Spring 2012

Modeling and validating joint based muscle fatigue due to isometric static and intermittent tasks

John Maurice Looft
University of Iowa

MODELING AND VALIDATING JOINT BASED MUSCLE FATIGUE DUE TO ISOMETRIC STATIC AND INTERMITTENT TASKS

by

John Maurice Looft

A thesis submitted in partial fulfillment
of the requirements for the Master of
Science degree in Biomedical Engineering
in the Graduate College of
The University of Iowa

May 2012

Thesis Supervisor: Associate Professor Laura Frey Law

Graduate College
The University of Iowa
Iowa City, Iowa

CERTIFICATE OF APPROVAL

MASTER'S THESIS

This is to certify that the Master's thesis of

John Maurice Looft

has been approved by the Examining Committee
for the thesis requirement for the Master of Science
degree in Biomedical Engineering at the May 2012 graduation.

Thesis Committee:

Laura Frey Law, Thesis Supervisor

Nicole Grosland

Nathan Fethke

David Wilder

Tim Marler

To My Family

Remember to always do what you love

My Dad: Duane Looft

ACKNOWLEDGMENTS

I would like to thank my advisor Laura Frey Law for accepting me into her lab and letting me grow as a researcher under her guidance. I am proud of the work we have done and I am excited to continue my education and growth as a researcher under her guidance. I would also like to thank Nicole Grosland for guiding me through my decisions to continue my education at The University of Iowa. I would also like to thank Nathan Fethke, David Wilder, and Tim Marler for their help guiding me through this process and helping me set high goals for myself and being there to help me reach them. They have all been a pleasure to work with and I appreciate their insight and support more than I can express in writing. I would also like to thank my family for their unwavering support through this journey. I would not have been able to get to this stage without them and they keep me determined to achieve my goals.

TABLE OF CONTENTS

LIST OF TABLES

Table

LIST OF FIGURES

Figure

LIST OF EQUATIONS

Equation

CHAPTER 1:

INTRODUCTION

Overview

The aim of digital human models (DHM) is to create a virtual representation of a person. DHM are used to model how the human will react and interact to stimulus within the environment. The stimulus could be a 3D computer aided design (CAD) design of some environment, or a force being applied to the DHM. DHM are used to interact with the stimulus and provide feedback. The feedback (muscle force, joint angles, discomfort, etc.) can be interpreted by the user and used to redesign the environment such that the DHM performs in an efficient and biomechanically safe manner. Being able to test and redesign environments before being implemented in the real world has great implications when it comes to designing a manufacturing assembly line or designing the interface between humans and motor vehicles. DHM allow modelers to test their designs and quickly determine if design problems are present. These problems can be quickly identified and corrected before the design is put into action. Thus, DHM are useful for with the useful for correcting modeling mistakes while the product or production line is still in developmental stages instead of after the product or production line has been built. Catching these mistakes early helps reduce production cost and can in turn make the products cheaper for the consumer.

In addition to analyzing products, commercially available DHM's such as Santos™, Jack™, and Anybody™ analyze how workers interact with their environments and are used to help protect the workers from getting injured. There are many aspects of ensuring workers can perform their tasks safely such as limiting worker exposures to: awkward postures, heavy lifting, contact stresses, extreme heat/cold, repetitive motions, and vibration. Another important factor is limiting the amount the worker fatigues while performing his task throughout the work day. This thesis will focus on developing a muscle fatigue model for use in Santos^{TM}, The University of Iowa's DHM.

Digital Human Modeling

One of the main assumptions for DHMs is that the human body can be modeled as a kinematic system (Yang et al., 2004), where link lengths are connected by single degree of freedom (DOF) joints. For example, to model a three dimensional joint, such as the shoulder, three 1-DOF joints are stacked on top of each other to achieve the required DOFs.

One such DHM, Santos^{TM}, is being developed by the Virtual Soldier Research (VSR) group at The University of Iowa. Santos^{TM} is based on predictive dynamics, which, unlike other DHM, uses optimization to predict how a human would reach or perform a task. Most DHMs (e.g. Jack^{TM}) use a database of motion capture information that can be played back. While motion capture is effective for visualizing the motion, the forces and joint torques the body produces cannot be estimated from this file. Santos^{TM} predicts how the human would walk and provides the user with force and joint torque information. This is important when determining how performing a task in the modeled virtual environment will impact the actual worker once the process is put into practice.

For Santos^{TM} to be able to use predictive dynamics, his kinematic "skeleton" is set up in accordance to the Denavit-Hartenberg (D-H) method (Denavit and Hartenberg, 1955). The D-H method allows Santos^{TM} to perform postural analysis using multi-objective optimization (MOO) to find the position of his appendages (e.g. arms and legs) with respect to his global reference system (located at the pelvis) (Yang et al., 2004).

The use of MOO allows Santos^{TM} to predict how humans will perform a task subject to some restraint. Currently, Santos^{TM} outputs a force history for each joint while the task is being performed. The force history data can be used to predict how Santos^{TM} would fatigue throughout the task. However, currently there is no predictive muscle fatigue analysis tool incorporated into Santos^{TM}, thus this thesis will focus on the development and validation of a muscle fatigue model that can predict the endurance time and the percent torque decline in muscle force due to intermittent isometric muscle contractions.

Muscle Fatigue

Muscle fatigue is a complex physiological phenomenon that can be defined as "any reduction in force generation in response to a voluntary muscle contraction" (Gandevia, 1992; Chaffin et al., 2006). There are two classifications of fatigue that ergonomists and researchers are interested in. The first is peripheral fatigue which refers to the change in "the muscle's contractile properties and transmission of electrical signals across the sarcolemma" (Stein, 1974; Gandevia, 2001; Petersen et al., 2007), while central fatigue refers to the "progressive reduction in voluntary activation of a muscle during exercise" (Gandevia, 2001; Petersen et al., 2007). This thesis will focus on the combined measured effects (reduction in produced muscle force) of peripheral fatigue and central fatigue.

Literature Review of Muscle Fatigue Models

Researchers have tried to understand muscle, muscle mechanics and anatomy since Leonardo Da Vinci's Vitruvian Man around 1490. Since that time researchers attempted to understand what makes muscles contract and produce force. (Bendall, 1952), first studied the relationship between muscle contraction and adenosine triphosphate (ATP). These early models first focused on why muscles contract and muscle response models that are still used today such as the Hill muscle model that uses a spring element in parallel with a contractile element and spring element is series (Figure 1- 1) to explain the muscle response (Hill, 1938). This muscle model is useful for estimating stress and muscle force, but Hill's model is unable to model changes in force-producing capability over time (i.e., muscle fatigue) and thus is not useful for our current purpose.

Once the technology became available muscle models focused on modeling the action lines of muscles to show a 3-D representation of the musculoskeletal system (Charlton and Johnson, 2001; Gatton et al., 2001; Desailly et al., 2010). These models along with finite element modeling (Van Der Helm et al., 1992; Van Der Helm, 1994) have developed a sophisticated approach to determining how muscle force is transferred to the tendons and bone attachments. However, these models take a significant amount of time to run and assumptions have to be made regarding the load-sharing between muscles as the musculoskeletal system is redundant. For example if the isometric maximal voluntary muscle force is being measured at the elbow using a dynamometer, the force generated by the subject can be determined by taking the average of three MVCs with a sufficient rest period between each contraction. The muscle models however will have to partition how much of that MVC is produced by: Biceps Brachii, Brachialis, Flexor Carpi Radialis, Flexor Carpi Ulnaris, Brachioradialis, and the Pronator Teres. Since each of these muscles cannot be individually measured there will be some error in the model. These models also focus on determining muscle force and are not applicable to modeling muscle fatigue per se.

Muscle fatigue has been studied since the late 1800's (Gandevia, 2001) and research has mainly focused on the time to fatigue at a variety of percent maximum voluntary contractions (Rohmert, 1960; Monod and Scherrer, 1965; Hagberg, 1981; Huijgens, 1981; Sjøgaard, 1986; Rose et al., 2000; Garg et al., 2002; El Ahrache et al., 2006). The common methodology for these studies includes testing on a dynamometer to ensure isometric testing conditions at a joint (e.g. ankle, elbow, knee, etc). The subject is then instructed to perform three MVCs. The researchers then take the average of these three maximum efforts to determine a reference point for each subject. The subjects are then asked to perform contractions at some percent of max until they can no longer produce the required force. The time where the force production can no longer be maintained is defined as the endurance time (ET).

One of the first people to look at the endurance time of muscles over a range of MVC's was Walter Rhomert in 1960. Rhomert discovered that ET is a nonlinear function of contraction intensity (Rohmert, 1960) and developed response cures that have been coined "Rhomert Curves".

While there are several approaches to modeling muscle fatigue, a statistical approach is rooted in Rhomert's original paper (Rohmert, 1960). Since Rohmert's original paper, multiple statistical muscle fatigue models have been developed to predict the endurance time (ET) of isometric tasks. Table 1- 1shows a list of maximum endurance time (MET) regression models that have been developed by a variety of authors.

These models have been used to validate other isometric regression models that have recently been developed (El Ahrache et al., 2006; Ma et al., 2009). Unfortunately, most of these MET regression models relied on relatively small sample sizes (El Ahrache et al., 2006), thus the models may not be reflective of normative fatigue behavior. To address this limitation, a systematic review and meta-analyses was recently completed to compile all available fatigue data on isometric contractions to definitively determine optimal intensity-ET curves. A total of 194 publications for isometric contractions were included, which provided sufficient data to curve-fit intensity- ET equations for several joint regions, including: ankle, knee, trunk, shoulder, elbow, and wrist/hand (Frey Law and Avin, 2010). The results of the meta-analysis not only validated the nonlinear time-endurance relationship first proposed by Rhomert, 1960, but also found that each joint region fatigues at a different rate. The discovery highlights the need for predictive muscle fatigue models to include these variations in joint regions, and provides a reasonable "gold standard" to use for validating predictive fatigue models.

Recently (Xia and Frey Law, 2008) provided a MET muscle fatigue model that can be used with digital humans that use the Modified Denavit-Hartenberg (modified DH) notation system which is the basis of the Santos^{TM} kinematic model. However, (Xia and Frey-Law, 2008)'s model has not yet been validated for isometric, intermittent, or dynamic tasks. The goal of this thesis is to validate the fatigue model proposed by (Xia and Frey Law, 2008) for both isometric static and intermittent contractions.

Specific Aims

A three compartment analytical muscle fatigue model first proposed by (Liu et al., 2002) (Figure 1- 2) was recently modified with a controller to allow sub maximal tasks to be evaluated (Xia and Frey Law, 2008). The fatigue rate (F) controls the rate of flow from the Active compartment to the Fatigued compartment, and the recovery rate (R) controls the rate of flow from the Fatigued compartment to the Resting compartment (Figure 1- 2).

The model proposed in (Xia and Frey Law, 2008) did not include optimized F and R parameters that reasonably predicted the fatigue and recovery rates. Thus the first aim of this thesis is to find optimal model parameters to predict endurance times for each joint within the 95% confidence interval from the meta-analysis performed by Frey Law and Avin, 2010 (Chapter 2). We hypothesize the model with the two optimized parameters will be able to reproduce the non-linear intensity-ET relationships found by Frey Law and Avin, 2010. To accomplish this aim, a monte-carlo simulation (i.e. grid-search strategy) of the model was run with a range of F and R parameters. This provided a large grid of possible solutions that can be compared to the meta-analysis data (Frey Law and Avin, 2010). From this large grid search method the optimal F and R parameters were determined. This provided validation for static isometric tasks for the model, since the meta-analysis data was for static isometric contractions.

The next aim for the model validation is to perform a meta-analysis for intermittent tasks, since the types of tasks found in industry are not isometric. Instead tasks found in industry are more intermittent and dynamic in motion. We operationally define an intermittent contraction as a repeated series of static isometric contraction held for a time followed by a rest period. The total time of the contraction and rest periods that define an intermittent contraction is the cycle time (CT). The percentage of time in either the contraction or rest period of the cycle time is the duty cycle (DC). A dynamic contraction is similar to an intermittent contraction, but there is no measureable (greater than 1 second) rest period between contractions.

We hypothesize an empirical model can be developed using DC and MVC to predict the percent toque decline. To accomplish this aim, the meta-analysis will focus on muscle force decline (% decline) due to intermittent tasks at four discrete time points. This approach was chosen since intensity-ET relationships for low DC and low MVC's are nonexistent due to the task time taking greater than an hour. Thus in order to get enough data points (>3) to create an empirical model, % decline data was chosen. Four discrete time points (30, 60, 90, and 120 seconds) were chosen, so the % decline at a particular MVC and DC could be compared across studies.

Once completed, the meta-analysis empirical models of % decline as a function of DC and MVC were created for each joint and at each discrete time point, where there were more than 3 data points were found (i.e. need three points to define a plane). 95% confidence intervals (CI) were then calculated for each 3D surface and compared to the data points to determine how accurate the empirical models predict the data.

The final aim for the model validation is to compare these empirical models to the model predictions. Similar to the optimization step, this will show how the model compares to the 95% CI for fatigue due to intermittent tasks. We hypothesize the optimized F and R parameters for sustained isometric contractions will also be valid for intermittent tasks. The prediction models were also compared to the found data points and a resulting 95% CI was also found to determine how well the prediction model can predict the meta-analysis data.

From these validation steps, this thesis hopes to provide validation that the model proposed by (Xia and Frey Law, 2008) can accurately predict static intensity-ET curves and % decline responses for intermittent tasks.

Terminology

This thesis presents the validation and continued development of the muscle fatigue model first proposed by (Liu et al., 2002) and later modified by (Xia and Frey Law, 2008). The description of the model includes terminology from various fields.

