (Shrout and Fleiss, 1979). The study of (Busso et al., 1991) uses the *Pearson correlation coefficient* r, and (Hellard et al., 2006) and (Mujika et al., 1996) are using the *coefficient of determination* r^2. Accordingly, results from the described fitting concept are stated as r_{ICC}, r or r^2 value. Correlation measures are computed between the simulated performance curve according to estimated parameters from the fitting concept, and measured performance values.

3.4 Statistical Analyses

Considering performance analyses, it is important to know the accuracy of the fitting for a specific method. The quality of a method is often given by the deviation between a simulated curve compared to the measured one.

Let n be the number of data points, x_i the measured values with mean $\bar{x}$ and let y_i be the simulated values with mean $\bar{y}$, $i \in \{1,2,\ldots,n\}$. The *absolute error* is defined by $e_i = |x_i - y_i|$. The *sum of squares error* (SSE) is defined by $\mathrm{SSE} = \sum_{i=1}^{n} e_i^2$, while the *total sum of squares* (SST) is given as $\mathrm{SST} = \sum_{i=1}^{n} (x_i - \bar{x})^2$. A total sum of squares for the simulation is indicated with SST_y. The *root-mean-square error* (RMSE) is defined by $\mathrm{RMSE} = \sqrt{\frac{SSE}{n}}$ and serves as kind of a standard deviation between the measured and the estimated curves.

Since different studies use different statistical measurements as described before, these values were computed as well with $r = \sum_{i=1}^{n} (x_i - \bar{x}) \cdot (y_i - \bar{y}) \,/\, (\sqrt{\mathrm{SST}} \cdot \sqrt{\mathrm{SST}_y})$, $r^2 = 1 - \mathrm{SSE}/\mathrm{SST}$, and $r_{ICC} = \mathrm{ICC}(1,1)$ according to (Shrout and Fleiss, 1979). In all of these correlation measures, a correlation value of 1 indicates a good correlation and values near 0 indicate a missing correlation. A value near -1 in r or r_{ICC} correlation value implies a negative correlation respectively.

Regarding statistical measures such as r with time series with within-series dependencies, some difficulties have to be considered. With correlation coefficients, goodness of fit and accuracy can not be modeled adequately, it does only model the time-series behavior in general. A good correlation value is achieved if the curve structure of measured performance and simulated performance are similar to each other independent of possible variation in range or scaling. Furthermore, if the measured performance is given by a straight line such that the total sum of squares sums up to zero or some small value near zero, r and r^2 are undefined or quite low even if the simulated performance contains only small variances. Figure 3 shows an example where the r-value is undefined and indicates no correlation whereas

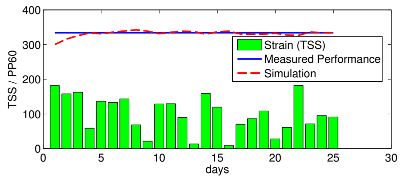


Figure 3: Example where the fitting process results in a small deviation, whereas the r-value is undefined.

Table 1: Comparison of the RMSE and r-value both as mean, median and standard deviation with and without the *traipor* concept.

	raw data	concept
RMSE		
mean	35.77	14.13
median	40.59	12.07
std	18.27	6.43
r-value		
mean	0.27	0.57
median	0.26	0.65
std	0.12	0.25

the simulated performance curve does not deviate much (RMSE = 8.72) from the measured performance curve.

Therefore, we consider the r-value as one exemplary correlation measure to analyze a possible general similarity between the fitting and the measurement. But for measuring the fitting quality itself, we particularly consider the RMSE.

4 RESULTS

Following we prove that the concept is useful to improve fitting quality for outdoor training, and is comparable to laboratory studies in some cases. Cases were correlation can not reach such high values as in laboratory studies are further analyzed in the end.

4.1 Usefulness of the Presented Concept

To prove that presented concept is able to improve fitting quality for outdoor training data, Table 1 shows the average, median and standard deviation of the RMSE and r-value over all subjects for both cases, the raw data and the preprocessed data according to the *traipor* concept. While the error can be reduced more than 50%, the correlation value doubles for the processed data sets proving both, a better correlation and smaller deviation compared to the highly fluctuating raw data.

