

Biomechanical loading during running: can a two mass-spring-damper model be used to evaluate ground reaction forces for high-intensity tasks?

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1 **Biomechanical loading during running: can a two mass-spring-damper**
2 **model be used to evaluate ground reaction forces for high-intensity**
3 **tasks?**

4 **Abstract:** Running impact forces expose the body to biomechanical loads leading
5 to beneficial adaptations, but also risk of injury. High-intensity running tasks
6 especially, are deemed highly demanding for the musculoskeletal system, but
7 loads experienced during these actions are not well understood. To eventually
8 predict GRF and understand the biomechanical loads experienced during such
9 activities in greater detail, this study aimed to 1) examine the feasibility of using
10 a simple two mass-spring-damper model, based on eight model parameters, to
11 reproduce ground reaction forces (GRFs) for high-intensity running tasks and 2)
12 verify whether the required model parameters were physically meaningful. This
13 model was used to reproduce GRFs for rapid accelerations and decelerations,
14 constant speed running and maximal sprints. GRF profiles and impulses could be
15 reproduced with low to very low errors across tasks, but subtler loading
16 characteristics (impact peaks, loading rate) were modelled less accurately.
17 Moreover, required model parameters varied strongly between trials and had
18 minimal physical meaning. These results show that although a two mass-spring-
19 damper model can be used to reproduce overall GRFs for high-intensity running
20 tasks, the application of this simple model for predicting GRFs in the field and/or
21 understanding the biomechanical demands of training in greater detail is likely
22 limited.

23 **Keywords:** GRF modelling, Model parameter optimisation, Training load
24 monitoring, Whole-body loading, Biomechanical demands

25 **Wordcount:** 200 (abstract); 2598 (main text)

26 **Introduction**

27 In running-based sports, the different structures of the body are repetitively
28 exposed to biomechanical loads. These loads can lead to beneficial adaptations on the
29 one hand (Couppe et al., 2008; Timmins, Shield, Williams, Lorenzen, & Opar, 2016),
30 but also risk of injuries (Gabbett & Ullah, 2012). High-intensity running tasks
31 especially (e.g. accelerating, decelerating, sprinting) (Akenhead, French, Thompson, &
32 Hayes, 2014; Vigh-Larsen, Dalgas, & Andersen, 2018), are deemed highly demanding
33 for the musculoskeletal system, but the biomechanical loads experienced during these
34 actions are not well understood (Vanrenterghem, Nedergaard, Robinson, & Drust,
35 2017). Therefore, measuring and monitoring the ground reaction forces (GRFs) for
36 these movements in non-laboratory settings would allow for a more detailed
37 understanding of the biomechanical demands of training.

38 GRFs resulting from collisions with the ground during running are absorbed and
39 returned by the body in a spring-like manner. Therefore, simple mass-spring models
40 (single point mass attached to a spring) have been used to investigate various GRF
41 characteristics (e.g. Blickhan, 1989; Dutto and Smith, 2002; Morin et al., 2005). The
42 sinusoidal GRF profiles predicted by this model do however not accurately represent
43 the typical double-peak GRF profiles of running (Alexander, Bennett, & Ker, 1986;
44 Bullimore & Burn, 2007). These characteristic force peaks can substantially deviate
45 between various tasks and are thus essential for examining the specific whole-body
46 loads experienced during different running tasks. Based on the distinct contributions of
47 the lower limb and upper body segments to the GRF during running (Bobbert,
48 Schamhardt, & Nigg, 1991; Clark, Ryan, & Weyand, 2017), a two mass-spring-damper
49 model can be used to describe the distinct impact and active peaks during simple elastic
50 movements, i.e. steady running (Alexander et al., 1986; Derrick, Caldwell, & Hamill,
51 2000). However, the ability of this model (which is based on eight parameters that

52 describe simple mechanical characteristics of the body) to reproduce GRF profiles for
53 high-intensity running tasks is yet completely unknown.