- Maximum Voluntary Contraction (MVC): The maximum about of voluntary muscle force a subject can produce at a given joint
- Cycle Time (CT): The total amount of time the task takes to complete
- Duty Cycle (DC): A percentage of the cycle time that indicates how much time the subject is active compared to inactive (e.g. %50 DC at a 30s CT means the subject contracted for 15s rested for 15s).
- % Decline: the amount of force decline from 100%
- Isometric Contractions: The muscle force at a joint is found by the subject pulling/pushing against a fixed lever arm (e.g. the muscle length and joint angle are constant).

Table 1- 1: Adapted list of MET muscle fatigue models from (El Ahrache et al., 2006) to include (Ma et al., 2009) and (Frey Law and Avin, 2010)

General Models	MET Equations (minutes)
(Rohmert, 1960)	$MET = -1.5 + (2.1/f_{MVC}) - (0.6/ (f_{MVC})^2) + (0.1/(f_{MVC})^3)$
(Monod and Scherrer, 1965)	$MET = 0.4167 + (f_{MVC} – 0.14)^{-2.4}$
(Huijgens, 1981)	$MET = 0.865 [(1- f_{MVC}) / (f_{MVC} - 0.15)]^{1/1.4}$
(Sato et al., 1984)	$MET = 0.3802 (f_{MVC} – 0.04)^{-1.44}$
(Manenica, 1986)	$MET = 14.88 e^{(-4.16 f_{MVC})}$
(Sjøgaard, 1986)	$MET = 0.2997 (f_{MVC})^{-2.14}$
(Rose et al., 2000)	$MET = 7.96 e^{(-4.16 f_{MVC})}$
(Ma et al., 2009)	$MET = \ln(f_{MVC})/(k (f_{MVC}))$
(Frey Law and Avin, 2010)	$MET = 0.3653 (f_{MVC})^{-1.98}$

*f_{MVC} is the task intensity

**k is the fatigue ratio (Ma et al., 2009)

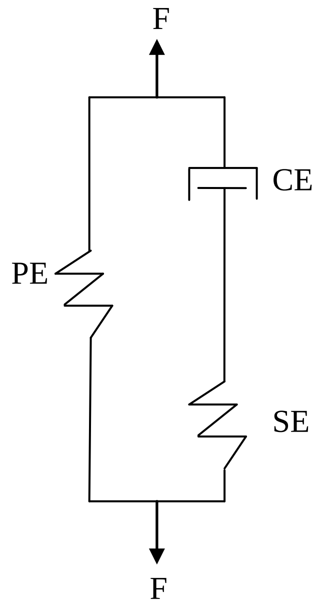

Figure 1- 1: A schematic representation of Hill’s muscle model. CE is the contractile element, SE is the spring in series element and PE is the spring in parallel element (Hill, 1938)

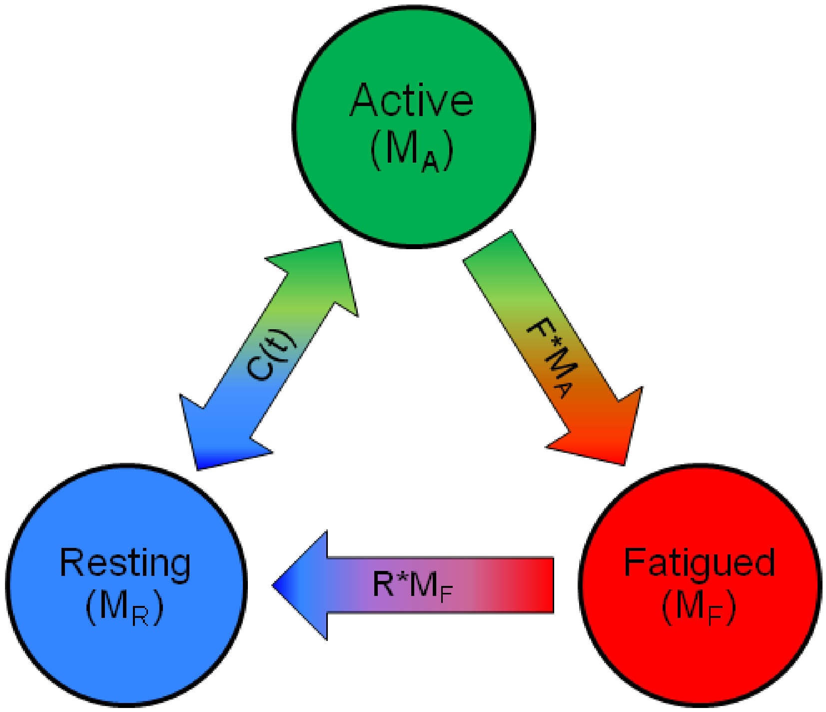

Figure 1- 2: A schematic drawing of the three compartment model, adapted from (Xia and Frey Law, 2008).

CHAPTER 2:

A THREE-COMPARTMENT MUSCLE FATIGUE MODEL ACCURATELY PREDICTS JOINT-SPECIFIC MAXIMUM ENDURANCE TIMES FOR SUSTAINED ISOMETRIC TASKS

Introduction

Muscle fatigue is considered a risk factor for musculoskeletal injury (Sejersted and Sjøgaard, 2000), yet few predictive tools are available to model this ubiquitous phenomenon. The development of localized muscle fatigue has classically been described by the intensity – endurance time (ET) curve in the ergonomic literature (Rohmert, 1960), sometimes referred to as "Rohmert's curve". In the past 50+ years, several authors have proposed updated versions of this classic nonlinear curve (Monod and Scherrer, 1965; Hagberg, 1981; Huijgens, 1981; Rose et al., 2000; Garg et al., 2002). More recently, comparisons between several of these models observed that equations varied by joint region (El Ahrache et al., 2006; Ma et al., 2009; Ma et al., 2011). Likewise, a large meta-analysis of 194 publications involving experimental fatigue data confirmed joint-specific intensity-ET relationships (Frey Law and Avin, 2010). Thus, ETs vary as a function of task intensity, but also based on the joint region involved.

These intensity-ET statistical relationships have been well documented and provide one practical tool to predict maximum ET. However this statistical approach is unable to predict fatigue outcomes beyond this single measure, such as the time course of fatigue development, the relative decline in force producing capability for a given task duration, or force recovery during rest periods. Thus more comprehensive, flexible models are needed to represent the complexity of localized muscle fatigue behavior.

We recently proposed a three-compartment, predictive fatigue model, consisting of active (M_A), fatigued (M_F), and resting (M_R) muscle states, to predict the decay and recovery of muscle force (Xia and Frey Law, 2008). We adapted this approach from a similar model first proposed by (Liu et al., 2002) with the addition of a feedback controller, C(t), and a variation of the 'flow patterns' between muscle states. These adaptations allow sub-maximal contractions and rest intervals to be modeled, yet preserves the use of two key parameters to define overall model behavior (fatigue, F, and recovery, R). While this model was shown to qualitatively reproduce expected curvilinear intensity-ET relationships (Xia and Frey Law, 2008), it has yet to be validated against experimental data.

There are many possible fatigue measures that could be used to test the accuracy of this model for predicting localized muscle fatigue. However, the well-characterized intensity- ET relationship (Frey Law and Avin, 2010) provides a useful metric as a first step in evaluating fatigue during simple, sustained isometric contractions. Further, sustained isometric tasks are commonly used to study fatigue behavior in humans (e.g., (Bystrom and Sjøgaard, 1991; Shahidi and Mathieu, 1995; Hunter et al., 2002)) as they provide a well-defined methodology. Thus, the primary purposes of this study were to: 1) determine optimal model parameter values, F and R, to predict joint-specific intensity – ET curves for sustained isometric contractions, and 2) assess the accuracy of the model using these parameter values.

Methods

Biophysical Model

The three-compartment model involves three differential equations (Equation 2-1-Equation 2- 3) describing the rate of "flow" from one muscle state to the adjacent state (Figure 1- 1). While the original Liu, et al. (2002) model proposed fatigued muscle would recover back into the active state, we have operationally defined the model such that fatigued muscle recovers to the resting state. In addition, we have added a feedback proportional controller to define the activation and deactivation of active muscle (C(t)). These changes alter the defining differential equations from the original equations proposed by Liu et al (2002) and require discrete analyses to solve for the three muscle states at each time point.

Equation 2- 1: Resting state

$$dM_R/dt = -C(t) + R*M_F$$

Equation 2- 2: Active state

$$dM_A/dt = C(t) - F*M_A$$

Equation 2- 3: Fatigued state

$$dM_F/dt = F*M_A - R*M_F$$

Where:

C(t) = the controller denoting the muscle activation-deactivation drive;

F = fatigue parameter defining the rate of change between the active and fatigued compartments; and

R = recovery parameter defining the rate of change between the fatigued and resting compartments.

The controller attempts to match the active muscle compartment (M_A) to the task requirements (e.g. target task intensity, TL, as a percent of maximum, % max), which for this investigation ranged from 10% to 95% max. The muscle activation or deactivation by the controller is defined for three possible conditions (Equation 2- 4-Equation 2- 6), showing the dependence of C(t) on the relative “volumes” of the three compartments relative to the target task intensity level (TL), see Xia and Frey Law, (2008) for more detail.

Equation 2- 4: If $M_A < TL$ and $M_R > (TL - M_A)$

$$C(t) = L * (TL - M_A)$$

Equation 2- 5: If $M_A < TL$ and $M_R < (TL - M_A)$

$$C(t) = L * M_R$$

Equation 2- 6: If $M_A \geq TL$

$$C(t) = L * (TL - M_A)$$

Where: L is an arbitrary constant tracking factor to ensure good system behavior. We used a value of 10 for all simulations based on our previous sensitivity analysis (Xia and Frey Law, 2008).

The initial model was developed using Simulink (Xia and Frey Law, 2008) but was revised into Matlab (Mathworks, Natick, MA) for greater flexibility. The differential equations were solved using the built in function, ‘c2d,’ to transform them into discrete space, in 1 sec time intervals (1 Hz). Thus, the precision of the model is limited to +/- 1 sec using this step size.

While the model could be employed at multiple levels of fidelity, ranging from single fiber to whole muscles, it is employed here at the ‘joint-level’. Similarly, most human fatigue studies are performed *in vivo* at the ‘joint-level’. The joint-level model assumes each muscle state represents the relative proportion of the total joint torque capability (% max intensity). While this could be considered to be the proportion of total motor units available about a joint, technically different motor unit types produce different levels of torque. In addition, biomechanical influences such as muscle length and joint moment arm influence total torque production. Thus generalizing the model to represent relative torque (% max) rather than simply motor unit activation or muscle force provides a means to better represent the various biomechanical and physiological influences on joint torque, and matches experimental methodologies in the fatigue literature (i.e, tasks performed at relative intensities).

Endurance time was used as the primary model outcome variable due to the extensive data available in the literature (see below) on ET as a function of relative task intensity. Predicted ET was operationally defined as the time at which the active muscle state could no longer maintain the target intensity ($M_R + M_A < TL$).

Parameter Optimization

To determine optimal F and R parameter values, a global optimization search strategy was employed. While gradient-based optimization techniques are often useful for minimizing differences between predicted and expected results as a function of time, this approach was not feasible for optimizing a single outcome assessed across multiple simulations (i.e. task intensities). Repeated model simulations with varying F and R values were performed, with the resulting model predictions compared to expected values. The optimization problem was optimized as follows:

Equation 2- 7: Optimization formulation

Find: F and R

To minimize objective function:

Absolute Error = $\sum_{i=1}^{9} \| x(F,R)_i^{\Pr edicted} - x_i^{Actual} \| \leq \varepsilon$

Subject to:

F > 0;

R > 0;

Where:

x_i = endurance time at the i^{th} intensity (1=10%, 2=20%, … ,9=90% of maximum)

A two-stage grid-search strategy was used. The first stage involved a course grid of potential F and R values; each possible permutation was used to predict maximum ET for nine task intensities ranging from 10 – 90% of maximum effort in 10% increments. This initial grid used 1000 F and 1000 R values ranging from 0.0001 to 0.1 in increments of 0.0001, for a total of 9,000,000 simulations (1,000,000 F and R combinations for each of the 9 task intensities). The second stage utilized a more refined grid of possible F and R values focusing in on the optimal regions observed for each joint in the first stage of simulations. A smaller range of F and R values were selected around the initial "best" F and R values (joint-specific), in increments of 0.00001. This produced 8572 additional simulations for each of the 9 relative intensities, for a total of 77,148 simulations in the second stage. Thus a total of 9.08 million simulations were run assessing maximum ET for each F and R combination.

The optimal F and R parameter values from the each search stage were determined as those producing the least error compared to the criterion intensity-ET relationships (see below) available for six joint regions: ankle, knee, trunk, shoulder, elbow, hand/grip, as well as a "general" intensity-ET curve (Frey Law and Avin, 2010).

Error was calculated as the root mean square (RMS) between the predicted and expected ETs across the 9 task intensities. Optimal F and R values were defined as those producing the least mean RMS error. In addition, model predictions at each intensity level were compared to the expected 95% prediction intervals previously observed due to normal variability (Frey Law and Avin, 2010). We chose *a priori* to define the minimum criterion for "adequate" model predictions as having a majority of the 9 optimized ETs fall within the 95% prediction intervals for each joint region (i.e., minimum of 5 of 9 intensities).

