Mixed linear modelling of training-performance relationship in elite swimmers

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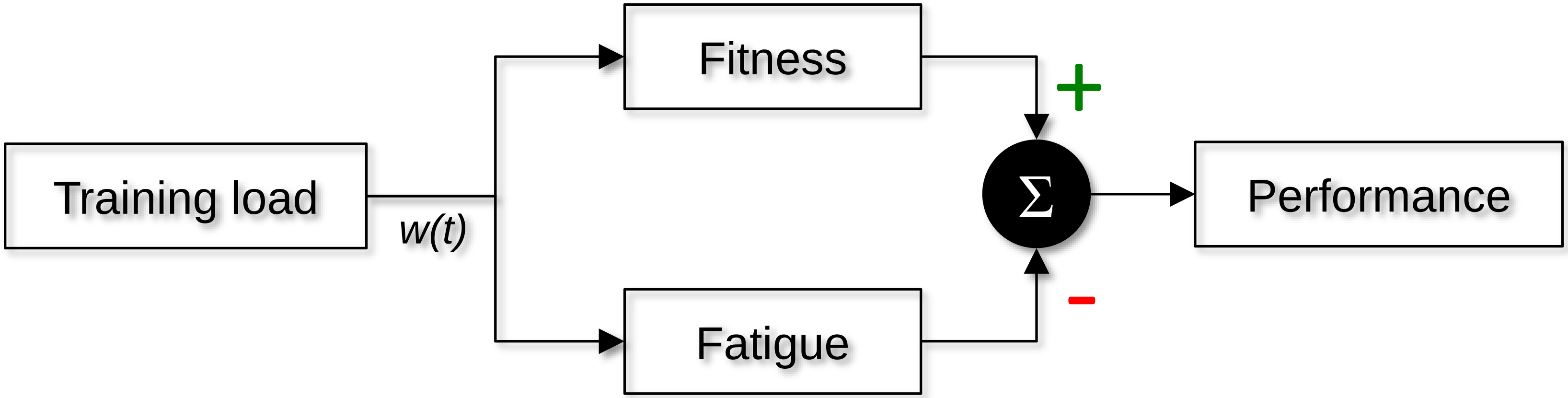
Introduction

- Banister, Calvert et al. first applied systems theory to quantifying the relationship between training and performance
- Busso et al. improved model accuracy by accounting for training-related changes on fatigue
- However, systems models have been unable to consistently predict performance on an individual basis in a “real-world” setting