54 If a simple two mass-spring-damper model can reproduce GRFs for non-elastic high-
55 intensity tasks, while retaining physically meaningful model parameters, this might
56 eventually be used to predict GRF in the field and understand the biomechanical
57 demands of such activities in greater detail. Therefore, this study aimed to use a two
58 mass-spring-damper model to reproduce GRF profiles for activities that are frequently
59 performed during running-based sports. It was hypothesised that 1) this model could
60 accurately replicate measured GRF and loading characteristics for high-intensity
61 running tasks, and 2) that its model parameters could be used to evaluate the
62 biomechanical demands of these activities.

63 **Methods**

64 Fifteen healthy and physically active team-sports athletes participated in this
65 study. Participants provided informed consent according to Liverpool John Moores
66 University ethics regulations. After a warm-up, participants performed rapid
67 accelerations from standstill to sprinting, decelerations from sprinting to standstill, and
68 running trials at constant speeds from 2 m/s to maximal sprinting speed (~6-9 m/s,
69 individual specific), with 1 m/s stepwise increases. For each trial, GRF data were
70 collected at 3000 Hz with a force platform (9287B, Kistler Holding AG, Winterthur,
71 Switzerland), filtered using a 50 Hz second-order Butterworth low-pass filter and
72 normalised to body mass. To evaluate the total magnitude of load experienced during
73 the different running tasks, resultant GRFs (overall whole-body loading) were
74 calculated from the three force components and used for this investigation.

75 A two mass-spring-damper model described by eight natural model parameters (Figure

76 1) was used to reproduce measured GRFs (Alexander et al., 1986; Derrick et al., 2000).
77 The model consisted of a lower mass m_2 on a spring and damper, representing the
78 support leg, with an upper mass m_1 on a spring on top, representing the rest of the body.
79 The positions of the upper and lower mass without any external load was described by
80 x_1 and x_2 , while l_1 and l_2 were the natural lengths of the upper and lower springs
81 respectively. The linear spring stiffness constants for the upper and lower spring were
82 defined as k_1 and k_2 , while c was the damper's damping coefficient. From these nine
83 parameters the eight natural parameters were derived according to Equations 1-8 (Table
84 1), with BM being the total body mass. The model's motion was described by the
85 accelerations of its upper and lower mass (Table 1, Equation 9 and 10), in which $a_{1,2}$,
86 $v_{1,2}$ and $p_{1,2}$ were the upper and lower mass accelerations, velocities and positions
87 respectively, λ the upper mass ratio relative to the lower mass, ω_1 and ω_2 the natural
88 frequencies of the upper and lower spring, ζ the damper's damping ratio, and g the
89 gravitational acceleration (-9.81 m/s^2). For each trial, a unique parameter set to fit
90 modelled GRFs to measured GRFs was determined by solving Equations 9 and 10
91 (Table 1). The equations were solved with a purpose-written Python optimisation script,
92 which included the L-BFGS-B numerical optimisation algorithm (Python, 2017; SciPy,
93 2017). Starting conditions for the optimisation were as described in Appendix A and
94 parameters following from the optimisation process were used to calculate modelled
95 GRFs (Table 1, Equation 11). Optimal model parameter combinations were determined
96 by minimising the sum of the root mean square error (RMSE) of the GRF and its
97 gradient, between modelled and measured GRF curves.

98 Modelled GRF accuracy was evaluated by RMSE and errors of relevant GRF loading
99 characteristics impulse (area under the GRF curve), impact peak (force peak during the
100 first 30% of stance) and loading rate (average GRF gradient from touch-down to impact

101 peak). Error metrics were averaged across trials and participants for each task, i.e.
102 accelerations, decelerations, and running at constant low (2-3 m/s), moderate (4-5 m/s)
103 and high (>6 m/s) speeds. RMSE was rated very low (<1 N/kg), low (1-2 N/kg),
104 moderate (2-3 N/kg), high (3-4 N/kg) or very high (>4 N/kg). GRF loading
105 characteristic errors were rated very low (<5%), low (5-10%), moderate (10-15%), high
106 (15-20%) or very high (>20%). Furthermore, correlation analyses were performed
107 between modelled and measured impulses, impact peaks and loading rates, and rated as
108 very weak ($R^2 < 0.1$), weak ($R^2 = 0.1-0.3$), moderate ($R^2 = 0.3-0.5$), strong ($R^2 = 0.5-0.7$),
109 very strong ($R^2 = 0.7-0.9$) or extremely strong ($R^2 = 0.9-1$) (Hopkins, Marshall,
110 Batterham, & Hanin, 2009).

