



Adapting a fatigue model for shoulder flexion fatigue: Enhancing recovery rate during intermittent rest intervals

John M. Looft^{a,b,*}, Laura A. Frey-Law^b

^a Minneapolis VA Health Care System, Minneapolis, MN 55417, United States

^b Department of Physical Therapy and Rehabilitation Science, University of Iowa, Iowa City, IA 52442, United States

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ABSTRACT

Although the rotator cuff muscles are susceptible to fatigue, shoulder fatigue studies reporting torque decline during intermittent tasks are relatively uncommon in the literature. A previous modification to the three-compartment controller (3CC) fatigue model incorporated a rest recovery multiplier (3CC-r model) to represent augmented blood flow to muscle during rest intervals (Looft et al., 2018). A rest recovery value of $r = 15$ was optimal for ankle, knee, and elbow joint regions, whereas $r = 30$ was better for hand/grip muscles. However, shoulder torque decline data was unavailable in the literature for comparison. Thus, the purpose of this study was to collect fatigue data for two different intermittent, isometric shoulder flexion fatiguing tasks and assess the 3CC-r model with $r = 15$ or 30 compared to the original 3CC model. Twenty healthy participants (9 M) completed two fatigue tasks: 50% maximum voluntary contraction (MVC) with 50% duty cycle (DC) and 70% MVC with 70% DC. MVCs were assessed at discrete time points (1, 3, 5, 10, and 15 min) until endurance time (MET). Mean observed percent torque decline (% TD) for the two tasks were compared to three model estimates: 3CC-r (using $r = 15$ and $r = 30$) and 3CC. Using these data, we confirmed that the addition of a rest multiplier ($r = 15$ somewhat better than $r = 30$) substantially improved predictions of shoulder fatigue using a previously validated analytical fatigue model (3CC). The relatively large reduction in model errors over the original model suggests the importance of representing augmented recovery during rest periods.

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1. Introduction

Shoulder musculoskeletal disorders (MSDs), including rotator cuff (RC) pathologies, are often debilitating and account for the most days away from work of all nonfatal occupational injuries and illnesses involving days away from work, exceeding even low back pain (BLS, 2017). Although challenging to clearly identify links between localized muscle fatigue and MSDs, muscle fatigue is related to both high force and high repetition tasks, two commonly accepted risk factors for the development of MSDs (Bernard and Fine, 1997, Gallagher and Heberger, 2013). Accordingly, muscle fatigue has been suggested as a potential risk factor for musculoskeletal disorder development in general (Kinali et al., 2016, Sonne et al., 2015, Sonne and Potvin, 2015) and specifically at the shoulder, where fatigue-induced kinematic alterations may

pose a risk for instability and tissue damage (Chopp-Hurley et al., 2016, Dickerson et al., 2015).

Quantification of localized muscle fatigue, however, is often more challenging than the identification of high forces or repetitive tasks as fatigue is a dynamic, time-varying phenomenon. While there are multiple approaches to assess muscle fatigue, operationally defined here as the reversible loss of force production capability due to prior muscle activity (Gandevia, 2001), not all are readily obtained. Two common fatigue metrics are: 1) the time a task can be maintained at some predefined level of force/torque, referred to as maximum endurance time (MET); and 2) decline in peak force/torque production during maximum efforts.

The potential value of fatigue models is their ability to estimate fatigue for use when direct measurement is not feasible. Traditionally, MET isometric fatigue models (see El ahrache et al 2006; or Frey Law and Avin 2010 for review) have provided valuable estimates of muscle fatigue development. Unfortunately, these MET models are limited to sustained isometric contractions without rest breaks (Monod and Scherrer, 1965, Rohmert, 1960, El Ahrache et al. 2006, Frey Law and Avin 2010).

* Corresponding author at: Minneapolis Adaptive Design & Engineering (MADE) Program, Prosthetic Patient Services, Minneapolis VA Health Care System, 1 Veterans Drive, Minneapolis, MN 55417, United States.

E-mail address: John.Looft@va.gov (J.M. Looft).

Several high-fidelity fatigue models have recently been proposed to accommodate either intermittent or dynamic contractions allowing for more accurate estimates of fatigue development during functional tasks (Looft et al., 2018, Ma et al., 2009, Ma et al., 2008, Sonne and Potvin, 2016, Xia and Frey Law, 2008). The three-compartment controller (3CC) fatigue model has been validated against large samples of experimental fatigue data for static contractions across multiple joint regions (Frey-Law et al., 2012), and was found to better predict MET than other models (Rashedi and Nussbaum, 2015).