Criterion Intensity-ET Relationships

Numerous authors have proposed intensity-ET models, or statistical fatigue models, to represent the single fatigue outcome, maximum ET (Monod and Scherrer, 1965; Hagberg, 1981; Huijgens, 1981; Rose et al., 2000; Garg et al., 2002). However, these models were based on fatigue studies involving relatively small sample sizes, e.g., ranging from 5 to 38 participants. To ascertain a 'gold standard,' or expected intensity-ET relationship, for comparison to the predicted ETs from our biophysical model, we used the statistical models developed previously based on data from a meta-analysis of the available literature on sustained isometric contractions (Frey Law and Avin, 2010).

The results of this study have been well-described, but will be summarized briefly here. A total of 194 publications were found that reported maximum ET for relative intensity tasks (i.e., % of maximum) about a single joint for voluntary contractions. These studies included 369 distinct intensity-ET data points as several studies reported ETs for multiple joints and/or task intensities. All studies included healthy young adults (18 - 55 yrs), with a range of reported activity levels (untrained to elite athletes). Sufficient data was available to curve-fit the intensity-ET relationship for six joint regions: ankle, knee, trunk, shoulder, elbow, and hand/grip and an overall general model (all joint regions combined). Total sample sizes, summed across studies for each joint were as follows: ankle (n=207, 20 studies, 40 data points), knee (n=875, 56 studies, 93 data points), trunk (n=307, 17 studies, 33 data points), shoulder (n=176, 13 studies, 17 data points), elbow (n=838, 60 studies, 126 data points), and hand/grip (n=754, 40 studies, 58 data points). A power curve best fit the intensity-ET relationship for each joint (see Equation 2- 7), with mean and 95% prediction intervals determined using Matlab Optimization Toolbox.

Equation 2- 8: Power-curve example

$$ET = a*(\text{task intensity})^b$$

Several of the joint-specific curves were significantly different from one another ($p < 0.05$). The order of the most fatigue-resistant to the most fatigable was: ankle, trunk, knee, elbow, hand/grip, and shoulder, respectively (Frey Law and Avin, 2010). The 95% prediction intervals for each joint ranged from 30 to 96% of the predicted ET (overall mean 48%), demonstrating the inherent variability observed in muscle fatigue between individuals.

Parameter Analyses

Finally, the ratios between the optimal F and R parameter values (fatigue to recovery rate ratios) were calculated for each joint region and a sensitivity analysis was performed to examine the influence of changes in F and R on the intensity-ET predictions. While our model differs somewhat from the original model proposed by Liu, et al. (2002) we tested whether an analogous equation relating the F and R values to an intensity asymptote (see Equation 2- 8) matched our simulated model predictions. The simulated asymptote for each joint was determined by running the model at decreasing task intensities until an ET could no longer be observed (i.e., the active muscle state plateaued at a level just above the task intensity).

Equation 2- 9: Asymptote calculation

$$\text{asymptote (\% max)} = (1/ (F/R + 1)) * 100\%$$

Model Evaluation

Using the joint-specific optimized parameter values, the model was then evaluated across a new set of 9 task intensities (15 – 95 % max, in increments of 10%) to test the resulting model accuracy using conditions not involved in the optimization process. The mean RMS errors (sec) and mean relative errors (%) were determined as described previously for the optimized intensities.

Results

The optimal, joint-specific, F and R values found as a result of the global optimization search strategy are provided in Table 2- 1. The model well surpassed our minimum criterion for each joint, with a minimum of 7 out of 9 ET predictions falling within the expected 95% prediction intervals (using the 'optimization task intensities'). Across each joint, the highest intensities (> ~80% max) were the most challenging to maintain within the narrow 95% prediction intervals, typically under-predicting expected ETs (see Figure 2- 1).

The resulting ET errors at the original optimization intensities (i.e., 10 – 90% max, by 10% increments) were small (see Table 2- 2). When evaluating the model accuracy at a separate set of test intensities (i.e. 15 – 95% max, by 10% increments) the errors increased compared to the optimization intensities, but remained below expected variation (see Figure 2- 1). Relatively minor differences were observed in ET errors between the different joint regions. Thus, the model performed nearly equally well across different muscle groups despite varying fatigue properties.

The observed and predicted intensity asymptotes were in agreement with one another across the joint regions (see Table 2- 1). This finding indicates the relationship between F and R parameter values and the ET asymptote proposed for the original Liu et al (2002) biophysical fatigue model holds for our modified model, despite the changes made and lack of an analytical solution. Intensity asymptotes ranged from 6 to 10% max for both the observed, simulated and theoretical predictions based on the optimal F and R values.

F and R parameter sensitivity analysis was performed relative to one joint region (elbow) for ranges of F and R values observed across the joint regions (see Figure 2- 2, panels A and B). Changes in F caused relatively large changes in ET at the lower intensities (about a fixed R value), thus altering the inflection points of the intensity-ET curves (and ultimately the intensity asymptote). The effects of changes in R (about a fixed F value) predominately influenced the spread of ETs, particularly at the lowest contraction levels. Thus the fatigue rate appears to have the largest influence on the curvature of the intensity-ET relationship, whereas the recovery rate parameter refines the ET response within that curvature.

Discussion

The main finding of this study is that a parsimonious three-compartment biophysical fatigue model can accurately predict fatigue, i.e., maximum ETs, for sustained isometric contractions across a wide range of task intensities for several distinct joint regions. While this fatigue model is inherently able to predict multiple aspects of muscle fatigue, including the time course of fatigue development and recovery, we were able to validate the model using the outcome variable, ET, due to the extensive normative data available for comparison.

The joint-specific optimal fatigue and recovery parameter values reproduced the expected nonlinear intensity-ET relationships reasonably well. The mean RMS and relative errors (i.e., errors relative to expected ETs, see Table 2- 2) ranged from 3 to 28 sec and 2 to 20%, respectively, which is well within expected ET variation. Our prior meta-analysis demonstrated the expected variation in ET (i.e., the percent difference between the 95% PI curve and the mean expected curve for ET) ranged from 29-47% (Frey Law and Avin, 2010). Thus, all of the mean model errors are well-below the normal variation expected between groups of individuals. Further, this estimate of normal variation in fatigue development is based on the culmination of multiple study means which is likely less than the underlying variation between individuals.

The F and R values generally varied as one might predict based on the expected fatigue resistance between joint regions, suggesting good construct validity for the model. For example, the most fatigue-resistant muscle group region we considered is the ankle (Frey Law and Avin, 2010), where the soleus and tibialis anterior muscles about the ankle have a greater proportion of slow-twitch, type I muscle fibers than observed in most other muscles (Johnson et al., 1973). Analogously the optimal F value for the ankle was the lowest of the 6 joints, indicative of a slow fatigue rate for the biophysical model. The most fatigable joint region we considered is the shoulder based on experimental data (Frey Law and Avin, 2010), which likewise had the fastest fatigue rate (i.e., highest F value) of the 6 joints. Thus, the model is able to realistically represent between-joint differences in fatigue rates through the optimal parameter values.

Overall, the fatigue to recovery rate (F:R) ratios varied from 10 to 15, indicating muscles can be thought of as fatiguing 10 to 15 times faster than they are able to recover during a sustained contraction (Table 2-1). (Frey Law and Avin, 2010) found that "although intensity dependent to some degree, the shoulder is the most rapidly fatigable followed by the knee, grip and elbow, trunk and the ankle is the most fatigue-resistant." However, the observed F:R ratio were found to be around 10. This is to suggest that the F:R ratio is not the significant factor determining which muscle group will more quickly fatigue. The hand/grip joint region is the lone outlier in this observation, but this could be due to many different tasking protocols the "hand and grip studies involving the first dorsal interosseus (FDI), abductor pollicis brevis (APB), adductor pollicis (ADP), and transverse volar type grip" (Frey-Law and Avin, 2010) where collapsed to create the empirical intensity-ET curve. This variety in the studies used to create the hand/grip intensity-ET curve and 95% PI could explain the deviation from an F:R ratio of 10.

The predicted intensity asymptotes ranged from 6 to 9 % of maximum. This is consistent with previous statistical intensity-ET models, which observed asymptotes ranging from 4 to 15 % of maximum (Rohmert, 1960; Monod and Scherrer, 1965; Huijgens, 1981; Sato et al., 1984; Ma et al., 2011), but different from those based on F and R values determined by Liu, et al. (2002) for maximum intensity tasks (22 – 33% max). Conversely, the intensity-ET power equations fit to the meta-analyses data (Frey Law and Avin, 2010) do not have explicit asymptotes and little experimental fatigue data exists for these very low intensity contractions. Thus, it remains unclear whether a true asymptote exists or whether task failure can eventually occur even at very low task intensities (albeit at very long durations). However, the Cinderella hypothesis posits that even very low intensity contractions can lead to musculoskeletal injury (Visser and van Dieen, 2006), suggesting even if no ET is predicted, fatigue may remain a concern.

Several different approaches have been used to model muscle fatigue. In addition to the statistical ET models already described, other analytical models have been developed which predict muscle force decay over time. Typically these are used to represent single muscles and rely on estimates of stimulus impulse inputs (Ding et al., 2003; Marion et al., 2010). These approaches, however, are better intended for clinical applications where electrical stimulation is employed on an individual basis (Marion et al., 2010). This compartmental, biophysical modeling approach has gained interest with applications including: maximal isometric contractions (Liu et al., 2002) and aerobic, endurance activities (Ng et al., 2011) in addition to the submaximal isometric contractions modeled in this study.

While these results suggest a certain level of validity for this model, this finding should not be over-generalized. These results were obtained using data for sustained isometric contractions only and may or may not translate to other task conditions (e.g. isometric tasks with intermittent rest intervals or dynamic contractions). A second caveat is that the optimized parameter values observed in this study were dependent on the expected endurance time-intensity equations reported (Frey Law and Avin, 2010). Both the mean curves and the 95% prediction intervals were influenced by the number and spread of data points that were available in the literature. Lastly, as our goal was to determine optimal ET predictions (minimizing ET error in sec), the RMS error was minimized. This choice of criterion weights the errors at the lower task intensities more than the higher intensities. This process could be repeated using relative error if desired for a particular application or different goal in mind. However, this alternate approach would produce exponentially greater absolute errors at low task intensities.

While this fatigue model could be used to represent single muscles, or individuals at the joint level, that would require experimental data collection for single muscles and/or individuals across a range of contraction intensities. We believe the greater value of this model is to predict normative fatigue behavior, so that no additional experimental data are needed. Accordingly, the model has potential to be used in isolation (when task intensity is readily estimated) or incorporated into digital human models that can estimate required joint torques (and task intensities) for the completion of a task.

In summary, the simplistic three-compartmental model produces heuristically accurate maximum endurance time predictions across a wide range of contraction intensities. Expected joint differences are well reproduced by differences in optimal F and R parameter values. Future work is needed to ascertain whether this simple modeling approach can be extended to predict fatigue when brief rest periods are allowed, during dynamic tasks, or how well it can predict recovery times following the development of fatigue. However, this study demonstrates this biophysical model is a valid means of predicting fatigue development during sustained isometric tasks across a wide range of task intensities.

Table 2- 1: Optimal fatigue (F) and recovery (R) parameters by joint region.

Joint Region	F	R	Within 95% PI	F:R Ratio	Observed Asymptote (%MVC)	Predicted Asymptote* (%MVC)
Ankle	0.00589	0.00058	8/9	10.2	8.99	8.96
Knee	0.01500	0.00149	8/9	10.1	9.05	9.04
Trunk	0.00755	0.00075	8/9	10.1	9.05	9.04
Shoulder	0.01820	0.00168	8/9	10.8	8.47	8.45
Elbow	0.00912	0.00094	8/9	9.7	9.36	9.34
Hand/Grip	0.00980	0.00064	7/9	15.3	6.14	6.13
General	0.00970	0.00091	8/9	10.7	8.59	8.57

*Predicted Asymptote = 1/(F:R+1)*100%

Table 2- 2: Model accuracy for ET predictions using optimal F and R parameters for optimization and test task intensities.

	Optimization Intensities†		**Test Intensities‡**	
Joint Region	**Mean RMS Error (s)**	**Mean Relative Error (%)**	**Mean RMS Error (s)**	**Mean Relative Error (%)**
Ankle	11.2	0.6	28.2	-4.0
Knee	6.7	14.0	15.4	-17.0
Trunk	9.3	2.2	23.1	-1.9
Shoulder	2.7	-6.9	6.1	-10.0
Elbow	9.9	12.0	25.5	7.9
Hand/Grip	5.6	16.2	6.0	-20.0
General	7.3	2.4	11.8	-2.0

† Optimization task intensities: 10% - 90% of maximum, in 10% increments (total of 9 simulations).

‡ Test task intensities: 15% - 95% of maximum, in 10% increments (total of 9 simulations).

Note: Errors calculated between predicted and expected ET based on statistical intensity-ET models previously reported (Frey Law and Avin, 2010).