Aim

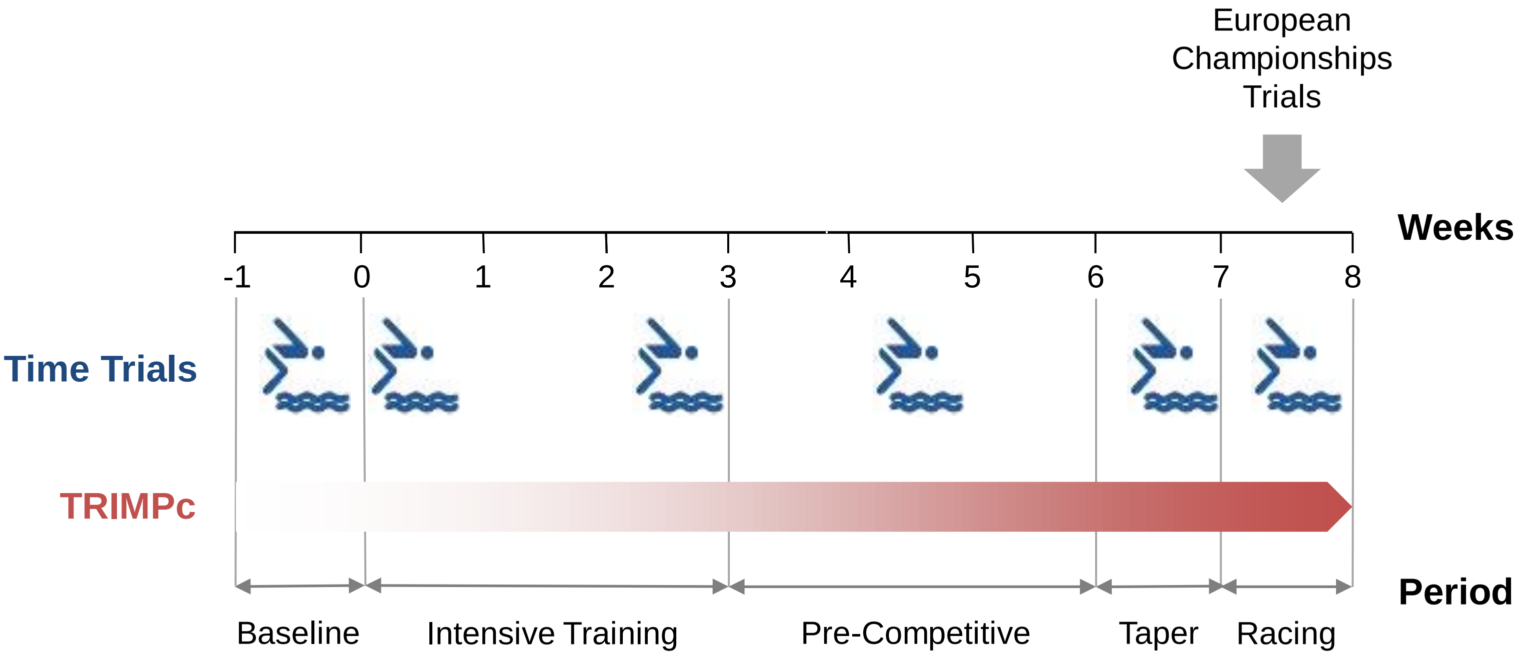
- To evaluate the modelling of the dose-response relationship between quantified training and performance with linear mixed-effects regression analysis (MixMod) in high-level competitive swimmers

- To compare the goodness-of-fit and robustness of the model with classical individual linear modeling (LinMod)