However, during repetitive, intermittent contractions, the 3CC model tended to overpredict percent torque decline (%TD) (Looft et al., 2018, Sonne and Potvin, 2016). Thus, fatigue does not develop as rapidly during intermittent tasks as the model predicts even after accounting for the rest intervals. This discrepancy may be a result of a circulatory phenomenon, reactive hyperemia, which involves enhanced muscle blood flow following muscle contraction (Humphreys and Lind, 1963, Toussaint et al., 1996, Wigmore et al., 2004). Recently, a model modification (Looft et al., 2018) was made to account for this enhanced muscle reperfusion during rest breaks by including a rest multiplier, *r*, to amplify the recovery rate, *R*, during relaxation (i.e., *r***R*). For a full model review see the Appendix.

This revised model (3CC-r) improved fatigue estimates for repetitive tasks, when evaluated at the elbow, knee and hand/grip regions using previously published %TD data (Looft et al., 2018). During rest intervals, increasing the recovery rate by 15 times was optimal for the ankle, knee, and elbow joint regions, whereas a 30-fold increase was better for hand/grip muscles (Looft et al., 2018). However, the shoulder region had insufficient intermittent %TD data available in the literature to be able to assess the original or revised 3CC models for the shoulder region.

Thus, the goals of this study were to 1) collect experimental fatigue %TD data for two different intermittent, isometric shoulder flexion fatiguing tasks; and 2) assess how well the original 3CC and revised 3CC-r fatigue models predict torque decay using previously determined rest recovery multipliers (i.e., 15- and 30-fold increases). We hypothesized modeling shoulder fatigue during intermittent tasks would behave similar to the elbow, knee and ankle joints. That is, shoulder fatigue predictions would more accurately match observed fatigue when using a 15-fold recovery multiplier than using either no augmented recovery or a 30-fold multiplier.

2. Methods

2.1. Subjects

Twenty (9 M) healthy subjects between the ages of 18–32 years, with no history of MSDs or shoulder trauma, were recruited from the surrounding university community to participate in this study.

Subject demographics are provided in Table 1. All subjects provided written informed consent prior to participation and were compensated for their time. The study protocol was approved by the University of Iowa Biomedical Internal Review Board. Participants were not asked to change their daily routine prior to their study visit in any way (prior activity, caffeine, or sleep) to best reflect their typical task performance capability.

2.2. Fatigue test

Two shoulder flexion fatigue tasks were assessed on the same day. One task involved 50% maximum voluntary contraction (MVC) intensity with 50% duty cycle (DC) (50:50 task); the second task involved 70% MVC and 70% DC (70:70 task). All testing was performed on a Biodex Isokinetic Dynamometer System 3 (Biodex Medical Systems, Shirley, NY), with a modified base for the torque motor (System 4). Both fatiguing tasks had a 10 s cycle time. The task order was pseudo-randomized such that 50% of participants performed each task first, to minimize order effects.

Before testing, participants warmed up for 5 min on a Schwinn Airdyne bicycle ergometer using both the bike pedals and the arm attachments at a comfortable pace. After the warm-up participants were seated in the Biodex chair. The Biodex torque motor center of rotation was aligned with the lateral center of the participants' humeral head, based on palpation. The isometric shoulder flexion task was performed with the arm positioned at 90 degrees of shoulder flexion. The participants were instructed to grab the handle of the standard Biodex shoulder testing arm attachment with their thumb pointed toward the ceiling. Participants were secured to the Biodex chair with heavy-duty straps to minimize trunk and chest movement during the shoulder flexion task.

Participants were then allowed time to familiarized themselves with the testing set up via performing 3–5 submaximal practice trials before MVC testing began. Once they were familiar with the testing set up participants performed three shoulder flexion MVCs, with strong verbal encouragement, separated by one-minute intervals. Maximum torque was operationally defined as the maximum of the three MVC trials (see Data Analysis section for more details). Participants were then provided a 5-min rest break before the fatiguing tasks were performed.

A computer monitor provided each participant with real-time visual feedback of their shoulder torque production as well as the task target intensity (i.e. 50% or 70% MVC) throughout the testing. Prior to each fatiguing task, participants were allowed a brief practice of matching the target line, typically requiring no more than 10–30 sec, to familiarize themselves with the task. The participants were instructed to follow the test administrator verbal cues, “Contract” and “Relax,” which augmented the computer monitor cues which provided both verbal and visual cues assist participants in staying on task.

Each fatigue task was performed until MET was reached, defined as one of the following: 1) subjects were unable to main-

Table 1
Mean (SD) subject demographics and fatigue metrics for two intermittent tasks: 50% MVC, 50% duty cycle (50:50) and 70%MVC, 70% duty cycle (70:70) for male and female participants.