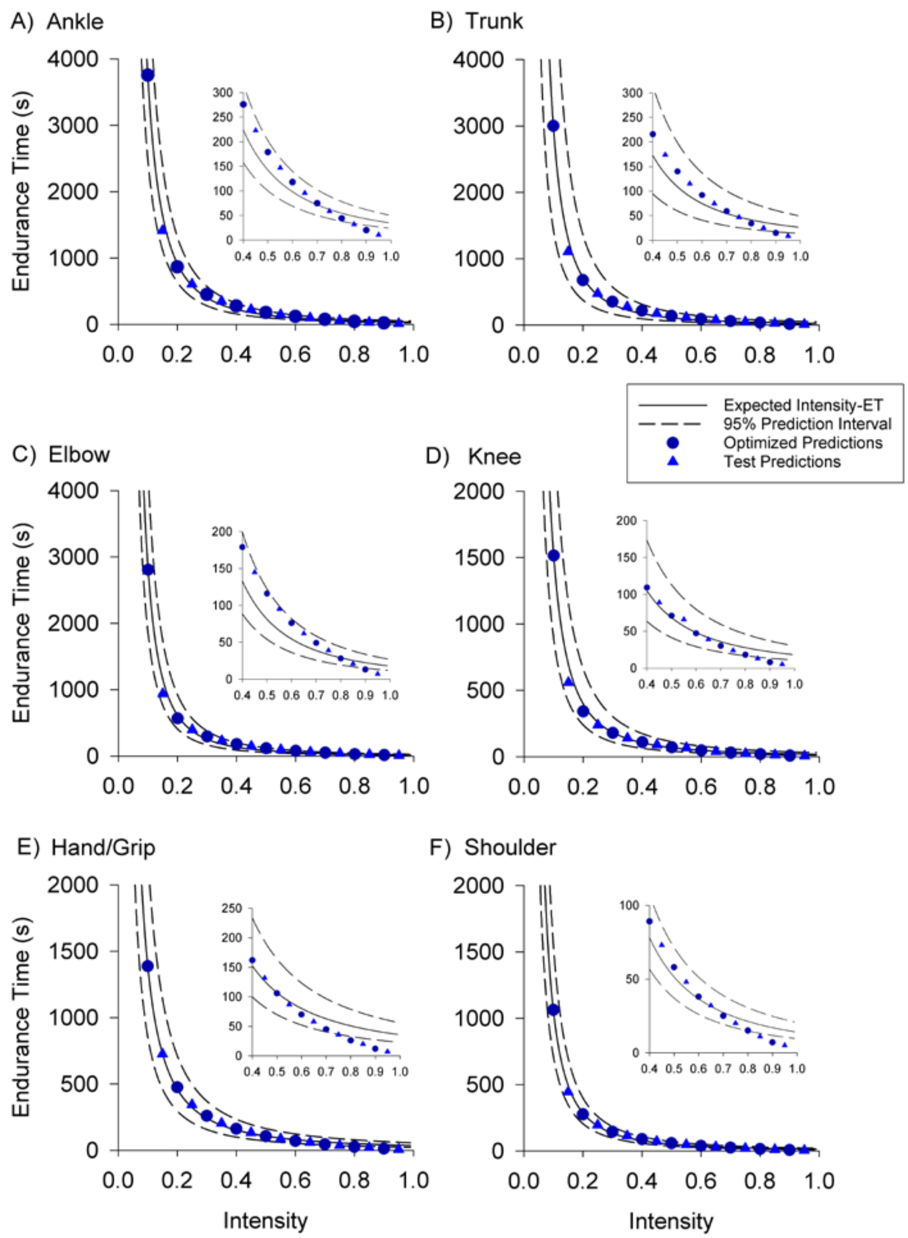

Figure 2- 1: Model predictions using optimal F and R parameter values (optimized intensities = circles, test intensities = triangles) by joint: A) ankle, B) trunk, C) elbow, D) knee, E) hand/grip, and F) shoulder relative to expected intensity-endurance time (ET) curves: modeled mean +/- 95% prediction intervals (PI) reported by Frey Law and Avin, (2010). Note the change in ET scaling between panels. Insets highlight the higher task intensities. The ETs which fall outside of the 95% PI consistently occur only at the highest intensities (>75% – 85% maximum).

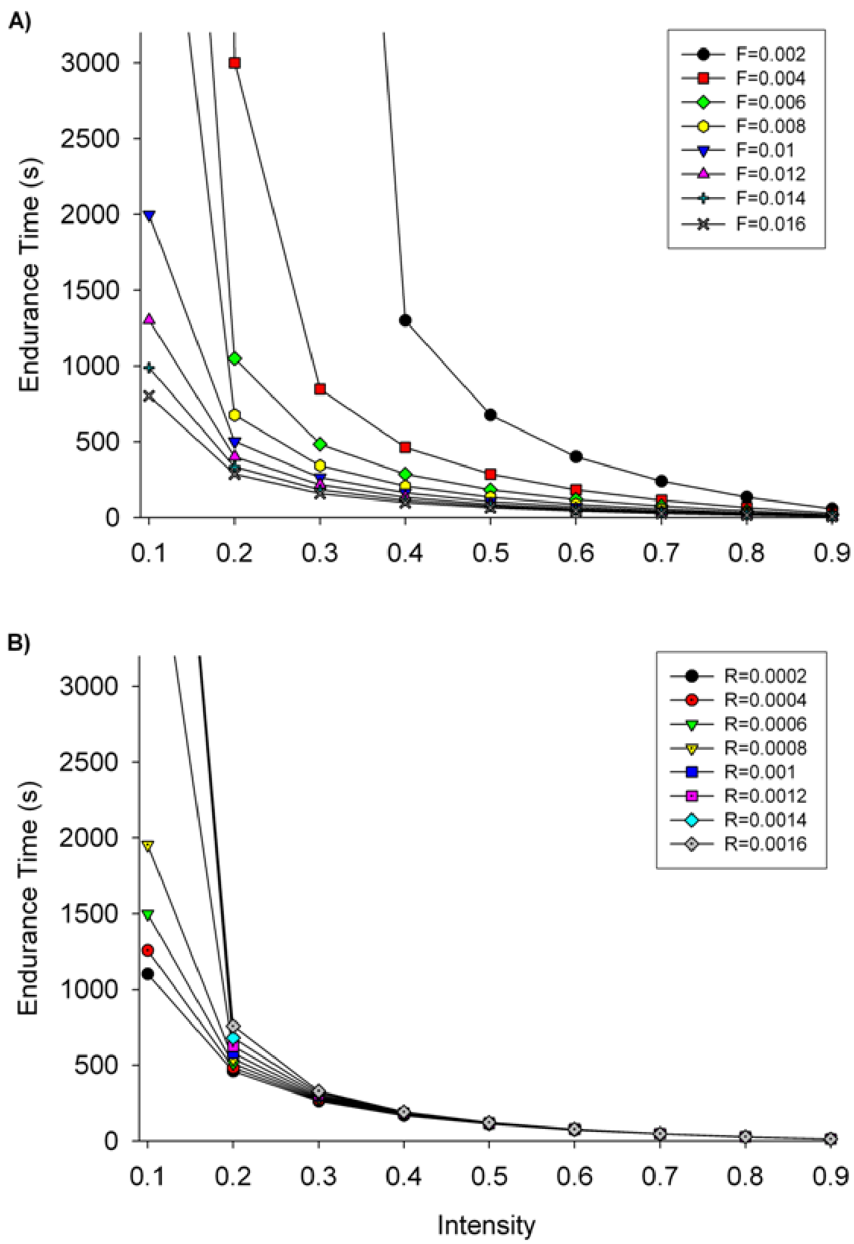

Figure 2- 2: Example sensitivity analyses for F and R parameter values spanning the optimal ranges observed across joints: A) F varying from 0.002 to 0.016 in increments of 0.002, with R fixed to optimal value for elbow (0.00094) and B) R varying from 0.0002 to 0.0016 in increments of 0.0002, with F fixed to optimal value for elbow (0.00912). Note changes in F strongly influence the inflection point of the intensity-ET relationship (e.g. asymptote of the curve), whereas changes in R refine the ET predictions about this curvature.

CHAPTER 3:

INTERMITTENT FATIGUE: META-ANALYSIS

Introduction

Intensity-endurance time (ET) curves for static isometric tasks have been created and studied since Walter Rohmert's original paper (Rohmert, 1960). These curves have been used by ergonomist to calculate work rest cycles and as a way to determine how workers fatigue while performing different job tasks. Recently (Frey Law and Avin, 2010) compiled a large comprehensive analysis to "update" the Rohmert curves for each joint region (ankle, knee, trunk, shoulder, elbow, and hand/grip). These provide more up to date and accurate versions of the static isometric intensity-ET curves first proposed by Rohmert and later studied by others (Rohmert, 1960; Monod and Scherrer, 1965; Hagberg, 1981; Huijgens, 1981; Sjøgaard, 1986; Rose et al., 2000; Garg et al., 2002; El Ahrache et al., 2006). These curves only represent static muscle contractions, whereas workers perform more intermittent and dynamic contractions throughout the work day. Unfortunately, there are no muscle fatigue models that represent the development of fatigue for these more complex contractions (i.e. intermittent work rest cycles).

We operationally define intermittent contractions as a repeated series of static isometric contractions held for a time followed by a rest period. The total time of one contraction and rest period is referred to as the cycle time (CT). The percentage of contraction 'on time' relative to the cycle time is the duty cycle (DC). While sustained static contractions can occur for some tasks, particularly postural muscles maintaining a static posture, many other work tasks may be more similar to intermittent contractions. Thus, for a fatigue model to be a viable tool for ergonomic analyses, it is important to validate the muscle fatigue model for these contractions.

While numerous authors have reported updated versions of the original intensity-ET curve, known as "Rohmert's curve" (Rohmert, 1960; Monod and Scherrer, 1965;

Hagberg, 1981; Huijgens, 1981; Sjøgaard, 1986; Rose et al., 2000; Garg et al., 2002; El Ahrache et al., 2006), there are few statistical models representing fatigue for intermittent contractions. (Iridiastadi and Nussbaum, 2006; Iridiastadi and Nussbaum, 2006b) developed a regression model based on experimental data in subjects for shoulder abduction tasks. They found task intensity, DC, and their interaction (intensity x DC) to be important predictors of ET. However, their data only covered a relatively narrow region of task intensities and DCs, making translation to a generalized model challenging (Figure 3- 1). Thus there are very few empirical models that are useful for predicting muscle fatigue due to intermittent tasks, and no studies have attempted to compile additional data from the literature to better develop statistical models, akin to “Rohmert’s curves,” for intermittent tasks.

The purpose of this study is to develop a useful empirical model to predict muscle fatigue through a wide range of intensities (1-100 % of maximum) and DC (1-100% of cycle time). A systematic review and meta-analysis of intermittent tasks to fit three dimensional statistical models of relative force decline (% decline) as a function of task intensity and DC was performed.

Methods

A comprehensive review of the literature was conducted to determine a range of data points for the % decline across multiple DC’s and maximal voluntary contractions (MVC’s) for each joint. Although ET was the main outcome variable used for sustained isometric tasks, the addition of low DCs and task intensities limit the availability of studies sustained sufficiently long to collect true ET, based on pilot investigations. Instead, the declines in torque production at given points in time were more widely available. For comparison across studies, decay in MVC (% decline) was extracted at a selected range of time points: 30, 60, 90, and 120 seconds across all joints. From each of these time points, a statistical model was created with a 95 % confidence interval.

Systematic Review of Literature

A comprehensive systematic literature search of relevant data relating intermittent isometric contractions with percent decline of force was performed. The search criterion was completed as previously described by (Frey Law and Avin, 2010). Searches of the following databases were performed: PubMed, Cumulative Index to Nursing and Allied Health Literature (CINAHL), Web of Knowledge, and Google Scholar. A total of 17 search terms/keyword combinations were used to elicit relevant articles, including: Intermittent static fatigue, intermittent fatigue, intermittent isometric, endurance intermittent, intermittent and fatigue, isometric and fatigue, and combinations of the above with specific joints: ankle, knee, elbow, trunk, shoulder, elbow, wrist/hand. In addition, early results found that studies on creatine supplementation often incorporated intermittent tasks in a control group, thus was added as a secondary search term. The inclusion/exclusion criteria below were then implemented to include only studies of interest.

Inclusion and Exclusion Criteria

The inclusion criteria included: studies with healthy human subjects, ages between 18-55 years old, intermittent tasks with force/torque data, a task time of at least 30 seconds, and published in English. Exclusion criteria included: dynamic contractions, simultaneous multi-joint testing (e.g. squat lifts), functional tasks, body/limb weight as primary resistance, and electrically stimulated contractions. Similar to (Frey Law and Avin, 2010), data from patient populations or intervention studies (i.e. creatine supplementation) were not used for the analysis, but any control subjects' data were included if available.

Data Analysis

All relevant data were compiled in Excel as described by (Frey Law and Avin, 2010). The authors, number of subjects, whether the subjects were male, female, or mixed, the % effort were compiled in the Excel database; additionally the duty cycle and the percent decline of the MVC and the standard deviation were recorded. The initial and final force values were recorded and the percent decline was calculated from this data. Since this study is only concerned with percent decline at the time points 30, 60, 90, and 120 seconds, data had to be pulled from graphical data reported in the selected papers. The values were extracted using the pixel analysis (Adobe Photoshop, San Jose, CA) (Frey Law and Avin, 2010). The percent decline at the given time points could then be included in the Excel database. Data sets were then established for each joint at each of the four time points. This allows for four graphs per joint at different time points throughout the fatiguing process. Only joints with a minimum of 3 (i.e. three points are needed to define a plane) data points were further analyzed at each time point.

Based on the power relationship observed in the intensity-ET curves for sustained contractions (i.e., 100% DC), a linear relationship exists between log transformed ET and intensity. We hypothesized a similar relationship would be present between %decline in torque and intensity, as well as with DC. Accordingly a log transform was applied to the collected fatigue data points (% decline) and to the independent variables (MVC and DC) from each study. TableCurve3D was used to fit a plane to the transformed data. The plane equation was then log transformed back to be able to predict the %force decline for each discrete time point. The equation for the surface fits the form of Equation 3- 1, where a, b, and c are the model coefficients.