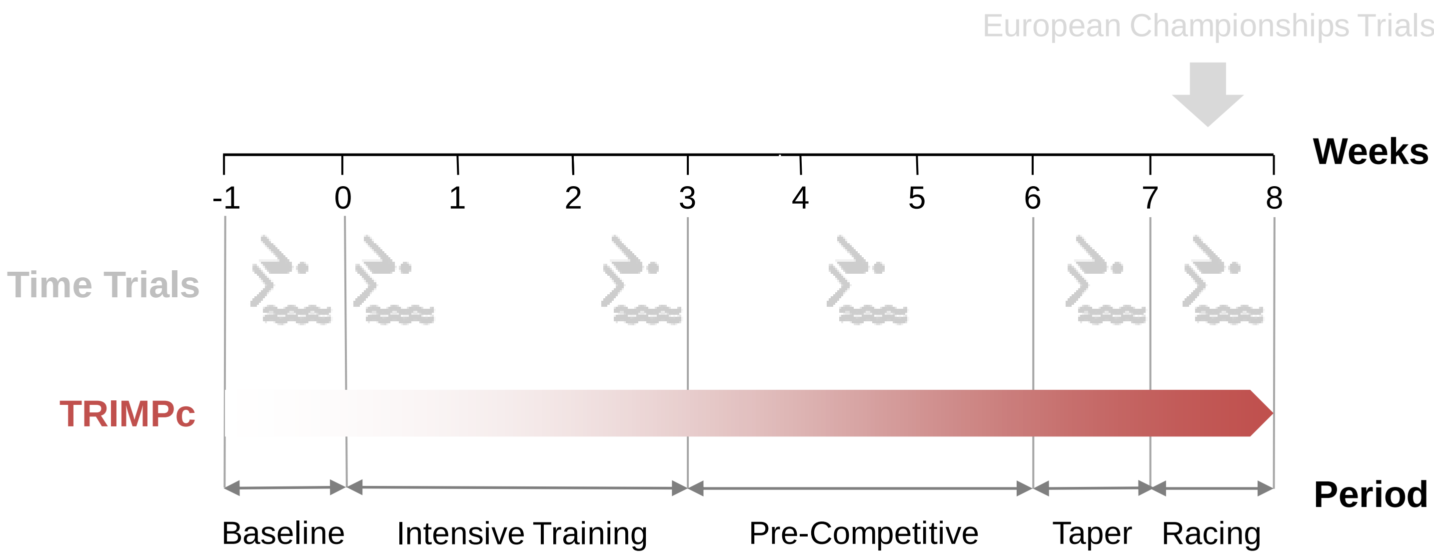
Methods

Design

- International-level swimmers (n=10)
- Training monitoring during an 8-week mesocycle



Training monitoring



- **Timing**: TX H2O (Freelap) beacon transmitters (50-m laps)
- **HR**: Water: CardioSwim monitors synced with beacons
  Dryland: Polar RS800CX monitors
- **Cummulative training impulse (TRIMPc*)**

* García-Ramos et al. (2015) Eur J Sport Sci, 15, 85-93.

Training monitoring

- **Timing**: TX H2O (Freelap) beacon transmitters (50-m laps)
- **Heart rate**:

  Water: CardioSwim monitors synced with beacons

  Dryland: Polar RS800CX monitors

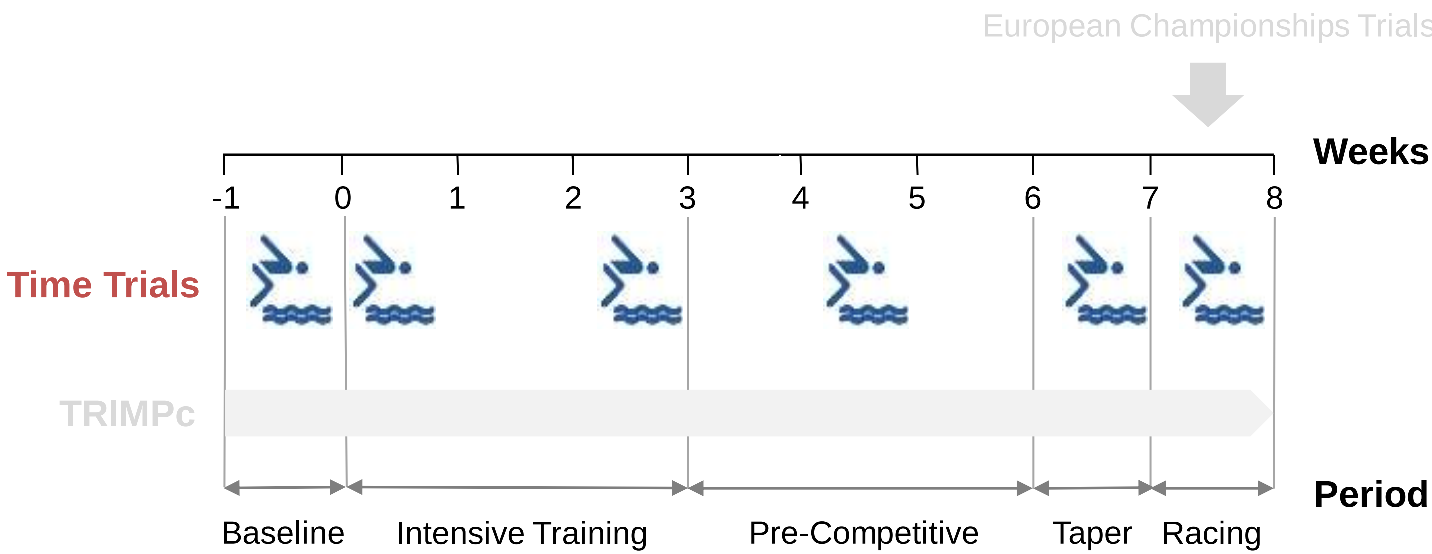
- **Cummulative training impulse (TRIMPc*)**