	Male (n = 9)	Female (n = 11)	t ₁₈	p-value
Age (years)	23.2 (3.5)	23.5 (4.8)	0.17	0.87
BMI (m/kg ²)	23.0 (3.8)	22.0 (1.8)	0.77	0.46
% Body Fat	13.8 (5.8)	24.4 (4.8)	4.50	<0.001
Peak Torque (Nm)	35.1 (8.5)	20.7 (3.5)	5.12	<0.001
Endurance Time (ET, s)				
50:50*	379.2 (247.7)	387.0 (244.2)	0.07	0.94
70:70*	76.5 (44.0)	62.7 (37.4)	0.76	0.46
Torque Decline at ET (%MVC)				
50:50*	34.7 (9.4)	30.4 (10.4)	0.96	0.35
70:70*	22.6 (10.4)	21.7 (7.3)	0.24	0.81

*Task condition (%MVC:%DC).

tain torque at the target level, operationally defined as either falling below 10% of the target level for more than 3 s or 3 times (even if less than 3 s each) within 30 s, despite verbal and visual feedback; or 2) volitional failure (participant indicated they could not go on, a requirement of the IRB). A maximum task duration of 15 min was imposed for those who did not meet the above criteria. Endurance time was recorded using a stopwatch and confirmed off-line based on recorded torque data. Participants were then given a minimum of 15-minutes rest break between the two fatigue tests.

Torque decline was assessed by having participants perform three-second MVCs throughout the fatiguing tasks at discrete time points (1, 3, 5, 10, and 15 min) and once MET was reached. The discrete time points were chosen to not only provide standardized time points across subjects, but also to minimize the effect of performing additional intermittent MVCs during the fatiguing task.

Torque signals were collected using custom LabVIEW software at 1000 Hz from the Biodex through a 16-bit analog to digital converter. Torque signals were low-pass filtered at 10 Hz (Matlab, Mathworks, Natick, MA) and passive torque (i.e., “gravity”) correction was performed offline. Absolute peak torque values were extracted from MVCs using the Matlab “max” function for use in the subsequent analyses. %TD was calculated by standardizing the discrete MVCs by the initial MVC value.

2.3. Predicted – Observed fatigue data analyses

Mean %TD data for the two intermittent fatiguing tasks were assessed relative to the 3CC and 3CC-r models using the original model value of $r = 1$ as well as with the previously identified augmented recovery rates of $r = 15$ and $r = 30$. F and R values previously determined for shoulder muscles ($F = 0.01820$, $R = 0.00168$) were used for all model predictions (Frey-Law et al., 2012). Directional errors were assessed as predicted minus observed %TD (in % MVC) at each assessed MVC and for total MET, to account for over- versus under-predictions. Absolute error was assessed as the absolute value of directional error to assess for total error magnitude (to avoid +/- errors cancelling each other).

2.4. Statistical analyses

Summary statistics were calculated for MET, peak torque, decline in peak torque (%TD), and demographic data. Data are reported as mean $\pm$ SD within the text tables and figures. Independent t-tests were used to compare MET and peak torque between sexes.

Mean (SD) directional and absolute errors for %TD were assessed for all three model predictions ($r = 1, 15$, & 30). Observed and modeled fatigue (% TD) were compared for assessments made just prior to or at the discrete time points (i.e., discretely at 1, 3, 5, 10, and 15 min). For example, if a subject reached endurance time at 2.5 min, their %TD error at MET (2.5 min) was evaluated with the next discrete time point. However, the model estimates were also assessed using the actual MET time, e.g. at 2.5 min. Thus, all comparisons of observed and modeled %TDs (e.g. errors) correspond to matching time points. Normality of model errors were tested using the Kolmogorov-Smirnov test. If normality was not violated, repeated measures analysis of variance (RM ANOVA) was used as an omnibus test to determine if model errors (predicted – observed %TD) were significantly different between models ($r = 1, 15$, or 30) for each task condition. Only time points with at least 75% of participants were included in the RM ANOVA assessments to maximize use of all subjects (i.e., RM ANOVA excludes subjects with “missing” data). When significant, 95% confidence interval estimates of the directional and absolute errors were used to assess which model predictions were significantly different from

observed %TD (i.e., errors significantly different from zero). To compare errors between models, 84% CIs were calculated to represent significant differences, as 95% CIs are overly restrictive when comparing two distributions (Austin and Hux, 2002; Julious, 2004).

