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A reasonable alternative to the W_{bal} models when maximal mean power profiling is used instead of critical power-based models

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Abstract

As an alternative to the W_{bal} models (Skiba and Clarke, IJSPP, 2021), a methodology based on maximum mean power profiling (MMP) is presented here to predict intermittent exercise performance potential. The methodology consists of 1) collecting the maximum values of exponentially weighted moving averages (EWM) with different time characteristics in a recent exercise history and 2) comparing the different EWM of a new session with the historical EWM. The methodology is applied here to six weeks of training data in a professional cyclist, using a set of EWM with time characteristics ranging from 12 seconds to 1 hour to create the MMP. During a new training session, the maximum ratio between each EWM and the corresponding historical maximum value provides the residual performance potential. A parallel can be drawn between the variations of the residual performance potential in this model and those of the W_{bal} model. On the one hand, the main advantage of the proposed method is that the accurate estimations of W' and CP are not needed, which allows wide applicability to field/outdoor data. On the other hand, the methodology presented here does not provide a direct physiological explanation for the variation in residual performance potential during exercise.

Keywords: exponentially weighted moving average; training data; residual performance potential.

Introduction

The W_{bal} models (Skiba et al., 2012, 2014) describe the fluctuations of the available anaerobic energy sources during intermittent exercise. The value of W_{bal} at the start of the exercise equals W' which, according to the critical power (CP) model (Morton, 2006), represents an individual's total anaerobic energy reserve. During exercise, W_{bal} is depleted by an amount of energy proportional to the work done above CP, which represents the upper limit to a sustainable power output (Poole et al., 2016). Ideally, if W_{bal} decreases too much and becomes negative, all anaerobic energy sources are depleted, and exercise intensity must drop below CP. Similarly, W_{bal} is increased by an amount of energy proportional to the work done below CP and reaches a maximum value of W' when recovery is complete.

The W_{bal} models are derived directly from the CP model and were intentionally developed to understand and predict high-intensity intermittent exercise. Both the CP and W_{bal} models have some known flaws (Skiba & Clarke, 2021). The most important is that they are highly dependent on an accurate estimate of the values W' and CP. Additionally, given that W_{bal} has its own kinetics, an estimation of the complex W_{bal} time-characteristic is also required.

The process of performance profiling consists of retrieving an athlete's performance/duration points and fitting curves (Leo et al., 2022). One strategy is to build the performance profile using the CP model, i.e., using repeated maximal efforts to exhaustion at constant power output. The estimation of W' output values and W_{bal} time characteristics is complicated by the intraindividual variability of performance to exhaustion. Another strategy is that of maximum mean power (MMP), which consists of taking maximum power values from a series of moving averages calculated in different time windows (Quod et al., 2010). Thus, power profiling with MMP requires maximal efforts, but power output during these efforts can fluctuate. For these reasons, power profiling based on the CP model appears to be better suited to laboratory conditions where standardized protocols can be carefully monitored. Conversely, MMP profiling seems to be better suited for outdoor conditions or when a large amount of data is available, as in the case of online training platforms.

In principle, while generating an MMP profile, there is no restriction on the kind of rolling average that can be applied. In general, rolling averages can be simple or weighted. A simple moving average is the average of a number of previous data points. A weighted average is computed by multiplying the data in different positions in the time sequence with different weights. For instance, the exponentially weighted moving average (EWM), is computed by applying weighting factors which decrease exponentially.

A simple method based on EWM calculations is proposed here as a possible alternative to the W_{bal} models for predicting intermittent exercise. This method relies on fewer assumptions than the W_{bal} models, as it only consists of a procedure for processing the exercise data. Compared to the W_{bal} models, it has no direct and immediate physiological significance, but it is more robust as it does not rely on the estimation of CP, W' or the W_{bal} time characteristics.

Methods

Training data

Cycling training data adopted in this proof-of-principle work was kindly donated to the author by a professional cyclist (M, 30 years, weight 76 kg, height 189 m, HR_{max} 185 bpm, 11 years of experience in professional cycling, more than 20,000 km cycled per year both indoors and outdoors). The data included six weeks of cycling training sessions. Ethical approval was obtained from the ethical committee of the University of Trento (2021-010). All the data was anonymized before being transmitted and saved on a local password-protected server.