$$\mathrm{TRIMPc} = \sum_{i=1}^{n} t k_1 x \begin{cases} \text{for men} = k_1 = 0.64 e^{1.92x} \\ \text{for women} = k_1 = 0.86 e^{1.67x} \end{cases}$$

$$x = \Delta \mathrm{HR}_{\mathrm{ratio}} = \frac{\mathrm{HR}_{\mathrm{exercise}} - \mathrm{HR}_{\mathrm{rest}}}{\mathrm{HR}_{\mathrm{max}} - \mathrm{HR}_{\mathrm{rest}}}$$

* García-Ramos et al. (2015) Eur J Sport Sci

Performance testing



Time trials:

50 and 400 m freestyle

100 m (sprinters) or 200 m (non-sprinters) best stroke

Mathematical modelling

- **Banister-Busso* individual linear regression model (LinMod)**

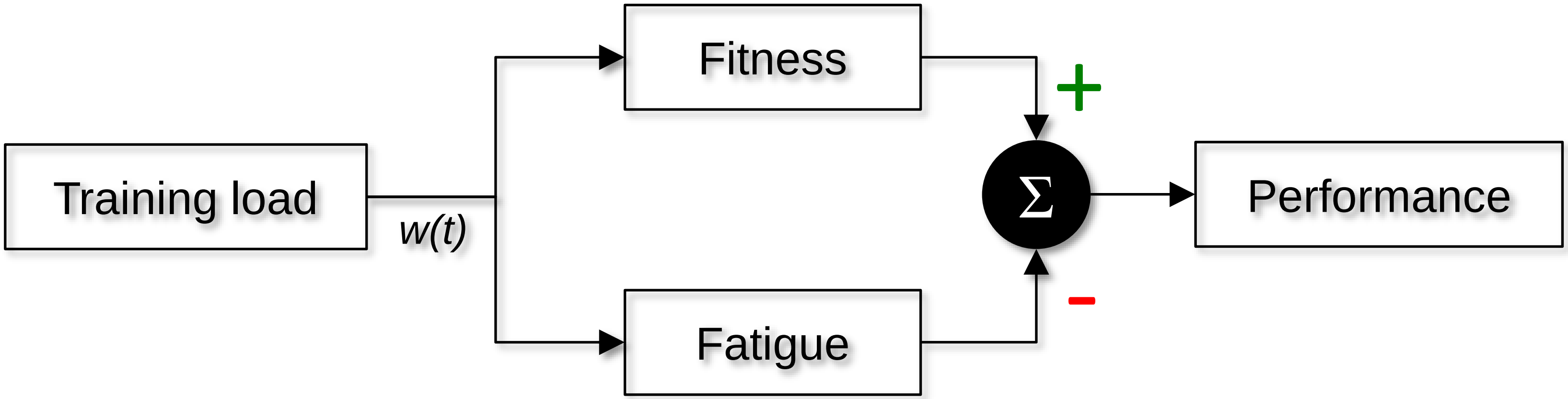
- **Linear mixed-effects regression analysis model (MixMod)**