To further evaluate which model produced the best overall fit to the observed shoulder joint fatigue data, the Akaike's Information Criterion (AIC) was calculated for each model using the results from both 50:50 and 70:70 tasks. Smaller AIC values correspond to better model predictions, while accounting for the additional model parameter. All statistical analyses were performed using the Statistical Package for the Social Sciences for Windows (Version 26.0, SPSS Inc., Chicago, IL) with alpha set at 0.05.

3. Results

3.1. Peak torque & MET

Shoulder flexion peak torque was significantly greater ($p < 0.001$) in males than females by 69.5% (Table 1). However, fatigue metrics at MET were not significantly different between the sexes for either task condition (Table 1). Endurance times for the 50:50 task averaged 383.5 s (SD 239.2 s) with an average %TD of 32.8% MVC (SD 10.2%) at MET. Two of the 20 participants sustained the 50:50 task for 15 min without failing to maintain the target torque based on our operational definition; their final %TD value was carried forward as best estimate for MET %TD. No participants requested to end the task volitionally, thus all others demonstrated inability to maintain target torque levels, thereby reaching MET. For the more intense 70:70 task, MET averaged only 68.9 s (SD 40.0 s) with a %TD of 22.1% MVC (SD 8.6%) at MET. All participants achieved MET for the 70:70 task prior to 5 min.

3.2. Percent (%) torque decline model comparisons

The mean (SD) observed and predicted %MVC values are shown in Fig. 2, and the corresponding declines in peak torque are provided in Table 2. For the RM ANOVA analyses, error differences between models were assessed using only time points 1, 3, and 5 min for the 50:50 task and 1 min for the 70:70 task to achieve the minimum of 75% of subjects able to maintain the fatigue tasks. For these time points, normality assumptions were not violated ($p > 0.20$). Directional errors differed between models ($F_{2,30} = 34.563$, $p < 0.0001$), increased over time ($F_{2,30} = 16.7$, $p < 0.0001$), and the difference between models varied over time ($F_{4,60} = 4427.7$, $p < 0.0001$) for the 50:50 task. For the 70:70 task, only model was included as a repeated measure due to the short METs, resulting in a significant difference between model errors ($F_{2,38} = 252.4$, $p < 0.001$).

The 95% confidence intervals of the mean directional errors (Supplemental Table 1) revealed the original 3CC fatigue model ($r = 1$) over predicted muscle fatigue development for both tasks significantly more than when recovery rates were amplified during rest intervals by either 15 or 30 times. A similar finding was observed for absolute errors (Supplemental Table 2). The only exception was for the 70:70 task at 1 min, where the revised model using $r = 15$ was not significantly different than the original model ($r = 1$) for either directional or absolute errors.

The overall errors for the revised model using either r value tested produced less error in predicting %TD over time than the original model (Table 3). This is further demonstrated in Fig. 3, where the predicted versus observed %TD values from both tasks more closely approximate the identity line for $r = 15$ or $r = 30$ and deviate the most from the identity line for the original 3CC ($r = 1$) model. Lastly the model AIC's calculations confirmed the revised 3CC-r models provided better model predictions of shoul-

Table 2
Observed versus predicted percent of maximum (%TD) torque decline and maximum endurance time (MET) for shoulder flexion at 90° of flexion for two intermittent tasks: 50% MVC, 50% duty cycle (50:50) and 70%MVC, 70% duty cycle (70:70).

Task (MVC:DC)	Time (min)	N*	Torque Decline (%TD)			
			Observed Mean (SD)	Original (r = 1)	Modified (r = 15)	Modified (r = 30)
50:50	1	20	13.8 (6.3)	26.0	18.0	12.7
	3	20	21.8 (8.4)	64.4	29.1	15.9
	5	16	27.9 (8.5)	77.5	31.7	16.1
	10	10	32.1 (10.6)	83.5	32.5	16.1
	15	3	35.0 (13.1)	84.0	33.0	16.1
70:70	1	20	17.7 (8.4)	42.9	36.0	30.1
	3	10	25.5 (7.9)	63.1	48.4	38.0

* Sample size declined as participants fatigued and reached their MET.
Note: significant differences ($p < 0.05$) in errors between models are indicated by superscripts where models with different letters were significantly different from each other, with Bonferroni adjustment for multiple comparisons.

Table 3
Mean absolute and directional errors for the original three-compartment controller (3CC) model ($r = 1$) and the two revised 3CC-r models ($r = 15$ or 30). While the two modified models produced similar error levels, the $r = 15$ produced the smallest Akaike's Information Criterion (AIC) value relative to the original model.