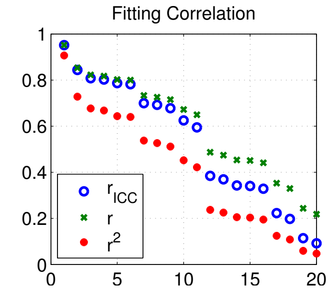


Figure 4: Correlation values of r_{ICC}, r, and r^2 for all 20 subjects (sorted).

Table 2: Average r_{ICC}-value, median and standard deviation over the correlating amount of subjects for studies from Pfeiffer and the *traipor* concept.

	Pfeiffer 1	Pfeiffer 2	traipor
Subjects	3	3	11
Mean	0.67	0.28	0.75
Median	0.64	0.45	0.78
Std.	0.12	0.38	0.10

4.2 Comparison to Laboratory Studies

Training data used in this study was obtained without any quality control. Therefore, we analyzed the reachable correlation according to the correlation values r_{ICC}, r, and r^2 for all single subjects. Figure 4 shows these correlation values for each subject, sorted descending by the corresponding value. Notwithstanding that these three values were sorted independently of each other, all three measures indicate a high fitting correlation for up to the same 11 subjects. We therefore restricted the following comparisons to these subjects first. The remaining nine subjects are analyzed more individually afterwards in subsection 4.3.

The first comparison is made between the *traipor* concept and two studies described in (Pfeiffer, 2008). Table 2 shows average, median and standard deviation computed for the intraclass correlation coefficient r_{ICC} for the correlating results. The mean and median value conducted over the best 11 subjects indicates a higher correlation than in results from (Pfeiffer, 2008) and even standard deviation is much smaller.

Table 3 illustrates the comparison of the presented method with a study from (Busso et al., 1991). Here, results of the presented *traipor* concept reach similar correlation in median as Busso's laboratory study, but seems to have more variation according to the standard deviation and the greater variation to the average r-value. A restriction to eight subjects is able to reach the same average correlation.

Regarding r^2-value and the study from (Mujika et al., 1996), Table 4 (left) indicates similar results:

Table 3: Average r-value, median and standard deviation over the correlating amount of subjects for the study from Busso and the *traipor* concept.

	Busso	traipor	
Subjects	8	11	8
Mean	0.83	0.78	0.83
Median	0.81	0.80	0.82
Std.	0.06	0.09	0.07

Table 4: Average r^2-value, median and standard deviation over the correlating amount of subjects for studies from Mujika and Hellard and the *traipor* concept.

	Mujika	Hellard	traipor		
Subjects	18	9	11	9	2
Mean	0.65	0.79	0.61	0.65	0.82
Median	–	0.78	0.64	0.64	0.82
Std.	0.12	0.13	0.14	0.12	0.13

traipor concept's average r^2 correlation regarding nine subjects is stated in a similar range as the average correlation coefficient in Mujika's study, for 11 subjects it is slightly below. Solely results of the study from (Hellard et al., 2006) (Table 4, middle) achieve an obvious better average correlation (0.79) than the *traipor* concept which yields comparable results for the best two subjects only. Depending on the particular study except for Hellard et al., data of between 8 and 11 subjects reached comparable correlations for simulating performance.

4.3 Analysis of Lower Correlated Data

The remaining nine data sets where results were not able to reach comparable correlation as in laboratory studies are analyzed in more detail. These nine data sets are therefore subdivided into groups with a similar performance behavior. Since it was necessary to exclude three data sets for comparison to Busso's study, these are analyzed first.