  fixed-effects parameters: general / sample pattern

  random-effects parameters: individual specific behaviour

* Busso T (2003) Med Sci Sports Exerc, 35, 1188-1195

Banister-Busso linear model



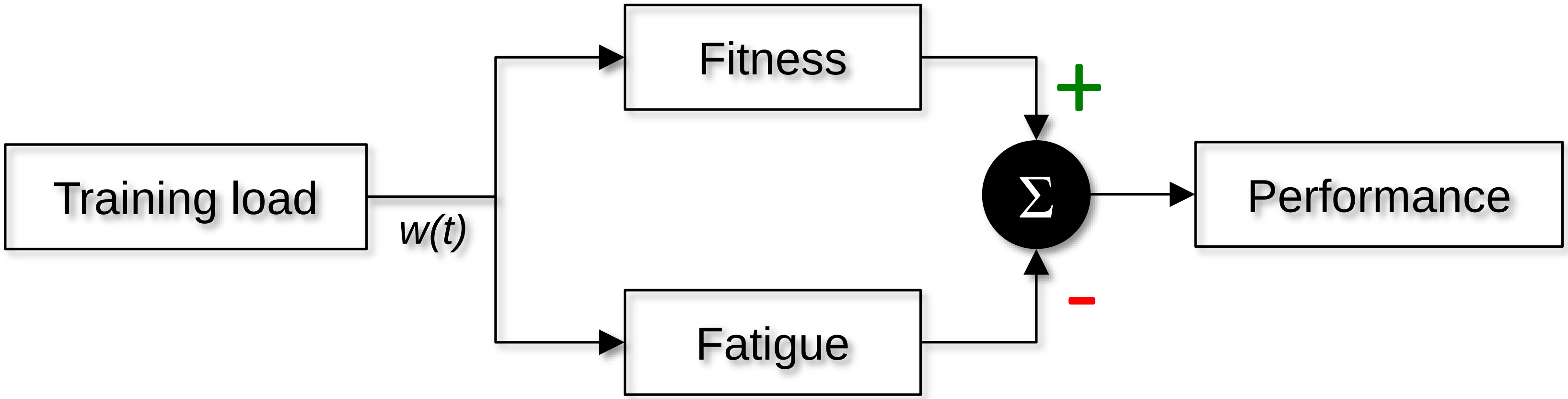
$$\hat{p}(n) = p^* + k_1 \cdot Fitness(\tau_1, w, n) + k_3 \cdot Fatigue(\tau_2, \tau_3, w, n)$$

$$\hat{p} = p^* + k_1 \sum_{i=1}^{n-1} w^i e^{-\frac{n-i}{\tau_1}} - \sum_{i=1}^{n-1} k_2^i w^i e^{-\frac{n-i}{\tau_2}}$$

$$k_2^i = k_3 \sum_{j=1}^{i} w^j e^{-\frac{i-j}{\tau_3}}$$

Banister et al (1991); Busso (2003)

Mixed linear model (MixMod)



$$y_i(t) = \beta_0 + b_{i0} + (\beta_1 + b_{i1})\cdot x_1(t) + (\beta_2 + b_{i2})\cdot x_2(t)$$

$$\hat{p} = p^* + k_1 \sum_{i=1}^{n-1} w^i e^{-\frac{n-i}{\tau_1}} - k_3 \sum_{i=1}^{n-1} \sum_{j=1}^{i} w^j e^{-\frac{n-i}{\tau_2}}$$