111 **Results**

112 GRF profiles were reproduced with high accuracy across tasks (Figure 2; Table
113 2). RMSE was very low for accelerations, as well as low- and moderate-speed running,
114 but increased for high-speed running and especially decelerations. Furthermore,
115 impulses were modelled with very high accuracy (errors <1%). Consequently, the
116 correlation between measured and modelled impulses was extremely strong ($p < 0.001$)
117 across tasks (Figure 3A) while errors were independent of task and magnitude (Figure
118 3B and C).

119 Since not all trials contained a distinct measured impact peak (e.g. accelerations (Figure
120 2A) or forefoot-strike sprints (Figure 2G)) and for several trials the impact peak could
121 not be modelled (Figure 2B, F and H), only a select number of trials were included in
122 the impact peak and loading rate analysis (Table 2). Impact peaks were modelled with
123 low to moderate errors for constant speed running, but high to very high for
124 accelerations and decelerations. Similarly, modelled loading rate errors were high to

125 very high across tasks. Nevertheless, modelled and measured impact peaks and loading
126 rates had an extremely strong correlation across tasks (Figure 3D and G). Absolute
127 errors significantly ($p < 0.001$) increased for higher impact peaks and loading rates
128 (Figure 3E and H), but relative errors remained constant independent of task and
129 magnitude (Figure 3F and I).

130 Despite the accurately reproduced GRF curves, all model parameters varied strongly
131 between and within tasks (Figure 4; Table 3). Especially motion (p_1 , p_2 , v_1 , v_2) and mass
132 (λ) related parameters were highly variable for decelerations, while ω_1 and ω_2 strongly
133 varied for all tasks. Although ζ varied less between tasks, within task variability was
134 large.

135 **Discussion and Implications**

136 The purpose of this study was to investigate whether a simple two mass-spring-
137 damper model can reproduce GRFs for high-intensity running tasks, while retaining
138 physically meaningful parameters. Across tasks, GRF curves could be reproduced with
139 low to moderate curve errors. The slightly higher errors observed in decelerations were
140 likely due to the distinct GRF profiles. The model typically underestimated the high
141 impact peaks and loading rates but overestimated the much lower second (active) peak
142 (Figure 2C and D). Previous studies also reported increased modelled curve errors in
143 tasks (Nedergaard, 2017) and individuals (Derrick et al., 2000) with considerably higher
144 impact peaks. Nedergaard (2017) suggested higher curve errors to be due to lower
145 spring stiffnesses, which reduces the magnitude of the impact peak (Derrick et al., 2000;
146 Nedergaard, 2017). Moreover, Derrick et al. (2000) showed that to increase the impact
147 peak, higher values are required for spring stiffnesses ω_1 and ω_2 , upper mass velocity v_1
148 and mass ratio λ , together with a reduced damping ratio ζ . In this study, mean v_1 and λ

149 values were indeed substantially higher for decelerations compared to other tasks, but
150 ω_1 , ω_2 and ζ were in a similar range as other tasks (Figure 4; Table 3). For GRF profiles
151 with high impact peaks, the model likely needs to adjust as many parameters as possible
152 to reproduce this first peak, while maintaining an accurate representation of the rest of
153 the curve characteristics (e.g. active peak, stance time).

154 Impulses were modelled with very high accuracy (≈ 0.01 Ns/kg) and had a perfect
155 correlation ($R^2=1$) with measured impulses. These results are in accordance with errors
156 (≈ 0.01 Ns/kg) and correlations ($R^2=0.98-1$) found by Nedergaard (2017), but much
157 lower than Derrick et al. (2000) who reported impulse errors of 5.5-8.5 Ns ($\approx 0.08-0.12$
158 Ns/kg). Since the latter study only optimised ω_1 , ω_2 and p_2 , the better results in the
159 present study are likely the result of including all model parameters in the optimisation
160 process. Therefore, the two mass-spring-damper model can give very good estimates of
161 overall loading across tasks.