Two out of three subjects which are excluded for comparison to Busso's study are identically to the subjects excluded for comparison to Mujika's study. Exemplary, data of two of these subjects is illustrated in Figure 5. Data of the third one shows a similar behavior as depicted in Figure 5a showing some huge performance leaps which are not always reasonable according to the underlying strain. As an example, the performance gain between day 67 and day 118 based solely on the performance peak right before on day 66. But with a training pause of over a month, real performance would rather decrease than stay at this higher level. Leaps like this are therefore questionable and a behavior like this is certainly not simulated by the model. Figure 5b shows a different be-

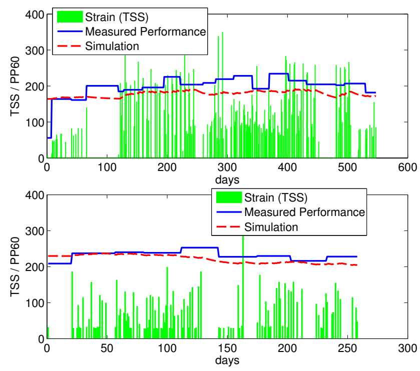
(a)
(b)


Figure 5: Exemplary subjects which has to be excluded for the comparison with Busso.

havior: Here, performance does not change much at all and varies around a mean performance value. As explained in subsection 3.4, the r-value is often very low when data is altering sparsely around its mean value.

For a better overview, the remaining nine subjects are numbered consecutively from 1 to 9.

Subjects 1-4: Regarding all 20 subjects, four of them stated a weekly reaching of the individual performance limit. But all of these four subjects are inside the set of the excluded nine subjects. Therefore, we analyzed correlation and fitting quality for these subjects again, assuming a monthly reaching of the performance limit. Table 5 shows the comparison between assuming a weekly and monthly performance limit for these subjects. Since the r-value of one subject reaches only a significance-level of $p < 0.5\%$ while the other three are significant at a $p < 0.01\%$ level, correlation and error values are considered for three and four subjects respectively. Regarding three subjects, assuming the reaching of a monthly performance limit improves the average correlation from $r = 0.42$ up to $r = 0.57$ within these subjects, while evaluating all four subjects shows an average improvement from $r = 0.4$ to $r = 0.47$. Ex-

Table 5: Assuming a weekly or monthly reaching of the individual performance limit regarding 4 or 3 specific subjects.

	4 Subjects		3 Subjects	
	weekly	monthly	weekly	monthly
	RMSE			
mean	26.52	17.74	29.27	19.10
median	28.18	14.80	31.95	15.93
std	8.45	7.24	7.86	8.22
	r-value			
mean	0.40	0.47	0.42	0.57
median	0.40	0.55	0.44	0.58
std	0.07	0.22	0.08	0.05

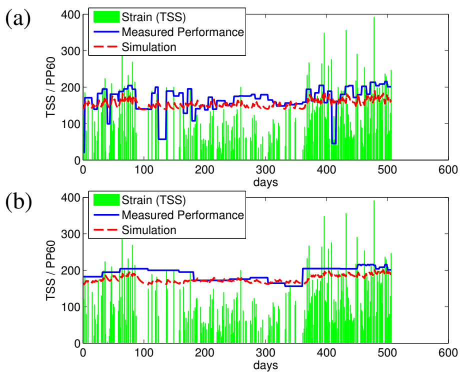


Figure 6: Example for a subject stating a weekly reaching of the individual performance limit.

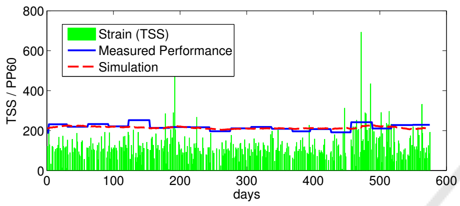


Figure 7: Example without huge performance gain resulting in a minor r-value.

emplary, Figure 6a shows a simulation with weekly assumed performance limit while Figure 6b illustrates the same dataset with a monthly assumed reaching of the performance limit.

The remaining five subjects with a correlation value of $r < 0.6$ can be classified into two classes:

Subjects 5 to 8 could not achieve any distinct performance changes and varied around their average performance as shown exemplary in Figure 7. This problem has been explained before.