Equation 3- 1: 3D power-surface example

$$\%\ \text{Force Decline} = a * (DC)^{b}(MVC)^{c}$$

Ninety-five percent confidence intervals (95% CI) of the model mean were calculated for the generalized fatigue model at each time point. This was accomplished using Equation 3- 2 and Equation 3- 3. The coefficient of variation (CV) was calculated by finding the standard deviation between multiple data points that had the same independent variables divided by the mean. This was done across all data available, when a minimum of three data points was available at matching MVCs and DCs. The median of all values was used as a global estimate for CV for the complete data set. The complete data set was used instead of each time point due to their being very few data points within each time point that had the same DC and MVC. Thus to gain an accurate view of variability the entire data set was used.

Equation 3- 2: Coefficient of variation calculation

$$CV = stdev/mean$$

Equation 3- 3: 95% confidence interval calculation

$$95\%\ CI = Mean \pm 1.96(CV * Mean)$$

Results

Literature Review

The database search strategy resulted in a total of 2781 potential publications. Search refinements to include only humans and articles written in English decreased the total number of potential articles to 2392. Of these articles 44 met the required inclusion and exclusion criteria. Since there were so few publications that fit the required inclusion and exclusion criteria, static fatigue papers that were used in (Frey Law and Avin, 2010) meta-analysis and fit the inclusion requirements for this study were used to fill in points at the extreme of the surface (DC=1). Of the 194 publications that were used in the prior meta-analysis, only 3 fit the required inclusion and exclusion criteria for this analysis, for a total of 47 studies (torque decline was typically the limiting factor).

The meta-analysis found no studies that met the inclusion and exclusion criteria for the shoulder and trunk joints, the final number of studies and data points, by joint, meeting the required inclusion and exclusion criteria for the rest of the joints is provided in Table 3- 1. Similarly to (Frey Law and Avin, 2010), the hand/grip joint is technically not an individual joint, but studies that included grip, first dorsal interosseus (FDI), abductor pollicis brevis (APB), and adductor pollicis (ADP) were condensed under the grouping 'hand/grip'. The total sample size for each joint (ankle, elbow, hand/grip, knee) ranged from 125 (elbow) to 306 (hand/grip). Table 3- 2 provides a summary of how many data points were found for each joint at each discrete time point. The total number of data points for each joint ranged from 28 (elbow) –to 68 (hand/grip) with a total of 193 data points extracted (Table 3- 2).

Statistical Model

Empirical %decline models for each joint using the log transform method described above were calculated using all the data points collected for each joint and a generalized % decline model (Figure 3- 2-Figure 3- 6). The model coefficients and the R^2 values for each joint region are described in Table 3- 3. The 95% CI was only calculated for the generalized model (Figure 3-7) due to the small number of data points used to create the surfaces at the individual joints.

Discussion

The goal of this study was to develop empirical muscle fatigue models for intermittent tasks for each joint region. Overall the data appear to be partially consistent with our hypothesized surface, relating torque decline to task intensity and DC.

Unfortunately there were not enough studies that fit the exclusion and inclusion criteria to get surfaces for the shoulder and trunk joint regions. There were enough data points to get surfaces for the other joint regions; however there is very little information in the literature for low intensity tasks at low DC. Instead, most of the research available focused on DC and MVCs ≥ 50%, with most of the data at these high regions curve fitting to this data become volatile (Table 3- 1). That is because with most of the data in one specific area the surface does not know what direction to pull towards. This can be viewed by observing the hand/grip surfaces (Figure 3- 4). Since most of the data revolve around 50% DC and 100% MVCs the surface peaks at around 50% DC instead of around 100% DC, which is observed at the other joint regions and is clearly observed in the generalized surface (Figure 3- 6).

This study has determined that more data are needed to improve these empirical models, more specifically lower intensities and DC need to be studied. However, this is not an elementary task. It is already known from numerous studies (Rohmert, 1960; Monod and Scherrer, 1965; Hagberg, 1981; Huijgens, 1981; Sjøgaard, 1986; Rose et al., 2000; Garg et al., 2002) that low intensity continuous isometric tasks can be performed for hours before reaching the ET. This time will be amplified by adding rest periods to the task, due to the muscle being able to recover during the rest periods. For this specific reason, this study focused on modeling fatigue due to intermittent tasks on force decline instead of the ET.

This study focus on four time points that were believed to have sufficient data available in the literature to create empirical fatigue response curves to compare to our fatigue model (Chapter 4). Although there may still be data available that was not yet found, this chapter has outlined a method for developing 3D fatigue response curves at various time points for intermittent tasks. These surfaces can be improved by collecting more data points at these lower intensities. Data can also be collected at more time points (e.g. 200, 300, 400 seconds) to get an appropriately more complete picture on how intermittent tasks at various intensities and work cycles affect different joint regions.

Although intensity-ET relationships are currently used for ergonomic analysis, modeling the relative torque decline due to intermittent work may be a more useful ergonomic tool. This study developed a model that provides a more developed picture into what is occurring at the muscle level (i.e. decline in force production). Empirical muscle fatigue models for intermittent contractions have not been developed for the full range of intensities and DC, thus empirical models for static contractions have been used. This study has established that empirical models for intermittent contractions can be developed and with this information new appropriate rest allowances, or job rotation cycles could be implemented.

More validation efforts and studies are needed due to the current models are only appropriate for short task time (< 2 minutes), but these surfaces provide new insight into muscle fatigue during intermittent tasks. This insight could have huge implications in ergonomics where the goal is to have the worker be the most effective while at the same time keeping the body refreshed and free of musculoskeletal disorders.

Table 3- 1: Studies included in the meta-analysis by joint for ankle, knee, elbow, and hand/grip, listed by author

						Discrete Time Points			
Joint	**Author, Date**	**N**	**Sex**	**Intensity (%MVC)**	**DC (%)**	**30s**	**60s**	**90s**	**120s**
Ankle									
	(Alway, 1991)	**24**	**M**	**100**	**100**				**X**
	(Bemben et al., 1996)	**101**	**M**	**100**	**40**		**X**		
	(Birtles et al., 2002)	**22**	**MX**	**100**	**50**				**X**
	(Birtles et al., 2003)	**10**	**MX**	**100**	**50**		**X**		**X**
	(Chung et al., 2007)	**12**	**M**	**100**	**50**	**X**	**X**	**X**	**X**
	(Egana and Green, 2007)	**14**	**M**	**30,40,50,60,80,90**	**33**		**X**		**X**
	(Fimland et al., 2010)	**13**	**M**	**100**	**83**	**X**	**X**	**X**	**X**
	(Kent-Braun et al., 1994)	**8**	**MX**	**10**	**40**				**X**
	(Kent-Braun et al., 2002)	**20**	**MX**	**10**	**40**				**X**
	(Kent-Braun and Ng, 1999)	**8**	**MX**	**100**	**100**	**X**	**X**	**X**	**X**

Table 3-1: Continued

						Discrete Time Points			
Joint	**Author, Date**	**N**	**Sex**	**Intensity (%MVC)**	**DC (%)**	**30s**	**60s**	**90s**	**120s**
	(Lanza et al., 2004)	9	M	100	50	X	X	X	X
	(Russ and Kent-Braun, 2003)	16	M/F	100	50		X		X
	(Russ et al., 2008)	16	M/F	100	70		X		X
	(Tachi et al., 2004)	5	M	50	60	X	X	X	X
	Totals: 14 studies	N=278		Range: 10-100	Range: 33-100				
Knee									
	(Armatas et al., 2010)	13	M	100	50	X	X	X	X
	(Bemben et al., 2001)	19	M	100	50		X		
	(Bigland-Ritchie et al., 1986)	6	MX	50	60	X	X	X	X
	(Bigland-Ritchie et al., 1986b)	10	MX	50	60	X	X	X	X
	(Burnley, 2009)	8	M	100	60	X	X	X	X
	(Hamada et al., 2003)	8	M	100	63	X	X	X	X

Table 3-1: Continued

Joint	Author, Date	N	Sex	Intensity (%MVC)	DC (%)	Discrete Time Points 30s	60s	90s	120s
	(Katayama et al., 2006)	6	M	62	50			X	
	(Mazzini et al., 2001)	28	MX	100	50	X	X		
	(Ordway et al., 1977)	27	M	100	50	X	X	X	X
	(Stackhouse et al., 2001)	20	MX	100	71	X	X	X	X
	Totals: 11 studies	N=145		Range: 50-100	Range:50-71				
Elbow									
	(Allman and Rice, 2003)	6	M	60	60		X		
	(Bemben et al., 2001)	19	M	100	50		X		
	(Jakobi et al., 2000)	14	M	50	60	X	X	X	X
	(Jubeau et al., 2012)	12	M	100	21		X	X	X

Table 3-1: Continued

Joint	Author, Date	N	Sex	Intensity (%MVC)	DC (%)	Discrete Time Points 30s	60s	90s	120s
	(Mazzini et al., 2001)	**28**	**MX**	**100**	**50**	**X**	**X**		
	(Muthalib et al., 2010)	**10**	**M**	**100**	**21**	**X**	**X**	**X**	**X**
	(Ordway et al., 1977)	**27**	**M**	**50**	**100**	**X**	**X**	**X**	**X**
	(Taylor et al., 2000)	**9**	**MX**	**100**	**50**	**X**	**X**	**X**	**X**
	Totals: 8 studies,	**N=125**		**Range: 50-100**	**Range:21-100**				
Hand/Grip									
	(Bemben et al., 1996)	**101**	**M**	**100**	**40**		**X**		
	(Benwell et al., 2007b)	**12**	**MX**	**100**	**70**		**X**		**X**
	(Benwell et al., 2007)	**8**	**MX**	**30**	**60**				**X**
	(Benwell et al., 2006)	**15**	**MX**	**100**	**70**		**X**		**X**

Table 3-1: Continued

						Discrete Time Points			
Joint	**Author, Date**	**N**	**Sex**	**Intensity (%MVC)**	**DC (%)**	**30s**	**60s**	**90s**	**120s**
	(Ditor and Hicks, 2000)	**12**	**M/F**	**100**	**71**	**X**		**X**	
	(Duchateau and Hainaut, 1985)	**18**	**MX**	**86**	**33, 50, 67**	**X**	**X**		
	(Fujimoto and Nishizono, 1993)	**8**	**M**	**40**	**60**				**X**
	(Fulco et al., 1994)	**8**	**M**	**50**	**50**		**X**		**X**
	(Fulco et al., 2001)	**33**	**M/F**	**50**	**50**		**X**		**X**
	(Gonzales and Scheuermann, 2007)	**32**	**M/F**	**50**	**50**				**X**
	(Liu et al., 2005)	**12**	**MX**	**100**	**67**	**X**	**X**	**X**	**X**
	(Pitcher and Miles, 1997)	**8**	**M**	**80**	**54**	**X**	**X**	**X**	**X**
	(Vigouroux and Quaine, 2006)	**19**	**MX**	**80**	**50**	**X**	**X**	**X**	**X**

Table 3-1: Continued

						Discrete Time Points			
Joint	**Author, Date**	**N**	**Sex**	**Intensity (%MVC)**	**DC (%)**	**30s**	**60s**	**90s**	**120s**
	(Wood et al., 1997)	**20**	**F**	**16, 32, 48**	**21, 31, 63**		**X**		**X**
	Totals: 14 studies	**N=306**		**Range: 16-100**	**Range:21-71**				

Table 3- 2: The number of percent torque decline data points per discrete time point for each joint region

Joint	30 seconds	60 seconds	90 seconds	120 seconds	Total
Ankle	**7**	**19**	**7**	**23**	**56**
Elbow	**6**	**10**	**6**	**6**	**28**
Hand/Grip	**11**	**20**	**14**	**23**	**68**
Knee	**10**	**12**	**10**	**9**	**41**
General (Total)	**34**	**61**	**38**	**61**	**193**

Table 3- 3: Model coefficients for each time point by joint, where intensity (MVC) and duty cycle (DC) are values between 0 and 100 percent, $\%Decline=a*(DC)^{b}*(MVC)^{c}$.