$\beta_0, \beta_1, \beta_2 =$ fixed (sample) effects

$b_{i0}, \beta_{i1}, \beta_{i2} =$ random (individual) effects

Statistical analysis

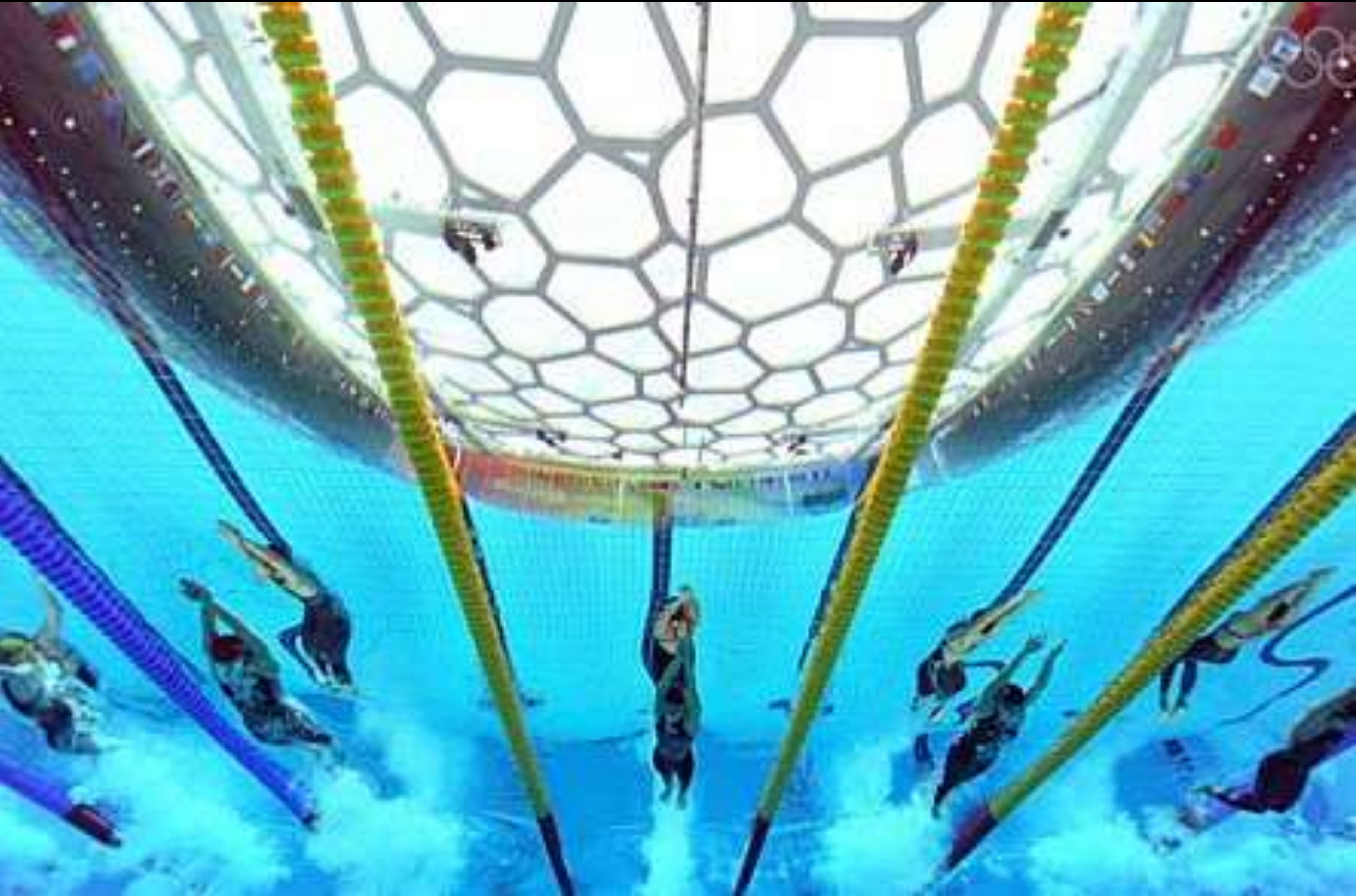
- **Akaike Information Criterion (AIC)** for model comparison
- **Mean absolute percentage error (MAPE)** to assess the relationship between estimated and observed performance
- **'Leave-one-out' cross-validation (LOO-CV)** for internal validation
- **Overfitting** of the model estimated from the ratio:

  RSS*(LOO-CV)–RSS(Apparent) / RSS(LOO-CV)

