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A Comparison of Models for Oxygen Consumption

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Introduction

Measurements of oxygen uptake are central to methods for assessment of physical fitness and endurance capabilities in athletes. Though respiratory gas exchange can easily be measured in a lab, these kind of measurements aren't practicable in the field and even less during competitions. Thus, we are looking for a model, which provides the means for fitting and prediction of oxygen uptake response.
Oxygen uptake kinetics are well researched for constant workrate exercises [4] and specific load profiles like ramps [3] or constant work rate, but hardly generalized for variable load profiles which occur often in the field. Thus, we compare six dynamic models with power as independent variable and evaluate their fitting and prediction abilities.

Data

Five healthy, recreationally to well trained subjects completed four different cycle ergometer (Cylus2, RBM elektronik-automation GmbH, Leipzig, Germany) tests with continuous breath-by-breath gas exchange and ventilation measurements at the mouth (Ergostik, Geratherm Respiratory GmbH, Bad Kissingen, Germany). The tests were designed to determine a set of useful physiological parameters of aerobic capacity ($\dot{V}O_{2\text{max}}$, ventilatory threshold 1 (VT_1), and maximal lactate steady state (MLSS)). Furthermore the tests featured a variety of load profiles in order to comprehensively evaluate the model prediction quality [1] (Figure 1 and Figure 2). A more detailed describtion of the testing procedures and test design can be found in Artiga Gonzalez et al. [1].

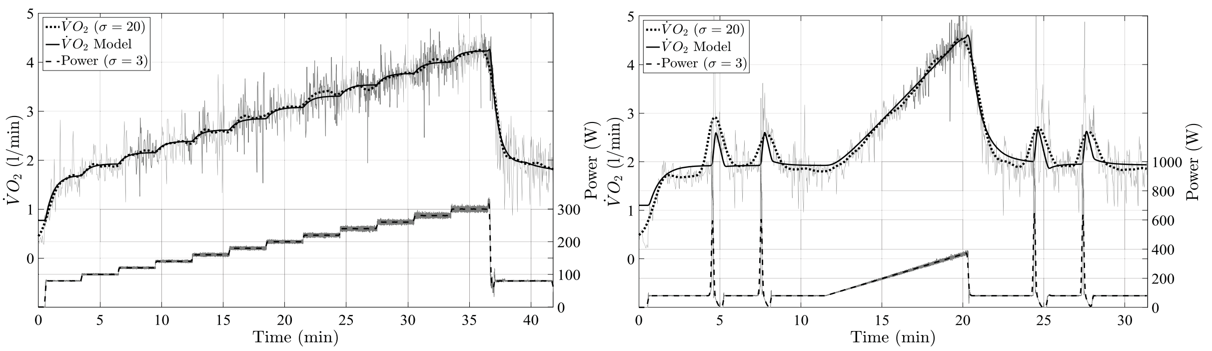

Figure 1: Test 1 and Test 2, Subject 2, Physiological Model

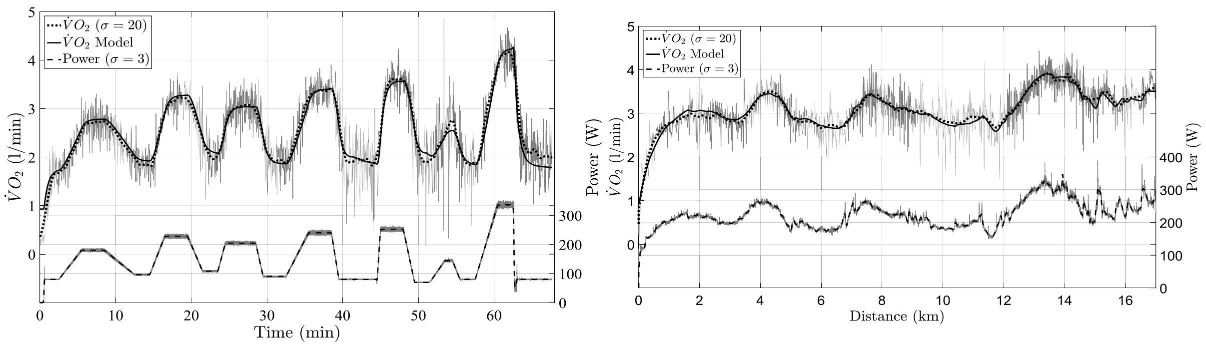

Figure 2: Test 3 and Test 4, Subject 2, Physiological Model

Models

3.1 Physiological Model

The first model from Artiga Gonzalez et al. [1] is based directly on a commonly accepted model for constant workrate [4] and takes most physiological evidence into account. We extended it by another two parameters to the following:

$$\dot{V}O_2 = \dot{V}O_{2\text{base}} + x_1(t) + x_2(t)$$

where $x_1(t)$, $x_2(t)$ are solutions of

$$\dot{x}_k(t) = \tau_k^{-1}\left(A_k(P(t)) - x_k(t)\right), x_k(T_k) = 0, k = 1, 2$$

with

$$A_1(P) = \min\left(s \cdot P, \dot{V}O_{2\text{max}} - \dot{V}O_{2\text{base}}\right)$$

$$A_2(P) = \begin{cases} V_\Delta \cdot \exp\left(-(P_c - P)/\Delta\right) & P \le P_C \\ \dot{V}O_{2\text{max}} - \dot{V}O_{2\text{base}} - A_1(P) & P > P_C \end{cases}$$

and parameters $\dot{V}O_{2\text{base}}$, $\dot{V}O_{2\text{max}}$, P_C, s, V_Δ, Δ,τ_1, τ_2, T_1, T_2.
The physiological model consists of two important parts. The steady-state function described by A_1 and A_2 and the differential equations describing the exponential behavior. Instead of changing the whole model, we can just exchange the steady-state function and also omit the second component. This leads to the following variations:

3.1.1 Smooth Steady-State

A smooth alternative avoiding the discontinuity at P_C:

$$A_1(P) = V_{1\text{max}} \cdot (1 - \exp(-s_1 \cdot P))$$

$$A_2(P) = \begin{cases} 0 & P = 0 \\ V_{2\text{max}} \cdot \frac{\left(1 + \tanh\left(\frac{P^2 - P_C^2}{P} \cdot s_2\right)\right)}{2} & P > 0 \end{cases}$$

3.1.2 Simple Linear Model

Only one linear component: $A_1(P) = \min\left(s \cdot P, \dot{V}O_{2\text{max}} - \dot{V}O_{2\text{base}}\right)$

3.1.3 Simple Exponential Model

Only one exponential component: $A_1(P) = V_{1\text{max}} \cdot (1 - \exp(-s_1 \cdot P))$

3.2 Stirling

The second model was introduced by Stirling et al. [5] and originally designed for running:

$$\ddot{V}O_2(t) = A \cdot \left(\dot{V}O_2(t) - \dot{V}O_{2\text{min}}\right)^B \cdot \left(\dot{V}O_{2\text{max}} - \dot{V}O_2(t)\right)^C \cdot \left(D(v,t) - \dot{V}O_2(t)\right)^E$$

We adapt it for cycling by replacing the speed based demand function $D(v,t)$ with a simple linear demand function

$$A(P) = \min\left(s \cdot P, \dot{V}O_{2\text{max}} - \dot{V}O_{2\text{base}}\right)$$

. With $E = 1$ the following parameters are estimated: $\dot{V}O_{2\text{base}}$, $\dot{V}O_{2\text{max}}$, s, A, B, C.

3.3 Cheng

The third model by Cheng et al. [2] was used for heart rate modeling on a treadmill. As heart rate behaves similar to $\dot{V}O_2$ (Figure 3), we modified the model for power as input instead of treadmill speed:

$$\dot{x}_1(t) = -a_1 \cdot x_1(t) + a_2 x_2(t) + a_6 \cdot P(t)$$
$$\dot{x}_2(t) = -a_3 \cdot x_2(t) + \frac{a_4 \cdot x_1(t)}{1 + \exp(-(x_1(t) - a_5))}$$

with $x(0) = [x_1(0)\ x_2(0)]' = [0\ 0]'$.

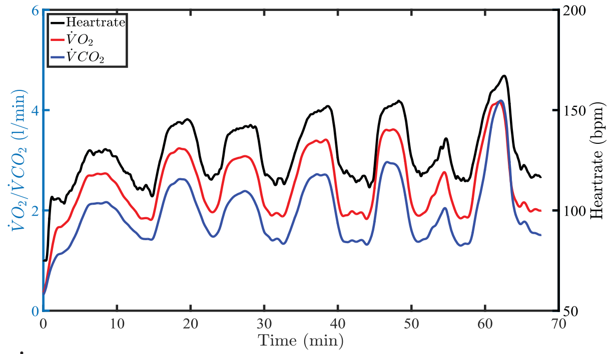

Figure 3: $\dot{V}O_2$, $\dot{V}CO_2$and Heart rate measured for one subject during Test 3.