Model	Absolute Error (%TD)	Directional Error (%TD)	AIC	Change in AIC from original
Original r1	34.7	34.7	-184.5	reference
Modified r15	9.0	8.9	-478.4	-293.9
Modified r30	9.3	-1.7	-392.6	-208.1

%TD = percent torque decline.

der fatigue development, even when accounting for the additional model parameter (see Table 3). The modified model with $r = 15$ produced the lowest AICs (based on 50:50 and 70:70 task data combined), indicating it is superior to the $r = 30$ model overall, however both produced lower AICs than the original model.

4. Discussion

This study successfully demonstrated the addition of a rest multiplier (i.e., the revised 3CC-r fatigue model), augmenting the recovery rate during rest intervals relative to the recovery rate during contractions, improved predictions of %TD over time for intermittent tasks involving shoulder flexion. Supporting our initial hypothesis: that the addition of a rest multiplier in the 3CC-r model, was appropriate as a general fatigue modeling approach, even for more fatigable muscles such as the shoulder. While the 15-fold augmentation in recovery was better than the 30-fold for the tasks assessed, as hypothesized, the precise optimal value for this rest recovery may require additional data across more task conditions. That is, the errors for the revised model appeared to vary with task intensity and duty cycle.

Joint-specific fatigue models (El Ahrache et al., 2006) and individual fatigue studies in a large meta-analysis (Frey Law and Avin, 2010) have clearly demonstrated the rotator cuff musculature is the most fatigable of the joint regions evaluated. Accordingly, muscle fatigue may play a greater role in shoulder function and risk of repetitive or traumatic injury than observed at other anatomical regions. (Dickerson et al., 2015). Unfortunately, muscle fatigue can be challenging to identify as a clear risk factor for injury, in part due to difficulty objectively assessing muscle fatigue, a time-varying phenomenon, during real-world functional activity. Additionally, the prevalence of shoulder musculoskeletal disorders (BLS, 2017), supports the need for improved methods to estimate muscle fatigue during time-varying tasks.

To account for some of the time-varying phenomenon, other studies have also suggested increased recovery rates when rest intervals are present (Rashedi and Nussbaum, 2015). We have speculated the original 3CC model's over prediction of fatigue

was related to augmented tissue reperfusion that reflexively increases following vascular occlusion, known as hyperemia. This can occur from exogenous (e.g., blood pressure cuff) or endogenous (e.g. muscle contraction) compression of blood vessels. Earlier evaluation revealed a simple revision to account for this physiologic phenomenon improved muscle fatigue modeling of tasks with rest intervals for regions with moderate to low rates of fatigue development (Looft et al., 2018). This current study further suggests these improvements are also seen with rotator cuff muscles, which are the most fatigable of large muscle groups evaluated in a comprehensive fatigue meta-analysis (Frey Law and Avin, 2010).

Unfortunately, shoulder fatigue development is not as well represented in the literature as compared to other joints regions in general. In a large meta-analysis of sustained fatigue tasks reporting METs, the shoulder region had some of the fewest studies and lowest cumulative sample sizes (Frey Law and Avin, 2010). While a few studies have investigated intermittent shoulder fatigue (see Table 4), other reports of %TD over time were unavailable. Thus, we are unable to make direct comparisons between the decline in peak torque observed in the current study with other reports of %TD akin to Looft et al., (2018). The endurance times observed in the current study, however, are consistent with other reports of METs for shoulder flexion intermittent fatiguing tasks (see Table 4). That is, tasks involving lower intensity or DC report longer METs than observed for either task in the current study. Tasks of similar intensity and DC but longer cycle time found a shorter MET than the 50:50 task in the current study. Whereas, our most intense task, the 70:70 condition produced the shortest METs of those reported. These comparisons suggest our results are in line with fatigue observations from other laboratories.

In addition to being task and muscle group dependent, fatigue varies between individuals. It is commonly recognized that training can dramatically improve muscle endurance. In one notable example, a repetitive hand-grip training study found substantial improvements after only 6 weeks of daily training at 30% MVC compared to a control group (Shields et al., 1999). Whereas, there are conflicting reports regarding sex differences in fatigue resistance, with some showing women having greater fatigue-resistance (Hunter and Enoka, 2001; Hunter, 2009) and others

Table 4

Mean (SD) maximum endurance times (MET) for the current study and similar studies investigating shoulder fatigue due to intermittent tasks.