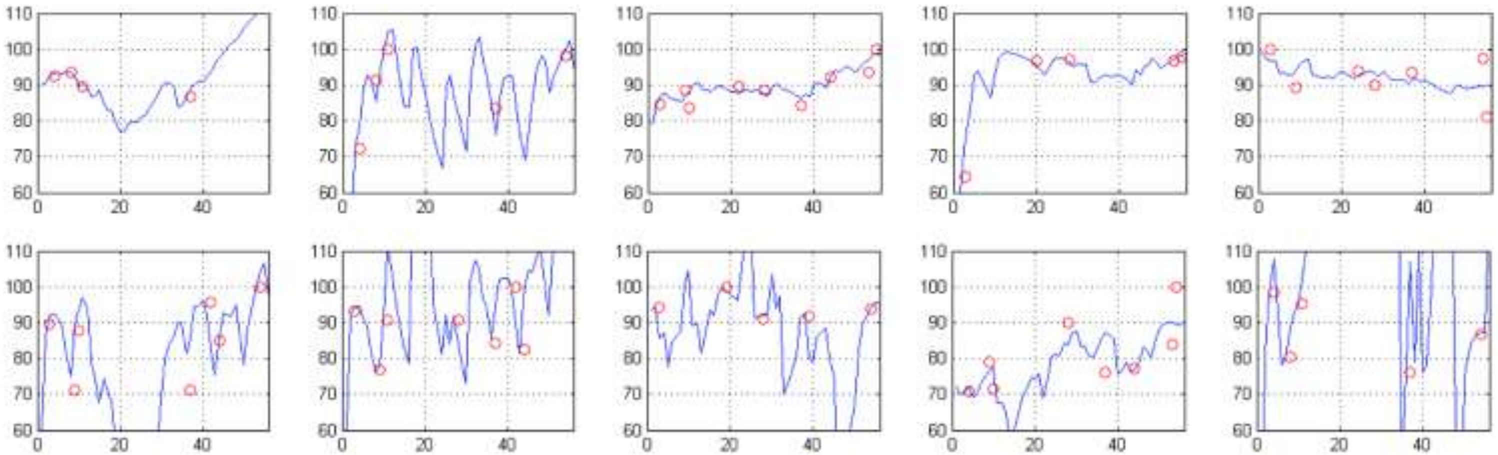
- Significance level: $P < 0.05$

*RSS = residual sum of squares

Results & discussion

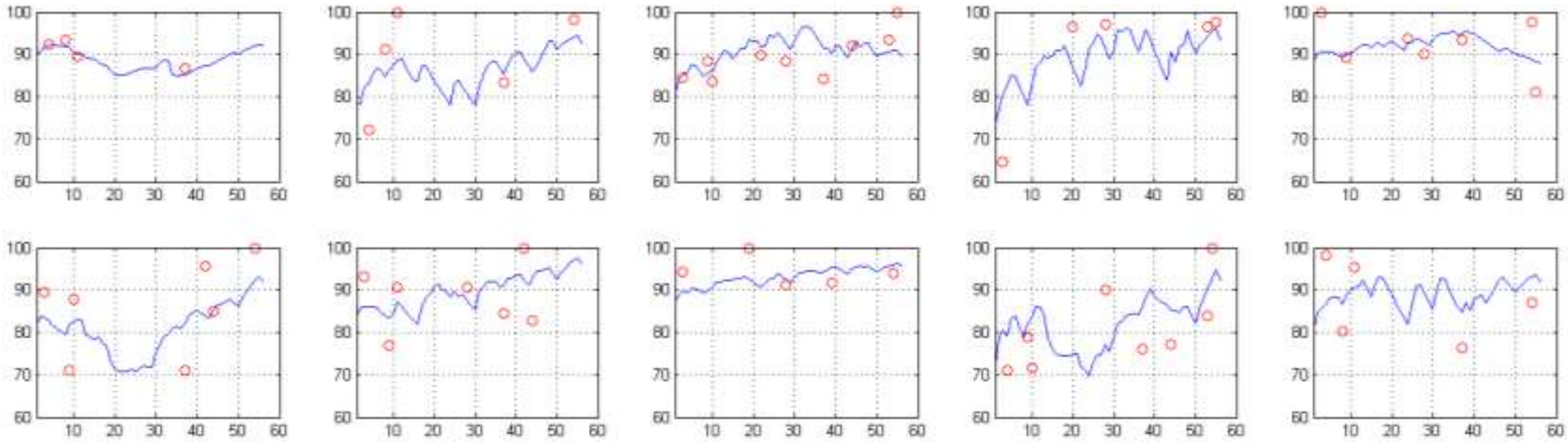


Model fitting (LinMod)



