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MODELLING TRACK CYCLING STANDING START PERFORMANCE: COMBINING ENERGY SUPPLY AND ENERGY DEMAND

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To date there has been limited practical application of energy supply models to sprint cycling performance due to difficulties in determining complex physiological parameters or oversimplifications limiting relevance to steady state performance. Here an energy supply and demand model is presented for track cycling drawing on research incorporating forward integration energy demand modelling, the Power-Cadence relationship in maximal sprint cycling, rate of fatigue per revolution relative to maximum power and the critical power model. All input parameters can be determined from simple field or laboratory testing and even training data. The model successfully predicted an elite cyclist’s timed 250-m performance from stationary start to within 0.31%.

KEY WORDS: power-cadence relationship, isokinetic, fatigue, critical power

INTRODUCTION: Forward integration modelling of sprint cycling performance has been reported to accurately predict velocity in dynamic sprint cycling events (R^2 = 98.9%; Martin et. al., 2006). While input parameters influencing energy demand can be optimised, power data must be measured during a race, lab test, or training to provide the energy supply to the model. Those power data cannot be optimised because they are dependent on energy demand parameters. An alternative approach is to model physiological energy supply, and observe power output evolving under different supply and demand parameters until the optimal combination is found. One of the simplest models of energy supply is the Critical Power model (CP; Monod & Scherrer, 1965), which can be derived from constant power/time to exhaustion testing or average power during a time trial (Quod et. al., 2010). However, this limits CP to modelling steady state energy supply only. More powerful models with greater predicative ability of dynamic energy supply have been developed utilizing exponential time decay constants (e.g. Morton, 2006), muscle structure and function (e.g. James and Green, 2012) or metabolic gas analysis (e.g. Olds, 2001). When attempting to create individualized athlete models a trade-off exists between predictive power and the simplicity in obtaining input parameters (e.g. de Koning et. al. 1999).
The power-cadence relationship (P-C), relative rate of fatigue (RRF) and CP are all derivable from training data, simple laboratory tests and/or field based testing, and can be used to model energy supply in sprint cycling. Sargeant et. al. (1981) demonstrated that the maximal non-fatigued power produced for a given cadence during maximal sprinting fits a parabolic relationship. Martin et. al. (1997) developed the inertial load test (IL) to determine P-C from a single 4 second sprint, allowing maximal non-fatigued energy supply at varying cadences to be easily measured and modelled. Recently Tomas et. al. (2009) noted that fatigue during isokinetic cycling (IK) at different cadences was influenced by the number of crank revolutions. This observation is particularly important in the context of maximal sprint cycling because pedalling rate is known to influence rate of fatigue (Gardner et. al., 2009) and pedalling rate changes throughout a track cycling sprint. Therefore fatigue could be modelled as a linear decrease in power per revolution relative to maximum power (i.e. RRF). This rate of fatigue per revolution of the cranks is easily obtained from an IK trial. Finally, total anaerobic work capacity (AWC) derived from CP provides a limit to the total amount of

anaerobic work done and a steady state power once AWC is exhausted (Monod & Scherrer, 1965).

The purposes of this research were to derive a combined energy supply and demand model for track cycling that uses readily obtained inputs and then examine the robustness of that model with real world test and performance data.

METHODS: One elite male cyclist performed IL and IK tests in a seated position to determine maximum power (P_{max}), optimal cadence (RPM_{opt}) and RRF. Standing P-C and CP parameters were estimated from training data. Standing and seated aerodynamic drag area (CdA) was measured via the virtual elevation method (Alphamantis Tech. Inc., Montreal, Canada). The cyclist also completed a 250 m time trial from an electronically controlled starting gate. Movement time (total time minus reaction time) to complete the lap was measured using video of the trial and Dartfish (v6.0; Fribourg, Switzerland) then compared against the modelled time derived from the test and training data.

Modelling Energy Demand: The energy demand side of the model from Martin et. al. (2006) was adapted with three modifications. Wheel velocity in the turns was determined by numerically solving a factor between the model centre of mass (CoM) radius and actual turn radius for lean angle at the wheels. A 15 meter transition in lean angle between straights and turns was estimated by linear interpolation where the radius at the entry or exit to a straight was twice the actual turn radius. The second modification was to give the model a CoM velocity prior to the wheels moving, which reflects forward movement of the cyclist before the start gate opens. Third, a check was made as to whether seated or standing, coefficient of rolling resistance (Crr) and CoM height values should be used.

Modelling Energy Supply: Energy was supplied to the model by calculating the maximum non-fatigued standing or seated torque deliverable at the current modelled cadence (Gardner et. al., 2009). Fatigue was introduced when the model reached a fixed number of revolutions. The equation for fatigue was as follows: Fatigued Torque = Non-fatigued Torque x (1 – RRF x number fatigued revs completed). Once the amount of work completed in the model equalled the athlete's AWC, fatigue was no longer applied and the energy supply came from the athlete's critical power.

Both the onset of fatigue and initial CoM velocity were specified by optimising the residual sum of squares between the actual and modelled power outputs. Table 1 details the model parameters additional to those previously described by Martin et. al. (2006) and how they are obtained.