Author	N	Mean Age (years)	Sex	Intensity (%MVC)	Duty Cycle (%)	Cycle Time (s)	Endurance Time (s)	
							Mean	SD
Current Study	20	23.4	MX (11F)	50	50	10	383.5	239.2
				70	70	10	68.9	40.0
Hermans and Spaepen 1997	10	18.9	F	20	70	10	1596	298
Mathiassen 1993 [†]	6	32.5	F	25	33	60	1320	na
					50	60	750	na
					67	60	810	na
					83	60	1507	na
					83	360	1365	na
					83	10	3390	na
Iridiastadi and Nussbaum 2006b+	36	21.8	MX (18F)	28	75	166	1242	684
					75	34	2022	1320
					25	166	3402	492
					25	34	3498	246
				30	50	100	3498	246
				20	80	100	1878	1344
Mehta and Agnew 2012	12	22.3M 21.3F	MX (6F)	35	50	30	979.1	218.8
				55	50	30	187.8	20.8

^{*}Only included conditions with METs less than the pre-defined cut off were selected. Six (3F) participants were assigned per condition, so our reported N is less than the total number of participants recruited for this study.

[†] MET Standard deviations were not reported.

showing no sex differences (Lindstrom et al., 1997; Russ et al., 2008). However, a later study revealed sex differences to be regional, where in the same individuals, women had significantly more endurance at the elbow but not the ankle than men (Avin et al., 2010). Lastly, aging muscle shows a preferential loss of type II muscle fibers (Lexell et al., 1988), resulting in a higher proportion of oxidative muscle fibers. This too, however, is less than straight forward when considering the effects of aging on observed muscle fatigue. Thus, the use of parameter values obtained from averaged fatigue data can provide reasonable fatigue estimates but will not account for inter-individual variation in fatigue development.

A large meta-analysis found that for static sustained or intermittent contractions, older adults were approximately 15% more resistant to fatigue than their younger counterparts, however, for dynamic contractions there was no difference (Avin and Frey Law, 2011). A subsequent modelling investigation showed that perceptions of older adults being more fatigable during functional tasks is likely a result of the trade-offs between these generally improved muscle fatigue properties versus the increased relative task intensity with aging due to strength loss (Avin et al., 2015).

While analytical fatigue models are far from having the fidelity needed to accurately represent these many influences on fatigue, highlighting the challenges of modeling “average” fatigue behavior, the first step in developing models is to account for known physiologic behavior. Accordingly, the revision to the 3CC model with augmented recovery rates during rest intervals is one such critical step.

This study is not without limitations. First our participants were a sample of convenience from the local university student population. Second, strong verbal encouragement was consistently provided by the test administrator (JML) throughout the study and the endurance time cutoff criteria were consistently applied across individuals. However, the rapid recovery even a few seconds may provide between task completion and subsequent MVCs and/or the heightened motivation and drive associated with the final MVC may have contributed to this occasional mismatch. Lastly, both tasks were assessed on the same day, with a 15 min or as needed rest break, such that individuals may have not fully recovered for the second fatigue task. However, the testing order was

randomized to minimize order effects and post-hoc analyses revealed no significant difference in METs for either task based on test order (see Supplemental Table 3).

In summary, this study is the first to report declines in peak torque generation over time for intermittent shoulder flexion fatigue tasks. Using this data, we confirmed that the addition of a rest multiplier ($r = 15$ somewhat better than $r = 30$) substantially improved predictions of shoulder fatigue using a previously validated analytical fatigue model (3CC). The relatively large reduction in model errors with either $r = 15$ or $r = 30$ over the original $r = 1$ model suggests the importance of representing augmented recovery during rests, thought to be due to reactive hyperemia.

Additional shoulder fatigue research data with more task conditions would be useful to better refine the identification of an optimal rest recovery multiplier for the shoulder. However, in the absence of more data availability, the use of the 3CCr model represented shoulder flexion fatigue with errors less than 10%TD, which was within the observed normal range of inter-individual variability. Thus, this model, and associated parameter values, may be used for future applications to estimate fatigue when direct assessment of MVCs is not feasible.

Declaration of Competing Interest

Dr. Looft serves on the Minneapolis VA Healthcare System's non-profit: Center for Veterans Research and Education (CVRE) Board of Directors as a non-paid member. Neither CVRE nor the VA were involved in the study design, implementation, data analysis or writing of this publication. Dr. Frey Law does not have any financial or personal conflicts of interest to report.