Subject 9: Data of the last subject again shows the converse behavior including large unexplainable performance leaps additional to some flat performance in the end. The overall performance did not change much over the whole time as shown in Figure 8.

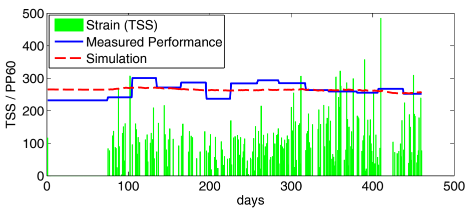


Figure 8: Example without huge performance gain but some leaps in the middle resulting in a minor r-value.

4.4 Evaluation and Discussion

Considering the intraclass correlation, a high correlation is accomplished with even better results than those achieved in the corresponding laboratory studies from (Pfeiffer, 2008). Pfeiffer himself found that results of his study 2 are inacceptable, but stated results from study 1 as good and very acceptable outcomes. For up to eleven subjects, the *traipor* concept reached higher correlation values than study 1.

Regarding the fitting correlation in comparison to studies from (Busso et al., 1991) and (Mujika et al., 1996), results implicate that the *traipor* concept is as accurate as laboratory studies for 8 to 9 out of 20 subjects, since average correlation values are stated in a similar range. Fitting accuracy of the *traipor* concept is only clearly inferior compared to (Hellard et al., 2006). One reason for this might be because of different types of athletes. The study of (Hellard et al., 2006) was performed for nine elite swimmers. (Mujika et al., 1996) analyzed performance in swimming, too, but regarding the considered studies, only Hellard et al. explicitly state dealing with elite sportsperson. Data of the *traipor* concept originates from ambitious but non-professional sportsperson, in case of the restricted data aged 34 to 49 years, whose fitness is certainly not comparable to elite swimmers. This difference regarding the subjects might be a reason for this various correlation quality.

As stated before, the elaborated *traipor* concept for fitting has some differences compared to laboratory studies. These lead to few limitations which might lessen the accuracy and correlation of fitting. Even in this approach it is necessary for a suitable fitting that the subject reaches its personal limit regularly, e.g., weekly or monthly. Without reaching the own individual limit, a realistic performance progress is not possible using the *traipor* concept. Furthermore, an oscillating training strain might lead to an inconvenient parameter set modeling a constant strain located between both performance values. Regarding correlation coefficients, the data grouping might lead to straight line performances resulting in an undefined r-value as explained in subsection 3.4. Additionally, this procedure might result in unrealistically high performance values during a training pause if computing a monthly performance maximum includes both, the training break and a high performance value achieved before the rest. Despite the fitting on training days only, some unrealistic performance changes may occur. These limitations are due to the unsupervised and uncontrolled training without any specified performance gain and the therefore constructed data preprocessing.

5 CONCLUSION AND FUTURE WORK

Compared to laboratory studies, the presented *traipor* concept yields comparable results with similar fitting accuracy using the Fitness-Fatigue model.

Since this model is based on a convolution with an exponential function, a straight line as it results by replacing all measurements within one period (e.g., month) by the maximum value can generally not be approximated. Changing this concept should therefore be considered. Other approaches using different filters should be analyzed. Using a moving maximum function might also reduce leaps between different performance measurements. This way, unrealistic performance values near to a training break might be avoided or reduced at least.

Predicting future performance based on a given training plan is an interesting application of training models, e.g., to generate training plans to reach a certain goal. Using the described method, it is possible to predict training effects for the upcoming month with similar accuracy as achieved in fitting (RMSE = 16.56). Even predicting six month into the future yields acceptable results (RMSE = 20.62) in all 11 subjects. Since in prediction preload plays an important role (i.e., accumulated strain at T = 0) special treatment of initial performance p^* was necessary. Further research will be required to examine the influence of preload as it should generally be considered in model identification.

Analysis of further performance metrics, especially for submaximal performances as these are more common in non-athletes, would be promising by enabling the utilization of training models in mass sports and training devices. To verify accuracy results, further experiments with more subjects, even less ambitious cyclists and additional laboratory control experiments have to be conducted.

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