Table 1: Additonal Model Inputs and Methods for Obtaining Them

Input	Determined By
Energy Demand	
Turn radius	Laser range finder and track markings
Length of straights	Laser range finder and track markings
Length of turns	Laser range finder and track markings
Distance from start of model to first turn entry or exit	Laser range finder and track markings
CoM velocity in start gate	Optimised with Microsoft Excel Solver Add-In
Energy Supply	
Standing & seated max power	Inertial load test and training data
Standing & Seated Optimal RPM	Inertial load test
Standing & Seated CoM height	Kinematic video analysis
Cadence where cyclist transitions from standing to sitting	Estimated from competition data
Onset of fatigue in # of revolutions	Optimised with Microsoft Excel Solver Add-In
Rate of fatigue relative to max power	Maximal isokinetic sprint at 120 RPM
Anaerobic work capacity	From CP estimated from training data or MMP
Critical power	From training data or MMP

RESULTS & DISCUSSION: The updated forward integration model accurately predicted the actual 250 m and intermediate split times throughout the trial (Table 2). Actual and modelled wheel velocity were highly correlated throughout the trial (R^2 = 99%) as was actual and modelled power (R^2 = 93%; Figure 1). While others had previously demonstrated that the forward integration model could accurately replicate a known performance from known power-time characteristics, these results extend upon those by demonstrating similar accuracy can be obtained using independently measured power-pedalling rate and fatigue characteristics as supply-side parameters.

Table 2: Actual and Modelled Data From 250m Time Trial

Split	Actual	Model	Difference
62.5 m	7.04 s	7.30 s	3.54%
125 m	11.04 s	11.19 s	1.37%
Final 125 m	7.08 s	6.98 s	-1.38%
250m	18.12 s	18.18 s	0.31%

Future research will seek to provide measured rather than predicted values for Crr, initial velocity CoM and the duration or number of revolutions before the onset of fatigue. Our lab and others are conducting follow up work to address whether expressing rate of fatigue as a function of cadence is appropriate, early results indicate the number of completed revolutions is responsible for up to 90% of the observed fatigue during maximal efforts. In contrast, accumulated work is responsible for <20% of the changes in power.

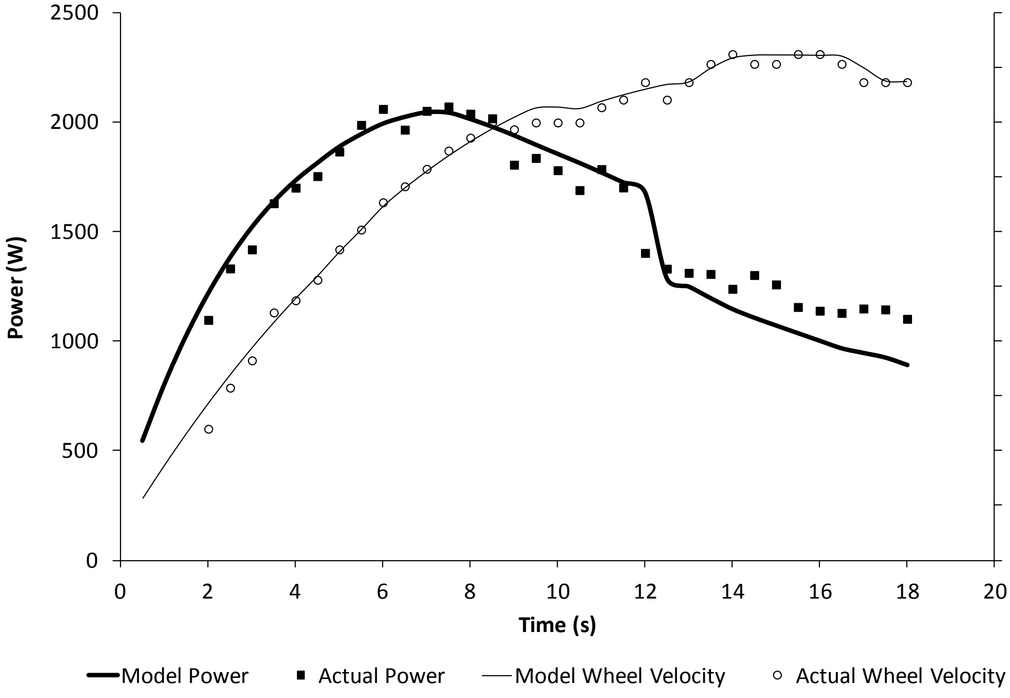

Figure 1: Modelled versus actual data for a 250 meter lap trial from start gate.

CONCLUSION: An energy supply and demand model for predicting track sprint cycling performance is presented. The model is simple enough for construction in a spreadsheet yet accurate when predicting highly dynamic short duration sprint cycling performance. In contrast a demand only model requires power-time data to be measured beforehand and care should be taken when interpreting changes to any inputs. For example, if a change increases modelled cadence then power output should also change according to P-C but the already measured power-time data cannot be altered possibly leading to erroneous predictions. Including energy supply in the model solves this paradox and allows for a more thorough optimization of performance.

The advantage of our model to athletes, coaches and sport scientists is all inputs are easily measured from simple performance tests and analysis of training data. When reliability of the test protocol is known a confidence interval can be constructed around the effect of that test result on modelled performance. Conclusions about the statistical certainty of a change in performance can then be expressed. This is a particularly powerful tool and a number of scenarios can be explored by quantifying the effects of changes to different inputs on modelled performance. For example gear selection, mass, training effects, ergogenic aids, and even tradeoffs between parameters like power production and aerodynamic efficiency of different riding positions.

In summary modelling both energy supply and demand in sport with practical inputs is a particularly useful tool for coaches in determining how time, money and energy should be focused to maximise gains in performance.

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