Model	**a**	**b**	**c**	**R^2**
30 seconds				
Ankle	0.058086	0.35375975	0.80967812	0.592
Elbow	0.000147	1.3931424	1.2184178	0.778
Hand/Grip	$2.65*10^{-12}$	-0.45963195	6.7779481	0.628
Knee	0.019551	0.6668447	0.82517338	0.202
General	0.000523	0.96044017	1.3107351	0.346
60 seconds				
Ankle	0.022638	1.6186979	-0.018837251	0.671
Elbow	0.003113	1.1300553	0.94296213	0.894
Hand/Grip	12.38852	-0.22351518	0.20425368	0.018
Knee	0.009352	1.1569275	0.66653691	0.358
General	0.133775	0.81883857	0.32617479	0.219
90 seconds				
Ankle	0.557265	0.81836074	0.082173286	0.534
Elbow	0.000843	1.1012282	1.3256107	0.990
Hand/Grip	$7.61*10^{-9}$	-0.23569634	4.9924243	0.968
Knee	0.036183	0.89686635	0.67788087	0.470
General	0.030335	0.88558254	0.68635163	0.457

Table 3- 3: Continued

Model	**a**	**b**	**c**	$\mathbf{R^2}$
120 seconds				
Ankle	0.01002	1.409681	0.464828	0.858
Elbow	0.0026	0.99020549	1.216966	0.986
Hand/Grip	18.53202	-0.30152	0.287124	0.157
Knee	0.093545	0.77112401	0.61915753	0.317
General	0.093675	0.765264	0.565585	0.560

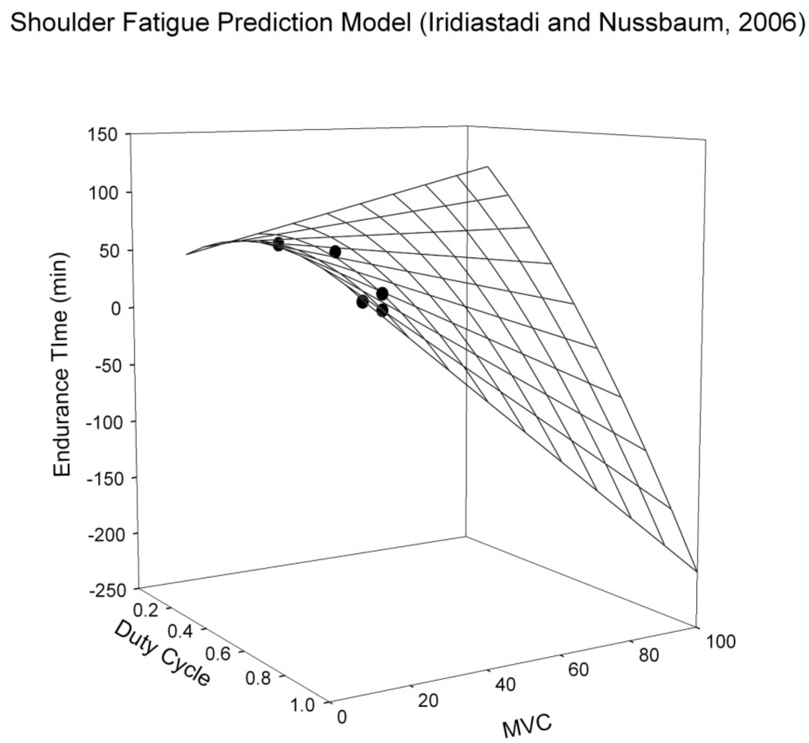

Figure 3- 1: 3D empirical shoulder fatigue prediction model plotted with the data points used to develop the surface. (Iridiastadi and Nussbaum, 2006)

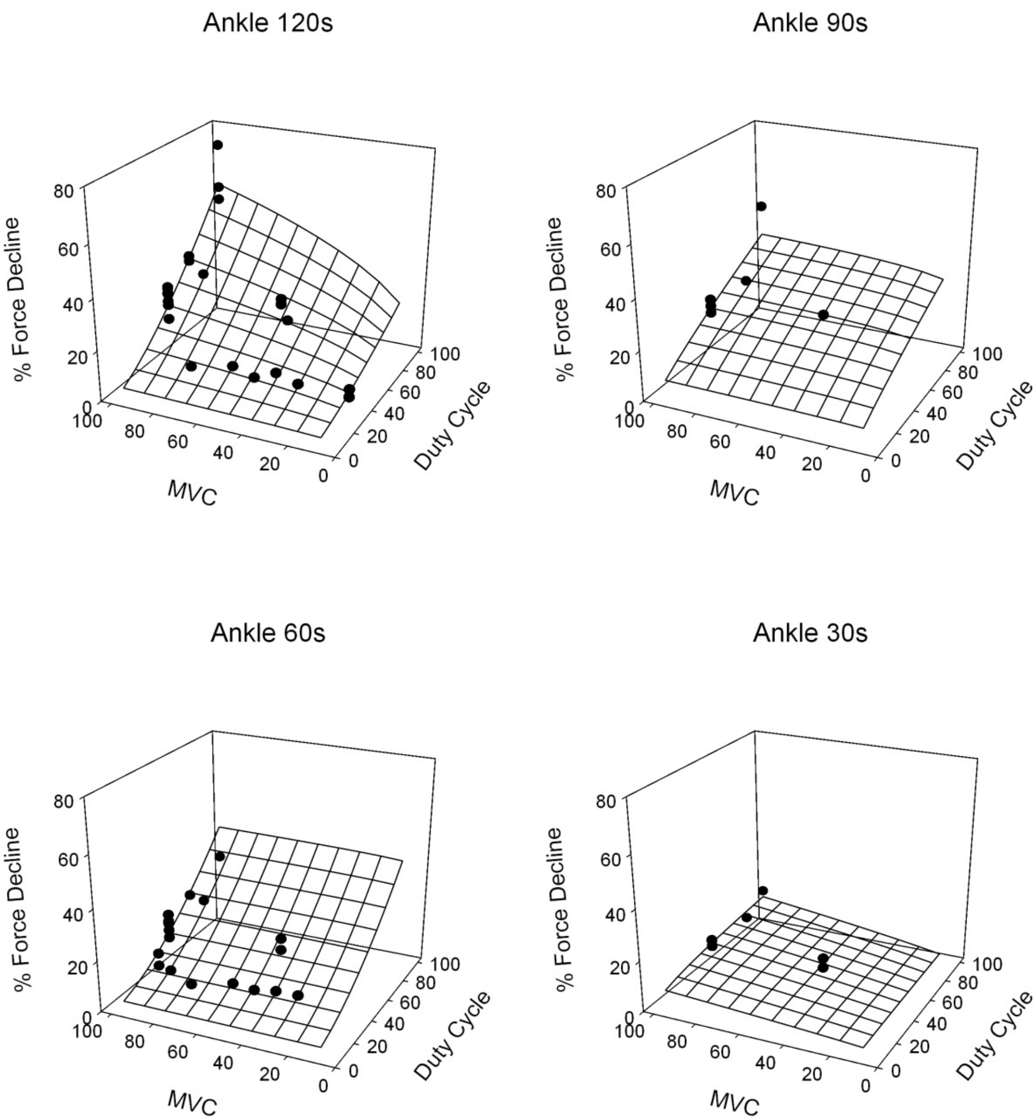

Figure 3- 2: Empirical percent torque decline model for the ankle at the four discrete time points (30, 60, 90, 120 seconds) and the data points used to create the empirical model.

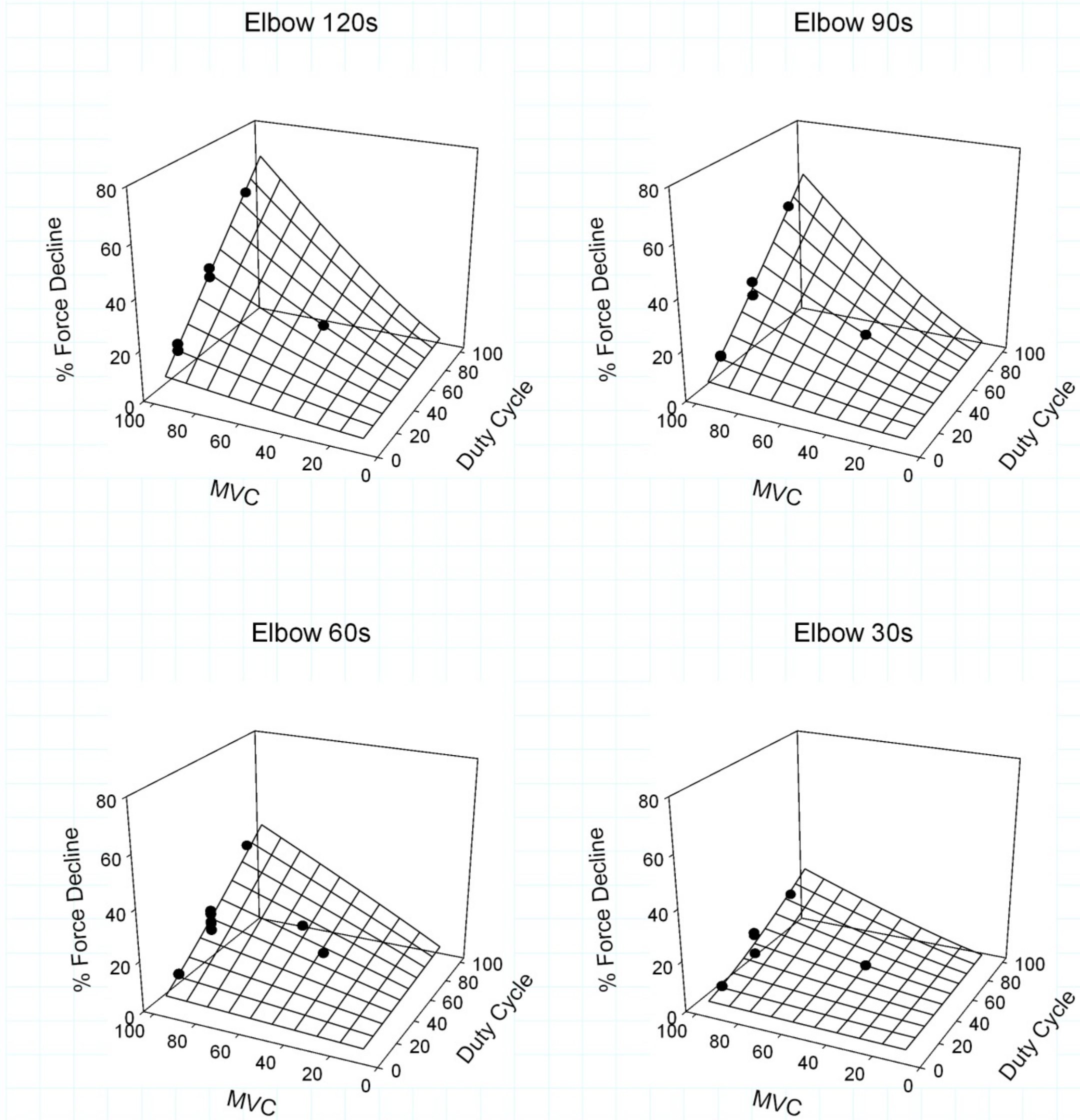

Figure 3- 3: Empirical percent torque decline model for the elbow at the four discrete time points (30, 60, 90, 120 seconds) and the data points used to create the empirical model.

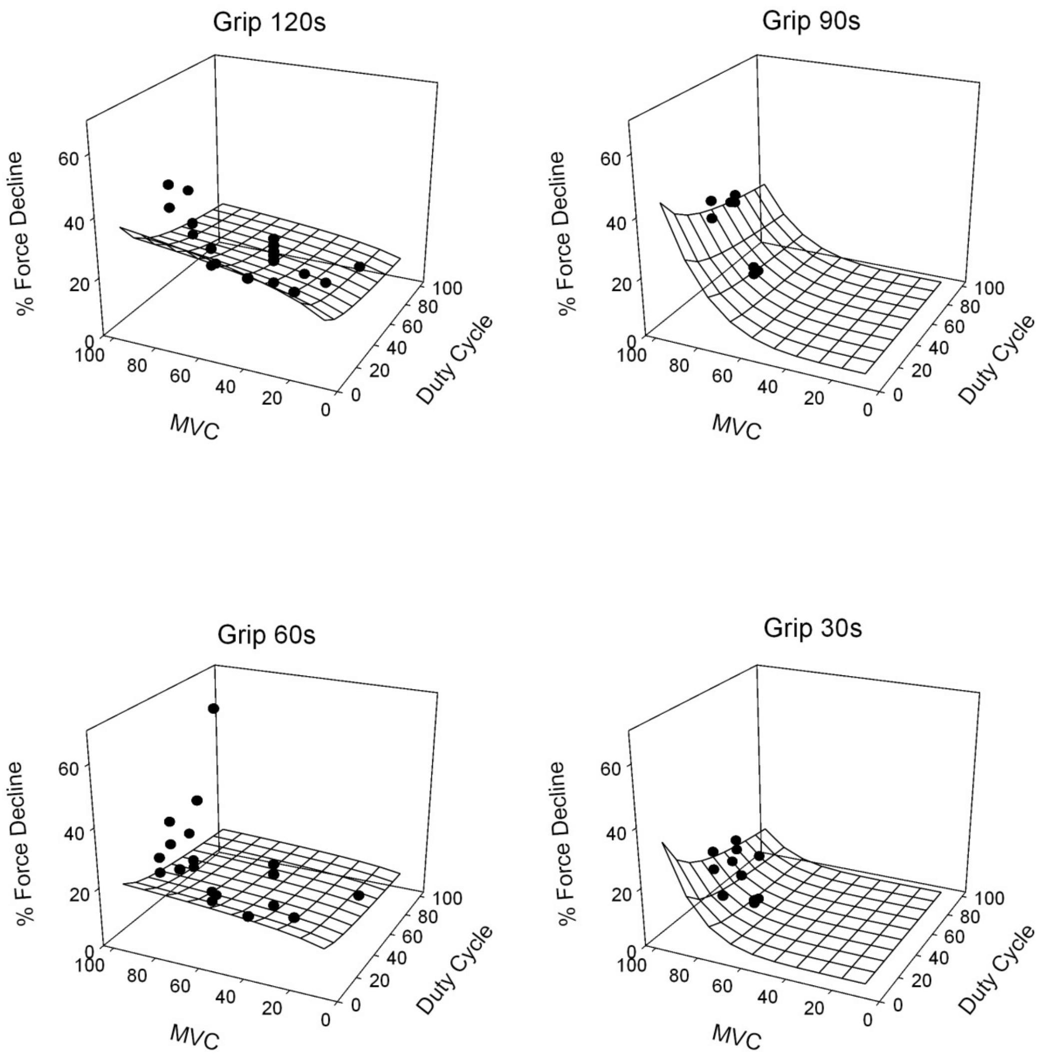

Figure 3- 4: Empirical percent torque decline model for the hand/grip at the four discrete time points (30, 60, 90, 120 seconds) and the data points used to create the empirical model.