162 In contrast to overall loads, subtle loading characteristics (impact peak and loading rate)
163 were modelled less accurately. The initial force peak due to the lower limb colliding
164 with the ground (Clark et al., 2017), is typically followed by a slight decrease in GRF
165 before gradually increasing to the active peak caused by the upper body (Bobbert et al.,
166 1991). For accelerations and steady running this force decrease is small and forms a
167 minor part of the whole GRF profile. Since curve gradients and RMSEs were used as
168 model parameter optimisation criteria, a continuously rising curve from touch-down to
169 mid-stance (thus ignoring the impact peak) affected these criteria minimally. This
170 explains that for 99% of the decelerations, in which the impact peak dominates the GRF
171 profile, impact peaks were visible in the modelled curves, compared to only 34-48% for
172 accelerations and steady running. Moreover, impact peaks (and loading rates) were
173 typically underestimated with errors increasing for higher impact peaks. In general,

174 differences between measured impact and active peaks increased for higher impact
175 peaks (compare for example Figures 2C and D). Most model parameters affecting the
176 impact peak influence the active peak simultaneously (Derrick et al., 2000). Therefore,
177 the model likely underestimated the higher impact peaks more, to limit the
178 overestimation of the second peak.

179 Despite the higher errors, correlations between measured and modelled impact peaks
180 and loading rates were extremely strong ($R^2=0.96-0.97$) (Figure 3D and G). These
181 correlations are stronger than Udofa et al. (2016), who used a two mass model to
182 reproduce GRFs found correlations of $R^2=0.82$ between measured and modelled impact
183 peaks, across different running speeds (3-6 m/s) and loading conditions. The strong
184 linear relationships observed in this study (Figure 3A, D and G) might be used to adjust
185 modelled impact peaks and loading rates to get more accurate estimates of these loading
186 characteristics.

187 A limitation of the two mass-spring-damper model is the assumption of spring-like
188 (elastic) behaviour, meaning a constant spring stiffness during stance. Moreover, the
189 model's damper absorbs energy while energy producing elements are not included. The
190 leg is however known to be stiffer during landing than take-off (Blickhan, 1989), while
191 the muscle-tendon units produce more work during the push-off phase (Cavagna, 2006).
192 Although the high-intensity tasks investigated in this study seriously violated these
193 model assumptions, reproduced GRF profiles were fairly accurate. The model likely
194 overcompensates for the absence of active elements by substantially increasing its
195 stiffness (i.e. higher ω_1 and ω_2), in accordance with reduced energy requirements for
196 higher leg stiffness (Dutto & Smith, 2002; McMahon & Cheng, 1990). This might
197 explain why higher stiffness was observed for accelerations and high-speed running,
198 where the muscles need to produce more energy, compared to decelerations, where

199 energy is primarily absorbed (Figure 4; Table 3). Due to the strong variability within
200 tasks however, parameters should be interpreted with caution.

201 Another limitation of this study is the complexity of model parameter combinations. As
202 described above, different parameters represent multiple physical aspects (e.g. leg
203 stiffness) and affect various GRF characteristics (e.g. impact peak, stance time) at the
204 same time (Derrick et al., 2000). During the optimisation process, numerical solvers
205 searched for optimal modelled GRF solutions in the highly complex eight-dimensional
206 parameter space. Therefore, numerous similarly good solutions might be found for
207 comparable GRF curves, leading to the high parameter variability and physically
208 unrealistic parameter values observed across trials (Table 3). For example, many
209 modelled GRF solutions were found to have λ values larger than 20, meaning that for
210 those trials the lower mass (support leg) was negligible relative to the rest of the body.
211 Model parameters found in this study therefore have little physical meaning, limiting
212 the biomechanical interpretability of the model. Moreover, an exploration during which
213 the parameter search spaces were restricted to physically meaningful values did not lead
214 to more consistency in parameter values within or between tasks, while the accuracy of
215 modelled GRF profiles was reduced (Appendix B).