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Appendix A

The 3CC (Frey-Law et al., 2012, Xia and Frey Law, 2008) and 3CC-r (Looft et al., 2018) muscle fatigue models use differential equations (see Appendix) to predict the flow between three muscle states: resting (M_R), active (M_A), and fatigued (M_F), as shown in Fig. 1. The fatigue models use a feedback controller to match the active state to target loads (TL) as a percent of maximum effort. Two joint-specific parameters define fatigue behavior: F , the fatigue rate controlling flow from active to fatigued states, and R , the recovery rate controlling flow from fatigued to resting states in a time-varying manner throughout a task. The revised 3CC-r model adds a rest multiplier (r) that can be used to augment the baseline recovery rate ($r \cdot R$) by a multiplicative factor only during rest periods, i.e., $TL = 0$. This augmented recovery during rest intervals represents muscle reactive hyperemia.

3CCr Model Equations.

$$dM_R/dt = -C(t) + (r \cdot R) \cdot M_F \quad (1)$$

$$dM_A/dt = C(t) - F \cdot M_A \quad (2)$$

$$dM_F/dt = F \cdot M_A - R \cdot M_F \quad (3)$$

Where:

$$C(t) = L_D \times (TL - M_A) \quad \text{If } M_A < TL \text{ and } M_R > (TL - M_A) \quad (4a)$$

$$C(t) = L_D \times M_R \quad \text{If } M_A < TL \text{ and } M_R < (TL - M_A) \quad (4b)$$

$$C(t) = L_R \times (TL - M_A) \quad \text{If } M_A > TL \quad (4c)$$

$$r = 1 \text{ if } TL > 0 \quad (5a)$$

$$r = r \text{ if } TL = 0 \quad (5b)$$

Note: original 3CC model $r = 1$ for all TL values.

The progression of the current muscle fatigue model has occurred in stages. The 3CC model was an advancement over a prior three-compartment model that was only able to represent maximal efforts (Liu et al., 2002). The addition of a feedback con-

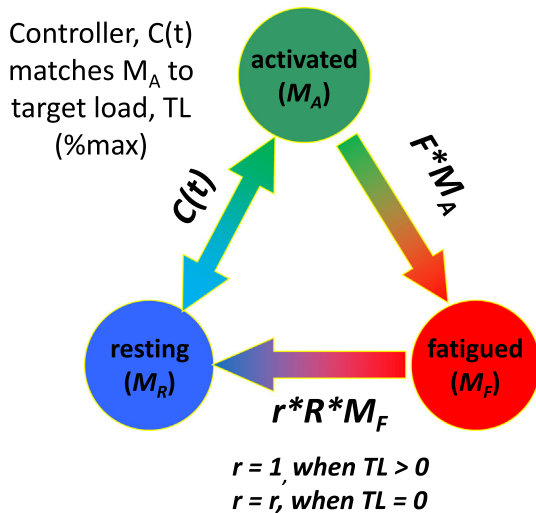


Fig. 1. Schematic diagram of the three-compartment controller (3CC) muscle fatigue model, representing muscle as being in 1 of 3 states: resting (M_R), active (M_A), or fatigued (M_F). $C(t)$ is the time-varying feedback control mechanism defining activation and relaxation of muscle to and from the M_A and M_R states. The original model did not incorporate the rest recovery multiplier, r , (effectively $r = 1$) and the revised version (3CCr) augments the recovery rate during rest intervals (i.e., target load, $TL = 0$).