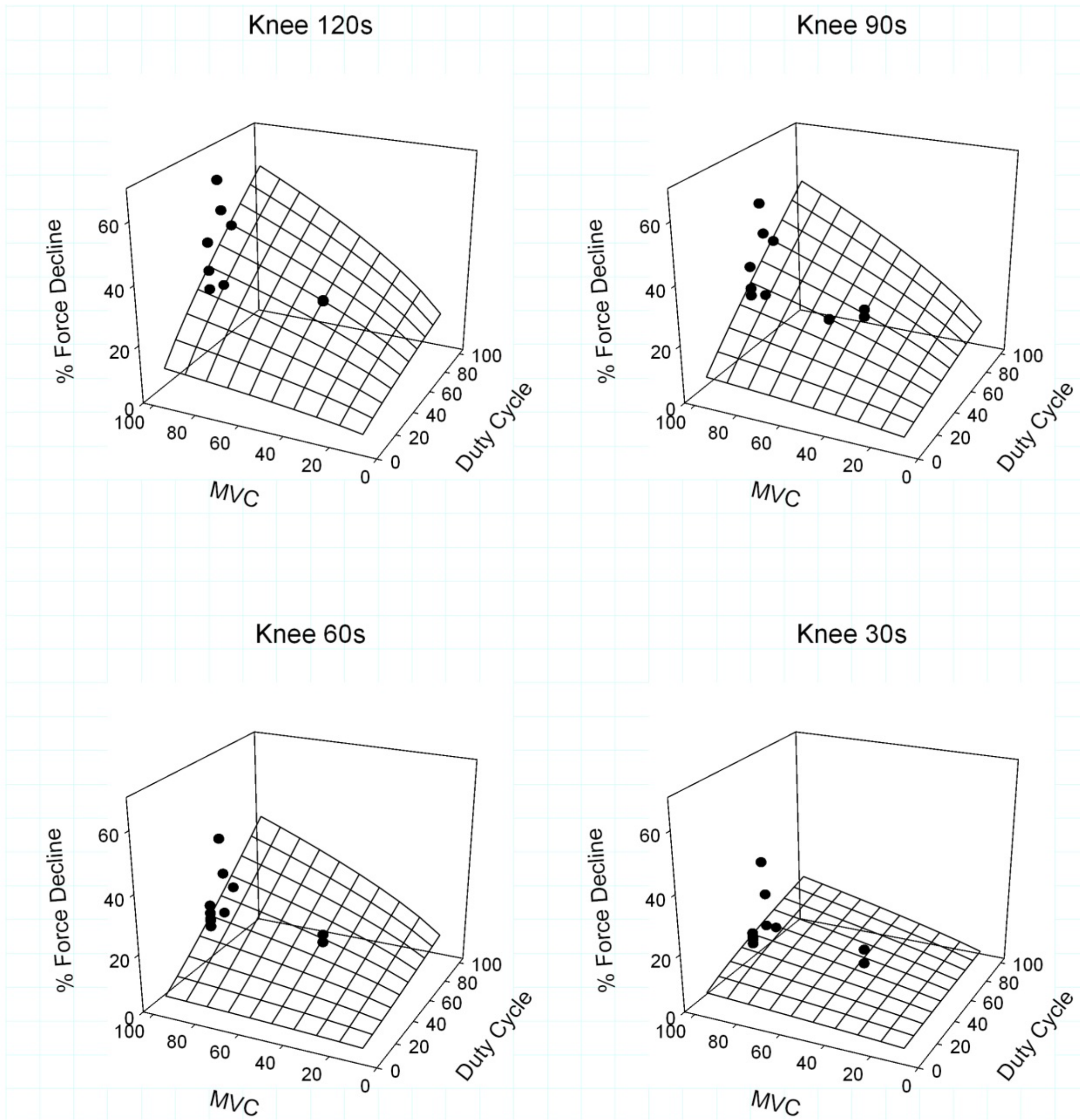

Figure 3- 5: Empirical percent torque decline model for the knee at the four discrete time points (30, 60, 90, 120 seconds) and the data points used to create the empirical model.

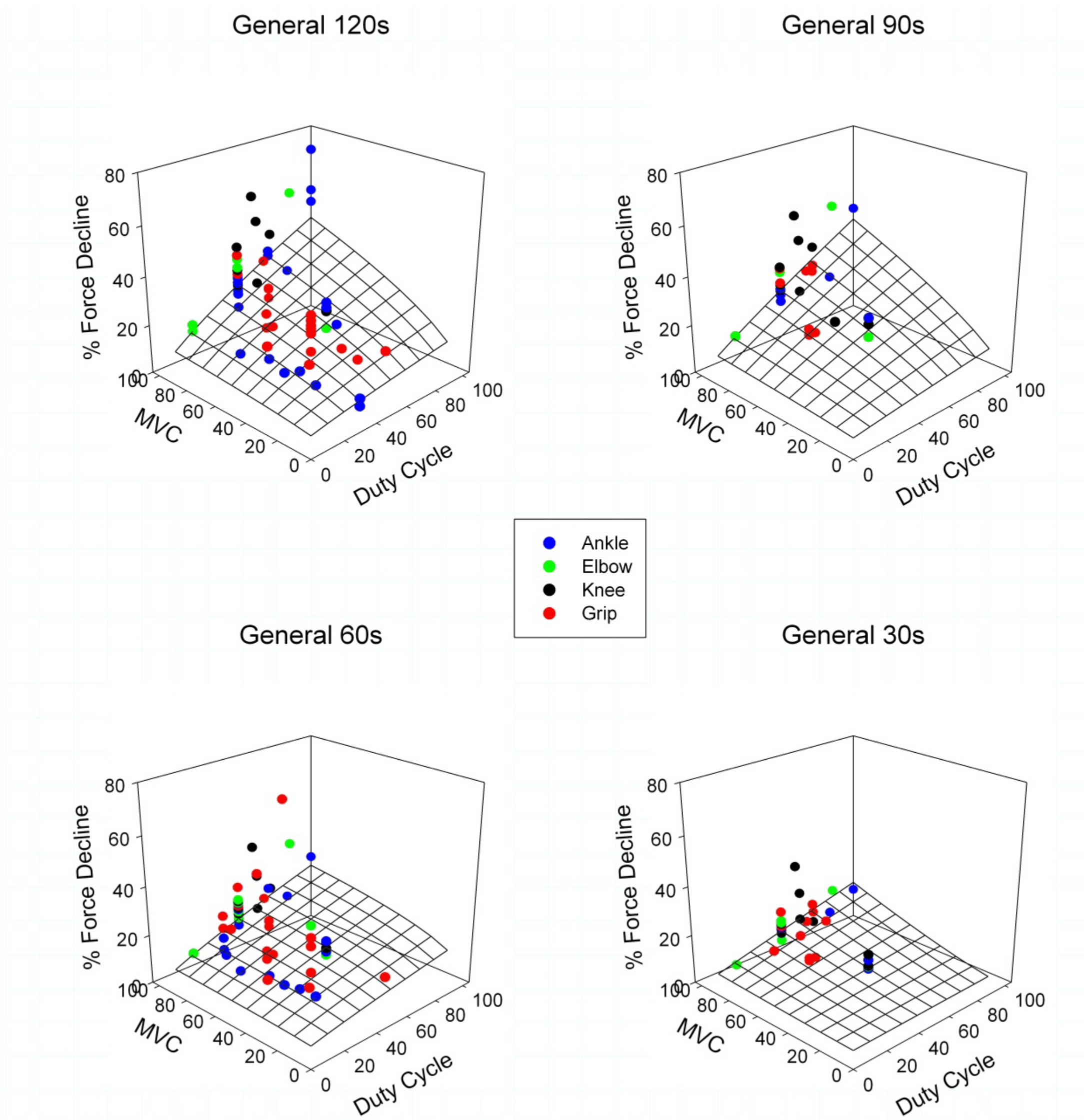

Figure 3- 6: General empirical percent torque decline model at the four discrete time points (30, 60, 90, 120 seconds) and the data points from each joint region used to create the empirical model.

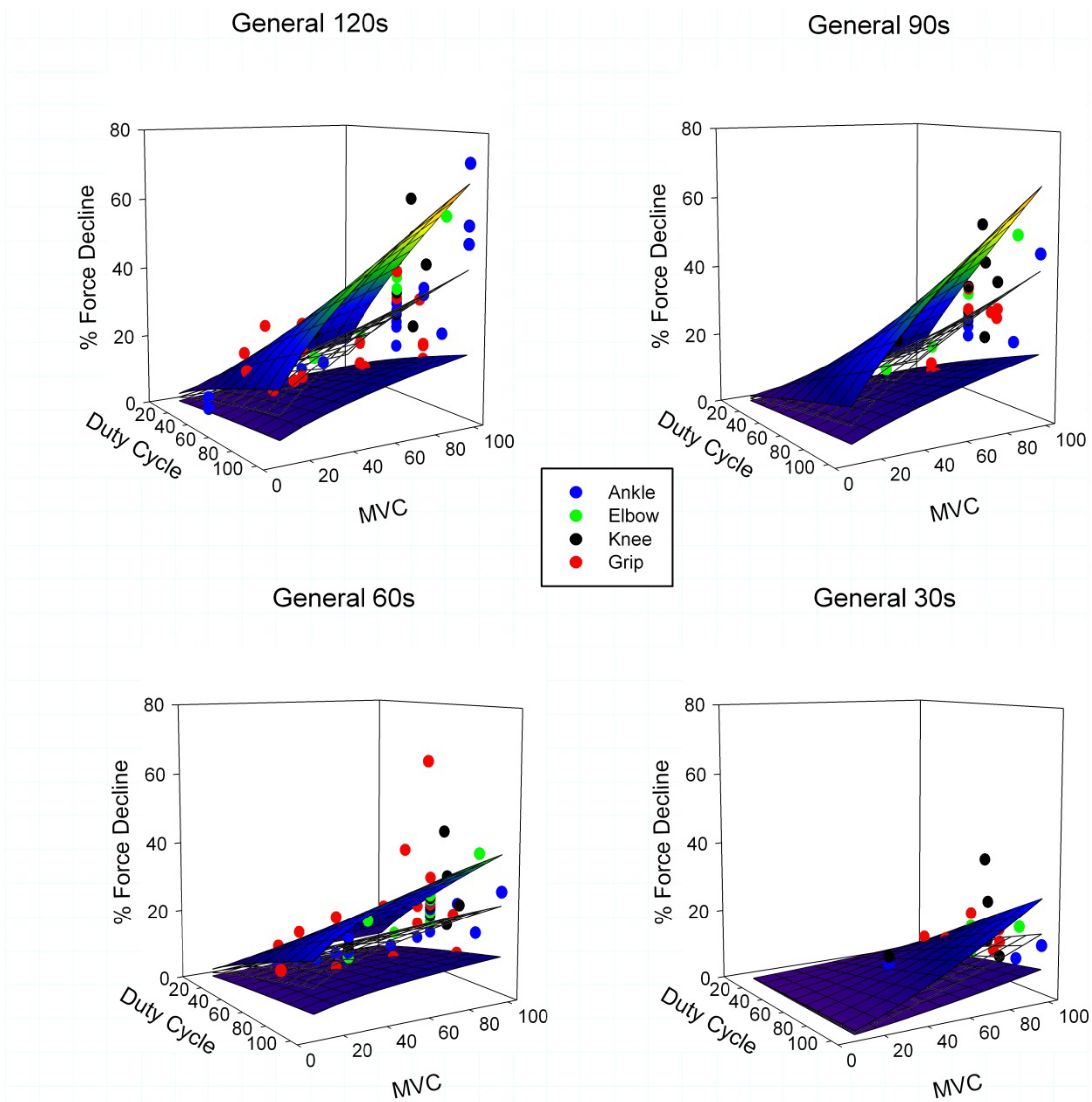

Figure 3- 7: General empirical percent torque decline model at the four discrete time points (30, 60, 90, 120 seconds) and the data points from each joint region used to create the empirical model. The 95% CI for each of the models are also shown as the colored surfaces.

CHAPTER 4:
PREDICTIVE INTERMITTENT TASK FATIGUE RESPONSE SURFACES

Introduction

Having a reliable model that can predict muscle fatigue response per joint has huge implications in industrial settings. Muscle fatigue is one risk factor for musculoskeletal injury (Sejersted and Sjøgaard, 2000), however there are very few available models that can predict muscle fatigue due to sustain isometric contractions. There are even less that can accurately predict muscle fatigue responses for intermittent tasks. The relationship between intensity and endurance time (ET) was first studied by (Rohmert, 1960). Since this original publication, others (Monod and Scherrer, 1965; Hagberg, 1981; Huijgens, 1981; Sjøgaard, 1986; Rose et al., 2000; Garg et al., 2002; El Ahrache et al., 2006; Frey Law and Avin, 2010) have developed updated “Rohmert Curves” (review of MET models refer to Table 1-1). These empirical muscle fatigue models for static isometric contractions are useful for determining how muscles fatigue under a constant load. However, these static contractions are not those found while performing daily work tasks.

The types of contractions that are seen in industry are more intermittent in nature (i.e. there is a contraction and then a rest period). (Iridiastadi and Nussbaum, 2006; Iridiastadi and Nussbaum, 2006b) developed a regression model for intermittent tasks based on experimental data in 90 subjects for shoulder abduction tasks. However this study was focused around a limited number duty cycles (DC) (20-80%) and maximum voluntary contractions (MVC) (12-30%). When Iridiastadi and Nussbaum’s (2006) model is expanded to include the full range of DC and MVCs (i.e. 10-100%) the empirical model becomes negative at the extremes (Figure 3- 1). Thus there is a need for a model to be able to predict the muscle fatigue response across the full range of intensties and DC.