216 A possible explanation for the limited model parameter interpretability described above,
217 is the choice to reproduce a three-dimensional (resultant) GRF with a one-dimensional
218 model. The authors chose to reproduce the total force magnitude to allow for
219 investigating the overall whole-body load experienced during the different running
220 tasks. Consequently, horizontal segmental movements leading to the horizontal forces
221 included in the resultant GRF, had to be accounted for by the vertical motion in the
222 model. Since vertical motion was described by the eight model parameters, this might
223 have contributed to the inconsistent parameter values observed and the lack of physical

224 meaning. Horizontal movements and forces are, however, relatively small compared to
225 the vertical components, and are thus unlikely to have considerably affected the results
226 in this study. Moreover, exploratory work revealed that using the vertical component of
227 GRF only, did not noticeably improve the reproduced GRF profiles or enhance the
228 interpretability of the model parameters.

229 In this study, GRFs were reproduced by adjusting model parameters to fit measured
230 GRFs. However, in applied sport settings (e.g. football pitch, running track, etc.),
231 measured GRF is not available and other methods are required to estimate model
232 parameters and predict GRF. Since the two mass-spring-damper model's motion is
233 described by the acceleration of its masses, currently popular body-worn accelerometers
234 (Akenhead & Nassis, 2016; Cardinale & Varley, 2017) might be used to estimate the
235 parameters and predict GRFs in the field. However, the large variability and minimal
236 physical meaning of the model parameter values likely limit the usefulness of this
237 approach.

238 **Conclusion**

239 This study aimed to use a two mass-spring-damper model to reproduce GRF
240 profiles for activities that are frequently performed during running-based sports. As
241 hypothesised, the model could be used to reproduce overall GRF profiles for high-
242 intensity running tasks. However, the required model parameters varied strongly
243 between trials and had minimal physical meaning, rejecting our second hypothesis.
244 Therefore, the application of this specific two mass-spring-damper model for predicting
245 GRFs in the field and/or understanding the mechanical aspects of the running tasks
246 investigated in greater detail is likely limited.

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- 319
- 320

321 **Appendix A**

322 The model parameter optimisation process for accurately reproducing ground
323 reaction forces (GRFs) described in this study, requires the definition of starting
324 conditions for the different parameters. Therefore, a pilot analysis was performed with
325 the model parameters as defined by Derrick et al. (2000), who used the two mass-
326 spring-damper model for constant speed running at 3.83 m/s ($\pm 5\%$) (Table A1). To
327 verify if these parameters were appropriate as starting conditions for reproducing the
328 GRF profiles for the high-intensity tasks investigated in this study, GRF data for these
329 tasks were modelled for four randomly selected participants. The parameter values
330 reported by Derrick et al. (2000) were used as initial starting conditions for the
331 parameters. After this optimisation process, the resulting median model parameters
332 (Table A1) from this analysis were then used as starting conditions for the whole data
333 set.
334

335 **Appendix B**

336 The two mass-spring-damper model parameters found in this study varied
337 strongly within and between tasks and had little physical meaning, limiting the model's
338 interpretability. However, due to the highly complex eight-dimensional parameter
339 space, several parameter combinations might result in similarly accurate modelled
340 ground reaction force (GRF) solutions. If the model can accurately replicate GRF
341 profiles across tasks within a range of values that are more physically meaningful, this
342 may improve the interpretability of the model parameters. Therefore, GRF profiles were
343 reproduced with the two mass-spring-damper model within a predefined range of model
344 parameter values. The model's mass ratio λ was fixed at a value of 3 au (i.e. lower mass
345 ~25% of the total body mass), which was estimated from previously described
346 segmental properties of the foot, shank, thigh and pelvis (Dempster, 1955). In addition,
347 the remaining parameter search windows were limited to a range of values that was
348 deemed theoretically reasonable and physically meaningful (note: p_2 was calculated
349 from v_2).