Power profiling

During a single cycling session, a generic EWM can be computed starting from the power output values P using the following equation:

$$\tau_k \frac{dEWM_k(t)}{dt} + EWM_k(t) = P(t) \qquad \text{(Eq. 1)}$$

Where τ_k is the time-characteristic of the corresponding EWM_k, d/dt is the time derivative, and P is the power output. In the discrete form, better suited for calculations on spreadsheets, the following formulation can be used for the generic time instant i:

$$\tau_k \frac{EWM_{k,i+1} - EWM_{k,i}}{t_{i+1} - t_i} + EWM_{k,i} = P_i \quad \text{(Eq. 2)}$$

So therefore:

$$EWM_{k,i+1} = \frac{(P_i - EWM_{k,i}) \cdot (t_{i+1} - t_i)}{\tau_k} + EWM_{k,i} \quad \text{(Eq. 3)}$$

The starting value is zero for each EWM with i=0 (i.e., $EWM_{k,0}$). The EWM calculation is repeated for all the τ_k values for a recent history of training sessions. In this study, the τ_k values selected were: 12, 30, 60, 120, 180, 300, 600, 1200, 1800, and 3600 seconds. Therefore, for each training session, a set of ten EWM (EWM_{12s}, EWM_{30s}, ..., EWM_{3600s}) is computed. The MMP profiling was completed when the maximum value of each EWM across all training sessions in the six-week training history (i.e.: $EWM_{MAX\text{-}12s}$, $EWM_{MAX\text{-}30s}$, ..., $EWM_{MAX\text{-}3600s}$) was plotted against the relative value τ_k.

Residual performance potential

During a new training session (i.e., a session which was not used to compute all the EWM_{MAX}), the ratio between every EWM_k and the corresponding $EWM_{MAX\text{-}\tau k}$ was computed. The maximum ratio, i.e.:

$$\max\left\{\frac{EWM_{12s}}{EWM_{MAX-12s}}, \frac{EWM_{30s}}{EWM_{MAX-30s}}, \ldots, \frac{EWM_{3600s}}{EWM_{MAX-3600s}}\right\} \quad \text{(Eq. 4)}$$

represents the margin from the best performance in the recent history of training, and the associated τ_k is a proxy for the duration of the effort closest to this limit. Therefore, both the limiting τk and the maximum ratio can change during a training session. For simplicity, the ratio can be expressed in percentage and subtracted from 100. Therefore, at the start of the exercise, the ratio is 100%. If the ratio becomes smaller than 0%, it means that for the specific τ_k a new record is set, and the corresponding $EWM_{MAX\text{-}\tau k}$ must be updated. The minimum percentage ratio registered during a new session can be used to express the residual performance potential.

Results

The MMP retrieved with the collection of the maximal EWM with different τ is reported in **Tab. 1**.

	τ_{12s}	τ_{30s}	τ_{60s}	τ_{120s}	τ_{180s}	τ_{300s}	τ_{600s}	τ_{1200s}	τ_{1800s}	τ_{3600s}
Time (s)	12	30	60	120	180	300	600	1200	1800	3600
$EWM_{MAX\text{-}\tau k}$ (W)	895	694	522	462	441	409	367	352	352	352

Tab. 1: Maximum power output values for the exponentially weighted moving average $EWM_{MAX\text{-}\tau k}$ for the different time characteristics τ (12 sec, 30 sec, ..., 3600 sec). These values constitute the athlete's maximal mean power profile.

In **Fig. 1**, the residual performance potential is plotted together with the **τ** associated with the EWM closest to the historical limit. The residual performance potential is expressed as a percentage of the historical best.