Model	3.1	3.1.1	3.1.2	3.1.3	3.2	3.3	3.4	3.5
	l/min	l/min	l/min	l/min	l/min	l/min	l/min	l/min
Subject 1	0.13	0.29	0.20	0.33	0.40	0.38	0.07	0.14
Subject 2	0.09	0.12	0.11	0.18	0.24	0.26	0.05	0.10
Subject 3	0.06	0.15	0.13	0.21	0.33	0.30	0.07	0.12
Subject 4	0.10	0.10	0.07	0.17	0.23	0.21	0.04	0.09
Subject 5	0.09	0.11	0.11	0.15	0.26	0.27	0.06	0.08
Average	0.09	0.15	0.12	0.21	0.29	0.29	0.06	0.10

Table 1: Average root-mean-square modeling error for all four tests.

3.4 System Identification: Wiener-Model

Going towards black box models in the field of system identification, the wiener model has proven well. The wiener model consists of a linear transfer function followed by a nonlinear function. For these output nonlinearity a piecewise linear function is selected. This model type coincides with the observation, that there is a linear and a smaller nonlinear relationship between power and $\dot{V}O_2$. This can also be seen in Figure 2 and Figure 3.

3.5 Feedforward Neural Networks

An even more recent approach in black box modeling are neural networks. Here a feedforward neural network is taken. The neural networks got trained with randomly resampled data from Test 3. Different network settings from one up to three hidden layers with between 10 and 400 neurons were tested.

Results

All models were implemented and evaluated in MATLAB®. For parameter estimation the Genetic Algorithm *ga* from the Global Optimization Toolbox™ was used. *nlhw* and *feedforwardnet* from the System Identification Toolbox™ were used for the Wiener model and the neural networks.

Table 1 shows the root-mean-square modeling error for all five subjects and all four tests. For prediction, the models were trained on Test 3 and applied on Test 4 (Table 2).

Model	3.1	3.1.1	3.1.2	3.1.3	3.2	3.3	3.4	3.5
	l/min	l/min	l/min	l/min	l/min	l/min	l/min	l/min
Subject 1	0.38	0.38	0.39	0.46	0.49	0.51	0.40	1.51
Subject 2	0.31	0.16	0.18	0.21	0.27	0.29	0.21	0.93
Subject 3	0.21	0.20	0.23	0.25	0.35	0.52	0.25	1.15
Subject 4	0.23	0.18	0.16	0.30	0.29	0.26	0.19	0.86
Subject 5	0.38	0.28	0.23	0.23	0.33	0.35	0.29	0.87
Average	0.30	0.24	0.23	0.29	0.34	0.39	0.27	1.07

Table 2: Average root-mean-square prediction error for all four tests.

The models by Stirling and Cheng show weak performance for both, modeling and prediction. The model by Cheng even turned out unstable for some predictions.

Surprisingly, the smooth variations of the physiological model (3.1.1, 3.1.3) performed worse than their counterparts for modeling.

Despite its simplicity, Model 3.1.2 performed well for modeling and prediction. The Physiological Model 3.1 reached a good modeling result but only average for prediction.

Better modeling results are obtained with Wiener models which also show some weakness on prediction.

The results of the neural networks are hard to evaluate. If they are trained only once on the time series from Test 3 than the fitting error is near zero. We trained them more often on differently sampled data series from Test 3 to avoid overfitting. Prediction results show, that this attempt was not successful. The networks trained once on Test 3 with fitting errors of 0.00 l/min performed similar for prediction.

Conclusions

Modeling results below 0.09 l/min are better than the natural variability in $\dot{V}O_2$ (unpublished work) and they can be regarded as very satisfactory results. The physiological Model, the Wiener models and neural networks are able to perform better than that threshold.

The best prediction was made by model 3.1.3 that also still fits well with 0.12 l/min. Overall, the models perform worse than expected for prediction. A reason for that may be, that the data set is too small and too specific. Most likely, prediction results can be improved by larger training and validation data sets.

Also off- and on-transient differences have to be taken into account [6].

Another improvement can be obtained by adding further measurements like heart rate as additional input.

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