350 - $p_1 = -0.4 - 0.1 \text{ m}$

351 - $v_1 = -3 - 1 \text{ m/s}$

352 - $v_2 = -0.5 - 2 \text{ m/s}$

353 - $\omega_1 = 0 - 50 \text{ N/m/kg}$

354 - $\omega_2 = 0 - 174 \text{ N/m/kg}$

355 - $\lambda = 3 \text{ au}$

356 - $\zeta = 0.1 - 1.5 \text{ au}$

357 Root mean square errors (RMSE) of the reproduced GRF profiles from a limited range
358 of parameter values increased for accelerations (+106%), decelerations (+6%) and
359 running at constant low (+29%), moderate (+10%) and high (+20%) speeds, compared

360 to using free parameters search windows. Moreover, the model parameters required to
361 reproduce the measured GRF profiles strongly varied within the defined parameter
362 boundaries (Figure B1). There was no consistency of parameters values within or
363 between any of the parameters or tasks. Moreover, many trials required parameter
364 values equal to the set upper or lower limit of different parameters, indicating the need
365 for higher or lower values than physically reasonable. Therefore, it was concluded that
366 the two mass-spring-damper model cannot be used to replicate GRF profiles with high
367 accuracy across a range of running tasks, using physically meaningful model
368 parameters.

Table 1 Equations describing the eight natural parameters of the two mass-spring-damper model

Initial position of the upper mass	$p_1 = x_1 - l_1 - l_2$	Equation 1
Initial position of the lower mass	$p_2 = x_2 - l_2$	Equation 2
Initial velocity of the upper mass	$v_1 = \dot{p}_1$	Equation 3
Initial velocity of the lower mass	$v_2 = \dot{p}_2$	Equation 4
Mass ratio	$\lambda = \frac{m_1}{m_2}$	Equation 5
Natural frequency of the upper spring	$\omega_1 = \sqrt{\frac{k_1}{m_1}} = \sqrt{\frac{(1 + \lambda) \cdot k_1}{\lambda \cdot BM}}$	Equation 6
Natural frequency of the lower spring	$\omega_2 = \sqrt{\frac{k_2}{m_2}} = \sqrt{\frac{(1 + \lambda) \cdot k_2}{BM}}$	Equation 7
Damping ratio of the damper	$\zeta = \frac{c}{2 \cdot \sqrt{k_2 \cdot m_2}}$	Equation 8
Acceleration of the upper mass	$a_1 = -\omega_1^2 \cdot (p_1 - p_2) + g$	Equation 9
Acceleration of the lower mass	$a_2 = -\omega_2^2 \cdot p_2 + \omega_1^2 \cdot \lambda \cdot (p_1 - p_2) - 2 \cdot \zeta \cdot \omega_2 \cdot v_2 + g$	Equation 10
Ground reaction force	$GRF = -\frac{BM \cdot \omega_2}{1 + \lambda} \cdot (\omega_2 \cdot p_2 + 2 \cdot \zeta \cdot v_2)$	Equation 11

Table 2 Modelled ground reaction force curve and loading characteristics errors

	RMSE		Impulse error		Impact peak error		Loading rate error	
	N/kg	%	Ns/kg	%	N/kg	%	N/kg/s	%
Accelerations (n=189)	0.69	9.9	0.01	0.6	2.43	18.9	487	31.3
	±0.47	±6.4	±0.01	±0.5	±1.49	±11.7	±342	±19.9
Decelerations (n=240)	2.48	33.9	0.01	0.7	7.43	20.6	431	18.7
	±1.17	±28.3	±0.01	±0.5	±4	±13.7	±276	±9.4
Constant speed running								
Low (2-3 m/s; n=126)	0.48	7.6	0.01	0.4	1.53	10.2	200	19.1
	±0.22	±5.8	±0	±0.3	±1.25	±8.5	±116	±9.8
Moderate (4-5 m/s; n=126)	0.78	9.4	0.01	0.3	1.54	7.5	254	20.8
	±0.25	±3.9	±0	±0.2	±0.86	±4.2	±101	±6.9
High (>6 m/s; n=176)	1.21	13.6	0.01	0.3	2.99	12	287	18.4
	±0.56	±7.1	±0	±0.2	±1.74	±8.1	±156	±9.7
All tasks (n=857)	1.28	17	0.01	0.5	5.74	17.4	385	20.3
	±1.06	±19.1	±0.01	±0.4	±3.85	±12.2	±247	±10.7

Mean ± standard deviations for root mean square errors (RMSE), impulse, impact peak and loading rate errors of the modelled GRF profiles for different tasks. Values are either absolute or relative errors compared to the measured GRF. Impact peak and loading rate (grey shaded) was modelled for 34%, 99% and 48% of the acceleration, deceleration and constant speed running trials respectively.