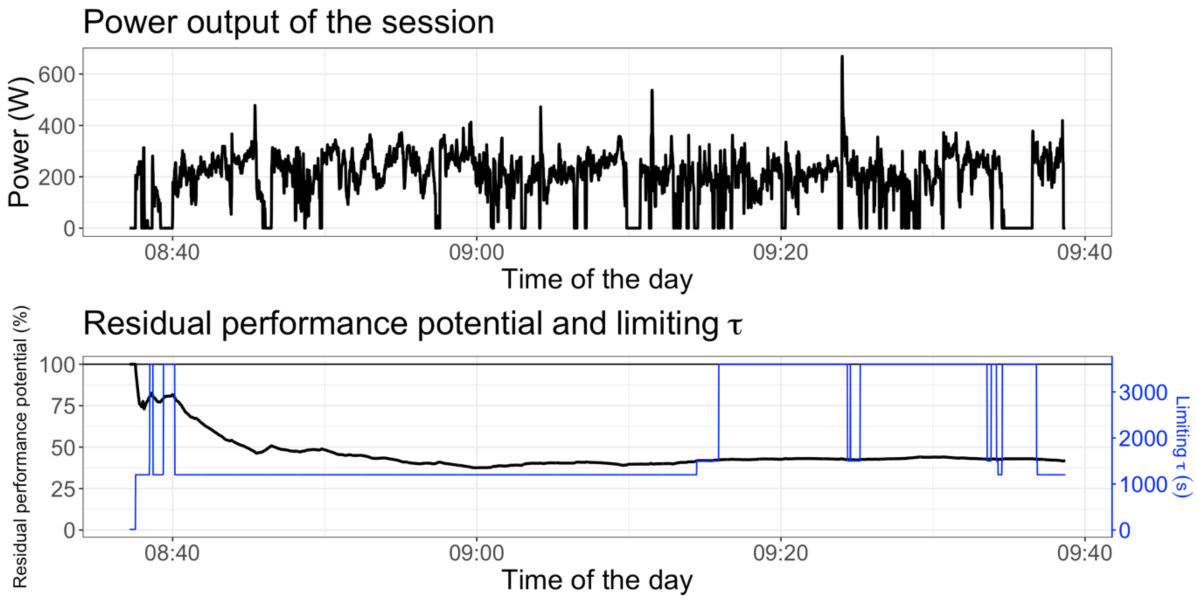

Figure 1: Power output of the session (top graph) used to compute the residual performance potential and limiting time characteristic **τ** (bottom graph). Throughout the cycling session, the residual performance potential and the limiting **τ** are both shown to be fluctuating. The minimum performance potential of this session is registered at 9:00, where the exponentially weighted moving average (with **τ**=1200 sec) hits closest to its historical maximum.

Discussion

The aim of this manuscript was to present a new method for predicting intermittent exercise performance potential. This manuscript constitutes a proof-of-concept and is by no means an exhaustive presentation of the methodology. Indeed, it does not include a comparison with other available methods (e.g., W_{bal}) and the accuracy of the predictions are not tested. However, based on the equations presented in this manuscript, researchers and developers operating in the field of sport performance models will require little effort to test the validity of the present methodology with their own data.

This method is best suited for online training platforms where a large amount of data is available and the MMP is calculated from multiple EWMs from an athlete's 6-week training history. It is suggested that this methodology may be the simplest alternative to the W_{bal} models to answer Skiba and Clarke's 'call to action' (Skiba & Clarke, 2021). In their review, Clarke and Skiba listed several limitations associated with variants of the original W_{bal} model. One of the most important limitations of the W_{bal} models is the dependence on the estimation of CP, W' and the W_{bal} time characteristics. In particular, inaccurate estimation of W_{bal} time characteristics could easily lead to strongly negative values for W_{bal} during intermittent training, and therefore to untrustworthy predictions even if CP and W' were estimated with accuracy. A negative W_{bal} value contradicts the basic assumptions of the CP models, where W' is considered to be the total anaerobic energy reserve of the individual (Morton, 2006).

If the W_{bal} models go directly back to the CP model, then the methodology presented here goes directly back to MMP profiling. Similar to the CP/W_{bal} and MMP models, it relies on the maximum efforts being included in the recent training history. Importantly, compared to the W_{bal} models, it does not provide direct physiological significance to the variations in residual power potential during exercise. If the goal was to gain insight into human physiology, then the lack of physiological significance would be a major limitation. Nevertheless, the proposed method is useful for performance prediction because it estimates the range between current and maximum historical performance. By simulating a training session and the remaining performance potential, this methodology can be used for training prescription and pacing strategy planning.

Unlike CP/W_{bal} models, this method has the advantage of providing the $\boldsymbol{\tau}_k$ representing the duration of effort closest to the maximum performance. An example is shown in **Fig. 1**, where the $\boldsymbol{\tau}_k$ varies along with the residual power potential. In the session of the example, $\boldsymbol{\tau}_{3600s}$ is the most limiting time characteristic for the entire exercise (with a minimum of 36% at 9:00, meaning that the ratio EWM_{3600s} /$EWM_{MAX\text{-}3600s}$ was 225/352=0.64→100-64=36%), but in correspondence with peaks in power output, the limiting time characteristic decreases to $\boldsymbol{\tau}_{1500s}$ or $\boldsymbol{\tau}_{1200s}$.

Although the application to cycling has been presented, the method can also be applied to other endurance activities such as running, swimming, or rowing. The formulation presented here (**Eq. 3-4**) can be easily implemented in a spreadsheet or used on lightweight hardware configurations that require low-level programming languages. Also, the low computational effort required to estimate an EWM (through the convenient discrete formulation of the corresponding ordinary differential equation, **Eq. 3**) makes this methodology suitable for real-time applications.

Conflicts of interests

AZ owns stocks at Athletica Inc. (athletica.ai), which sells subscriptions for the online training platform Athletica.

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