Subject	Tests	τ_1	τ_2	τ_3	p^*	k_1	k_2	r^2
1	4	60	18	6	90.1	0.013	-0.00002	1.000
2	5	11	15	2	40.4	0.285	-0.00066	1.000
3	9	27	30	3	79.0	0.067	-0.00018	0.779
4	5	11	7	10	50.0	0.134	-0.00015	1.000
5	7	19	30	1	99.0	0.041	-0.00016	0.193
6	7	6	7	2	56.6	0.25	-0.00043	0.678
7	7	8	9	2	57.7	0.436	-0.00097	0.982
8	5	5	5	1	93.6	0.309	-0.00151	0.921
9	8	11	3	2	72.3	0.024	-0.00017	0.556
10	5	54	24	4	26.4	0.603	-0.00157	1.000
Mean	**6.2**	**21.2**	**14.8**	**3.3**	**66.5**	**0.126**	**-0.00058**	**0.811**
SD	1.6	20.0	10.3	2.8	24.2	0.197	0.00058	0.269

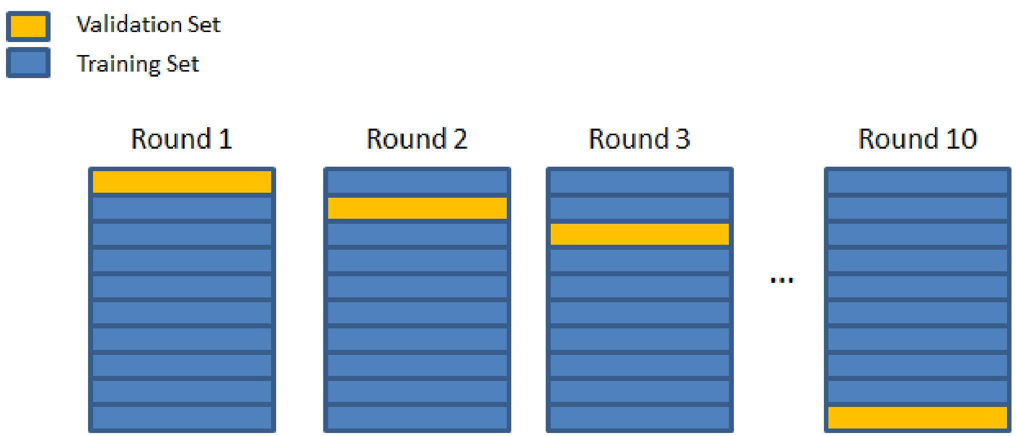
Model fitting (MixMod)



Subject	Tests	p^*	k_1	k_2	r^2
1	4	90.86653	0.00138	-0.43183	
2	5	78.81936	0.02137	-3.21892	
3	9	82.51912	0.01523	-2.36298	
4	5	67.37463	0.04036	-0.58666	
5	7	89.76855	0.00320	-0.68585	
6	7	79.08181	0.02093	-3.15820	
7	7	83.81238	0.01308	-2.06379	
8	5	87.48704	0.00698	-1.21366	
9	8	68.82400	0.03795	-5.53132	
10	5	88.23705	0.00574	-1.04015	
Mean	**6.2**	**90.86653**	**0.00138**	**-0.43183**	
SD	1.6	78.81936	0.02137	-3.21892	

Accuracy and internal validation

	MAPE (%)	RSS(Apparent)	RSS(LOO-CV)	Overfitting (%)
LinMod	**6.6**	1513	11982	**87.4**
MixMod	**6.8**	4998	6009	**16.8**



Conclusions

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- The usual strategy for fitting the classical Busso-Banister model can be affected of an extreme overfitting
- This arises from the high number of observations per parameter needed (ca. 60 performance data points per individual)

Conclusions

- Another important limitation is that the adjustment is performed ignoring the correlation between the different observations on the same individual
- MixMod reduces overfitting because time parameters are common for all individuals (fixed-effects parameters) and are jointly estimated individual predictions (random-effects parameters)