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Table 3 Mean ± standard deviation values for the eight model parameters for the different tasks

	p₁ (m)	p₂ (m)	v₁ (m/s)	v₂ (m/s)	ω₁ (N/m/kg)	ω₂ (N/m/kg)	λ (au)	ζ (au)
Accelerations	0.09	-0.7	16.5	0.37	32	102	0.4	0.9
	±8.19	±5.47	±146.03	±5.03	±27	±155	±2.29	±3.9
Decelerations	-12.97	-0.33	80.98	45.87	24	114	161.4	0.4
	±26.35	±1.18	±184.71	±132.34	±32	±91	±474.73	±0.5
Constant speed running								
Low (2-3 m/s)	0.63	0.07	-2.89	-0.12	31	72	5.87	0.9
	±3.14	±1.22	±56.17	±1.22	±28	±78	±5.9	±2.4
Moderate (4-5 m/s)	0.91	0.09	12.67	-0.2	37	101	4.16	0.6
	±5.2	±0.8	±137	±1.13	±35	±106	±6.34	±1.1
High (>6 m/s)	-2.21	-1.74	-1.83	0.98	34	134	1.93	1.9
	±13.37	±10.31	±115	±12.62	±35	±148	±4.99	±7
All tasks	-4	-0.57	28.49	13.71	31	109	49.38	0.9
	±17.12	±5.32	±146.94	±74.86	±32	±129	±267.09	±3.7

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Table A1 Initial conditions for the model's eight parameter values for reproducing GRF

	p₁ (m)	p₂ (m)	v₁ (m/s)	v₂ (m/s)	ω₁ (N/m/kg)	ω₂ (N/m/kg)	λ (au)	ζ (au)
Derrick et al. (2000)	0.015*	0.0074	-0.73	-0.66	207**	626**	2	0.35
Optimised	-0.01	0.00	-1.29	-0.19	18.33	58.32	2.81	0.31

The starting parameter values for the model optimisation process as described by Derrick et al. (2000) and those following from a pilot analysis using data for high-intensity running tasks. New (optimised) starting parameters are median values.

* *The upper mass position p_1 was not reported and its value was estimated to be double that of the position p_2 of the lower mass.*

** *The natural spring frequency values were estimated from the reported spring stiffness values k_1 and k_2 .*

375 **Figure captions**

376 **Figure 1** The two mass-spring-damper model consisted of a lower mass (m_2)
377 representing the support leg and an upper mass (m_1) representing the rest of the body.
378 Both masses were given an initial position (p_1, p_2) and velocity (v_1, v_2), and the mass
379 ratio λ was defined as the upper mass relative to the lower mass (m_1/m_2). The stiffnesses
380 of the upper and lower spring were defined by their natural frequencies (ω_1, ω_2) and the
381 model was damped by a damping coefficient ζ . The model's motion was described by
382 the acceleration of its two masses (a_1, a_2) based on the eight natural model parameters,
383 from which the modelled GRF was calculated.

384 **Figure 2** Typical examples of measured (black continuous line) and modelled (red
385 dotted line) ground reaction force (GRF) profiles including the root mean squared error
386 (RMSE) between both curves.

387 **Figure 3** Errors for relevant ground reaction force (GRF) loading characteristics
388 impulse, impact peak and loading rate for accelerations (blue circles), decelerations (red
389 triangles), and running at a constant low (light grey crosses), moderate (dark grey
390 crosses) and high (black crosses) speed. Negative errors are an underestimation of the
391 measured value and positive errors and overestimation.

392 **Figure 4** Model parameter values for accelerated, decelerated, and low-, moderate- and
393 high-speed running. Means (black dotted line) and standard deviations (grey dashed
394 line) were taken across tasks.

395 **Figure B1** Model parameter values for accelerated, decelerated, and low-, moderate-
396 and high-speed running. Mass ratio λ was fixed at 3 au, while the other parameters were
397 bound to a range of values deemed physically reasonable.