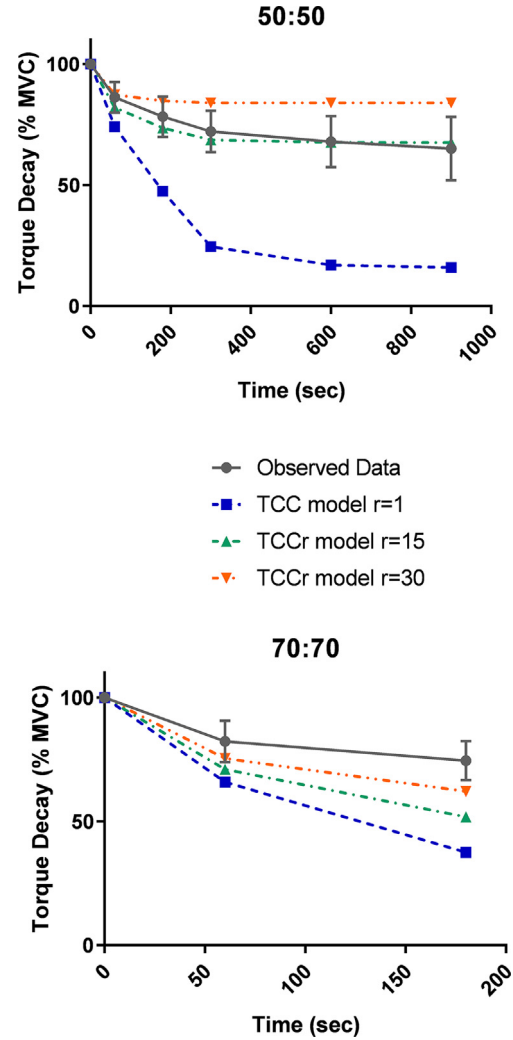


Fig. 2. Mean predicted fatigue (% MVC over time) for the Original TCC model ($r = 1$ blue squares), the modified TCCr model with $r = 15$ (green triangles), and the modified TCCr models with $r = 30$ (orange triangles) relative to mean (SD) observed fatigue (gray circles) over time. The top panel shows the 50%MVC, 50%DC task and the bottom panel shows the 70%MVC, 70%DC task. Note the sample size decreased over time (see Table 2), as participants reached their maximum endurance time (MET). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

troller relative to a target load enabled the 3CC model to handle submaximal and time-varying tasks (Xia and Frey Law, 2008). Other efforts to improve the 3CC model, often for specific purposes, have occurred, including the addition of the rest multiplier (Looft et al., 2018) considered in the current study and applying a proposed motor-unit activation approach (Xia and Frey Law, 2008) for hand muscles (Sonne and Potvin, 2016). However, there are trade-offs between increasing the fidelity and the complexity of any mathematical model. The determination of which model modifications best represent the underlying target behavior, in this case muscle fatigue, in as simple a manner as possible, is referred to as the Law of Parsimony (Simon, 2004). Arguably, a parsimonious approach provides greater generalizability with less risk of over-fitting available data. While the inclusion of the rest multiplier, r , to the muscle fatigue model adds an additional parameter, and thereby increases model complexity, the improved AIC values (Looft et al 2018) for the revised over the original model support that this is more than offset by the improved fatigue predictions.

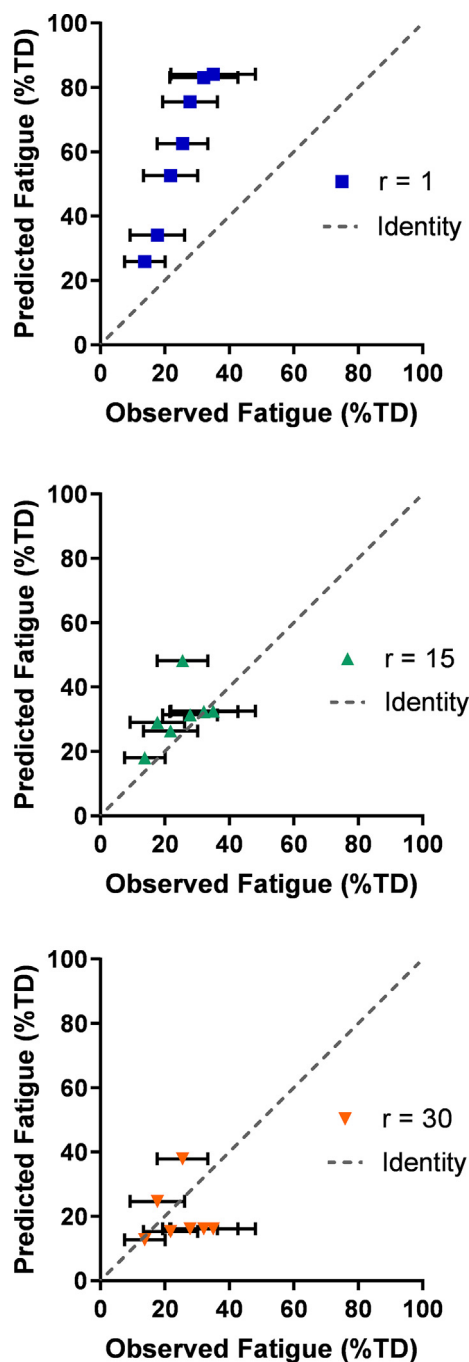


Fig. 3. Scatterplot of mean (SD) observed versus predicted fatigue (relative decline in peak torque, % torque decline) for the Original ($r = 1$, blue squares) in the top panel; modified TCC model ($r = 15$, green triangles) in the middle panel; and the modified TCC model ($r = 30$, orange triangles). Both 50:50 and 70:70 %MVC:DC tasks are plotted together for time = 1, 3, 5, 10, and 15 min when available. The identity line (gray dashed) is shown to indicate 100% agreement. Data above the identity line reflects an over prediction of muscle fatigue, while data below the line reflects an under prediction. Note both $r = 15$ and $r = 30$ produce substantial improvement over the original model. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Appendix B. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jbiomech.2020.109762>.

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