Xia and Frey Law, (2008) proposed an analytical fatigue model that was capable of predicting fatigue due to a variety of tasks, though it had not yet been validated against a “gold standard” empirical model. The validation of the proposed fatigue model by (Xia and Frey Law, 2008), began with optimizing the fatigue parameters (F and R) to a “gold standard” isometric intensity-ET relationship (Chapter 2). The “gold standard” empirical model was based on data from a meta-analysis of available literature on sustained isometric contractions (Frey Law and Avin, 2010). This investigation provided evidence that the model could predict muscle fatigue for isometric contractions. However, the accuracy of the model (with its optimized F and R parameters for isometric tasks) had yet to be investigated for intermittent tasks.

In order to compare the model against a “gold standard” empirical model for intermittent tasks, a meta-analysis of available data for the percent torque decline in force for a variety of DC and MVC was conducting (Chapter 3). percent torque decline was chosen over modeling Intensity-ET relationships for intermittent tasks due to the long time periods that are needed to get ET information at low intensities at low DCs. Intensity-ET relationships such as the curves presented by (Frey Law and Avin, 2010), demonstrate that sustained tasks at low intensities (15% MVC) the ET can be upward of 1.1 hours. Tasks at low intensities and low DCs would be able to be sustained magnitudes longer than the low intensity static task due longer rest periods compared to contractions. Taking this limitation into account it was determined that instead of modeling ETs, the percent decline in torque would be modeled.

The meta-analysis resulted in a “gold standard” empirical fatigue response surfaces for determining the percent torque decline for four discrete time points, similar to (Frey Law and Avin, 2010). An empirical 95% CI (eCI) for these surfaces was then calculated using the coefficient of variation between the found data points. These response surfaces and eCI's were found in order to have a systematic approach to validating the predictive response surfaces.

Though there are many ways to validate this model, percent torque decline surfaces will be used to investigate model's (Xia and Frey Law, 2008) ability to predict muscle fatigue due to intermittent tasks. Thus the goals of this chapter are to: 1) qualitatively and quantitatively compare the predicted surfaces vs. the empirical surfaces found in Chapter 3 and 2) calculate the predictive 95% confidence interval (pCI) and determine what percent of the data points found in by the meta-analysis can accurately be predicted by the model.

Methods

Using the empirical models developed in Chapter 3 as the "gold standard", we assessed the differences (i.e. errors between the predictive model estimates for & decline in force vs the expected values. First the predictive surfaces were qualitatively analyzed with both the data points found by the meta-analysis. The model was run for each of the four discrete time points (30, 60, 90, and 120s) in Matlab (Mathworks, Natick, MA). The surface points were exported to SigmaPlot and graphed with the data points found for each joint (ankle, elbow, hand/grip, knee, and general) during the meta-analysis (Chapter 3).

Then the shapes of the predictive response surfaces were qualitatively assessed with the empirical model by graphing each surface on top of each other (SigmaPlot) for each joint. This allowed the shapes to be qualitatively analyzed to determine whether the shapes of the predicted surfaces match that of the empirical surfaces.

Second the predicative response surfaces were quantitatively assessed vs. the empirical response surfaces by determining the percent of the predictive surface in between the 95% eCI. The percent of the predicted surface that fit between the 95percent torque eCI was determined by comparing the percent torque decline for a range of DC and MVC points (10-100% with steps of 10%) with the 95% eCI. The absolute and root mean square errors were also calculated between the empirical and predictive surfaces for each joint at each of the discrete time points in the same manner.

Lastly, the percent of data points that fell in between the predictive 95% CI (pCI) was assessed. The percent of data points for each joint within the 95% pCI was determined for each joint at each discrete time point to analyze the effectiveness of the predicted model. The 95% pCI of the predicative means were calculated for the each of the joints with empirical models (e.g. ankle, elbow, hand/grip, and knee) and a generalized fatigue model for each of the discrete time points. This was accomplished using Equation 4- 1, where the coefficient of variation (CV) was determined in Chapter 3.

Equation 4- 1: 95% Predicted confidence interval

$$95\%\ pCI = \ Predicted\ \pm 1.96(CV * Predicted)$$

Results

The predictive surfaces were found to qualitatively predict the spread of the data points found by the meta-analysis (Figure 4- 1-Figure 4- 5). The predicted surfaces also generally matched the empirical models (Figure 4- 6-Figure 4- 10), except with the hand/grip predicted surfaces varying the most from the empirical surfaces (Figure 4- 8). The qualitative analysis also found most of the data points found by the meta-analysis fell between the 95% pCI (Figure 4- 11-Figure 4- 15).

From the quantitative analysis, it was found the percent of the predicted surfaces within the 95% eCI ranged from 8-95%. The abs error was also found to range from 0.02 sec to -16.52 sec and the RMS error ranged from 23.62 sec to 238.01 sec (Table 4- 1). The percent of the data points from the meta-analysis that fell within the 95% pCI ranged from 45 to 100% (Table 4- 2).

Discussion

The shape of the predicated 3D surfaces of percent torque decline as a function of intensity and DC were found to resemble the empirical surfaces, except at the hand/grip joint (Figure 4- 8). From this qualitative analysis it can be concluded that the model does predict the right percent torque decline response that was determined by the meta-analysis.

Quantitative analysis showed the mean absolute errors of the surfaces varied from 0.02 to -15.10 seconds and the RMS errors varied from 23.62 to 186.25 seconds (Table 4- 1). The percent of the predicted surface within the 95% eCI ranged from 30-95% (Table 4- 1)This indicates that while there are some large differences from each other they are overall very similar in shape. This provides further evidence that the predictive model accurately models what is found experimentally. However, this is not conclusive evidence since the predicted surfaces have not been compared to the data collected.

The final quantitative analysis that was performed was determining a 95% pCI for the model results and determining how well the predictive model predicts the data found by the meta-analysis. The joints with their 95% pCI were graphed with the data points found by the meta-analysis (Figure 4- 11-Figure 4- 15). From these graphs, it can be seen that the 95% pCI encompasses most of the data points; this was validated when the percent of the data points within the 95% pCI was calculated to range between 45-100% (Table 4- 2).

As briefly mentioned earlier, the predicted 3D surface of the hand/grip joint region varies the most qualitatively and quantitatively from the empirical surface. This can be explained by the large number of data points found at the low DC and high intensities. Thus the empirical model becomes steeper at that end of the surface instead of at the high DC and high MVC end. This difference between these surfaces does not indicate that the predicted surface is incorrect; instead it highlights the need for more research at a wider range of DC and MVCs so the complete response surface can be determined.

The hand/grip data points from the meta-analysis was shown to be predicted by the model fairly well (Table 4- 2). However this joint region had the fewest number of data points are encompassed by the 95% pCI. This is likely due to the CV being found between all joint regions instead of being determined for each joint region individually. This was originally done due to the lack of data points for each joint region compared to them as a whole. Thus it was decided to use a general CV instead of being by joint. While this joint region shows the need for individual CVs, it also highlights the need for more data points at each of the joint regions and discrete time points.

The validations of the muscle fatigue model have focused around the optimization of the F and R parameters (Chapter 2). It is these parameters that define the response of the model. Chapter 2 showed that these parameters accurately predict the ET of isometric contractions at various intensities. This chapter assumed that the F and R parameters would remain the same as the optimized parameters found in Chapter 2. The RMS errors found in Chapter 2 ranged from 2.7 - 28.2 seconds (Table 2-2) for isometric contractions. This validation effort found RMS errors ranged from 23.62-238.01 seconds.

While comparing errors between two different tasks (isometric vs. intermittent) cannot be quantitatively analyzed, qualitatively it shows that there is more variation between the intermittent predicted surfaces vs. the isometric intensity-ET curves. As previously discussed, this could be due to the lack of a complete set of percent torque decline data as a function of intensity and DC. However this could also be due to the R parameter being optimized with no rest periods (the R parameter determines the “flow” from fatigued to resting). When the muscle is not contracting different recovery mechanisms could be involved, thus the “flow” from fatigued to resting could be faster due to increased blood flow, or something else.

This study has shown that the predicted 3D surfaces of torque decline as a function of intensity and DC are similar to those found by the meta-analysis and can predict experimental points (Chapter 3). From these findings it can be concluded that the proposed fatigue model by (Xia and Frey Law, 2008) with the optimized parameters (Chapter 2), can accurately predict the percent muscle torque decline due to intermittent tasks at these selected discrete time points. Through this validation effort, the question has raised the question whether more data points need to be collect, or if the R parameter needs to be modified due to the increased blood flow during rest periods. Further research needs to be done before the model can be called accurate for all types of work, and can be used for ergonomics. Until those research efforts are accomplished this model has been proven to be accurate for predicting torque decline as a function of intensity and DC for short task durations, up to 120 seconds.

Table 4- 1: Errors between the empirical models and the predictive models and the percent of the predictive surface within the empirical 95% CI for each joint and at each discrete time point.

	% Within Empirical 95% CI				ABS Error (s)				RMS Error (s)			
Joint	30s	60s	90s	120s	30s	60s	90s	120s	30s	60s	90s	120s
Ankle	76	72	56	30	0.02	8.07	5.10	0.02	34.02	129.63	85.63	52.15
Elbow	83	95	34	33	-2.12	-2.34	-6.20	-8.30	23.62	28.72	74.82	96.31
Hand/Grip	8	39	11	33	-5.32	-4.58	-16.52	-10.99	92.66	133.31	228.83	238.01
Knee	44	30	34	40	-5.37	-9.39	-12.57	-15.10	73.60	115.67	154.59	186.25
General	30	74	95	79	-3.16	-2.49	-4.46	-6.23	38.85	65.23	72.89	108.67

Table 4- 2: The percent of the data points within the predictive 95% CI for each joint and at each discrete time point.

Joint	30s	60s	90s	120s
Ankle	86%	74%	71%	83%
Elbow	83%	100%	100%	100%
Hand/Grip	73%	45%	63%	52%
Knee	70%	83%	91%	89%
General	79%	74%	88%	78%

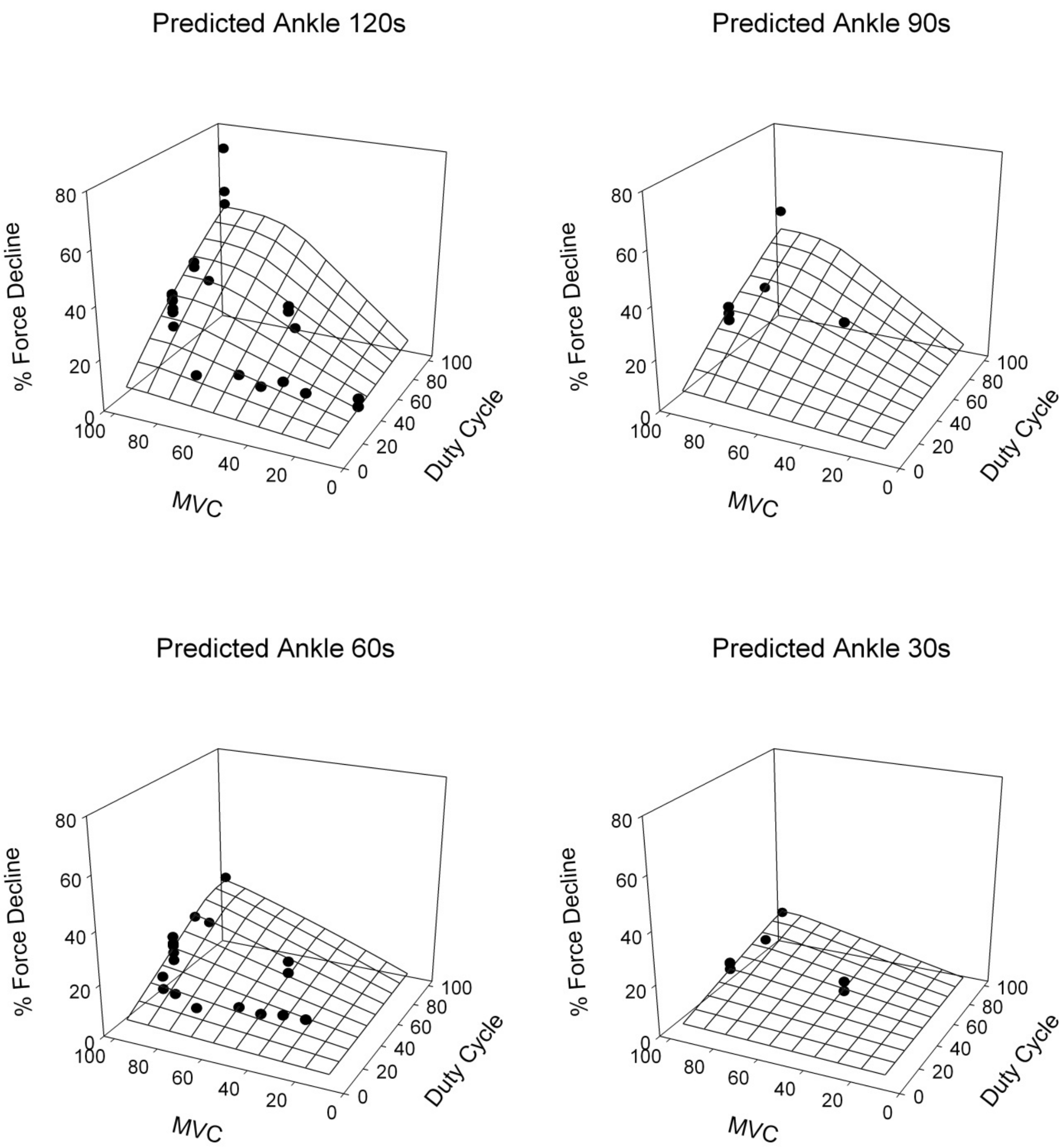

Figure 4- 1: Predictive percent torque decline fatigue response surface for the ankle and the data points found from the meta-analysis at each discrete time point.

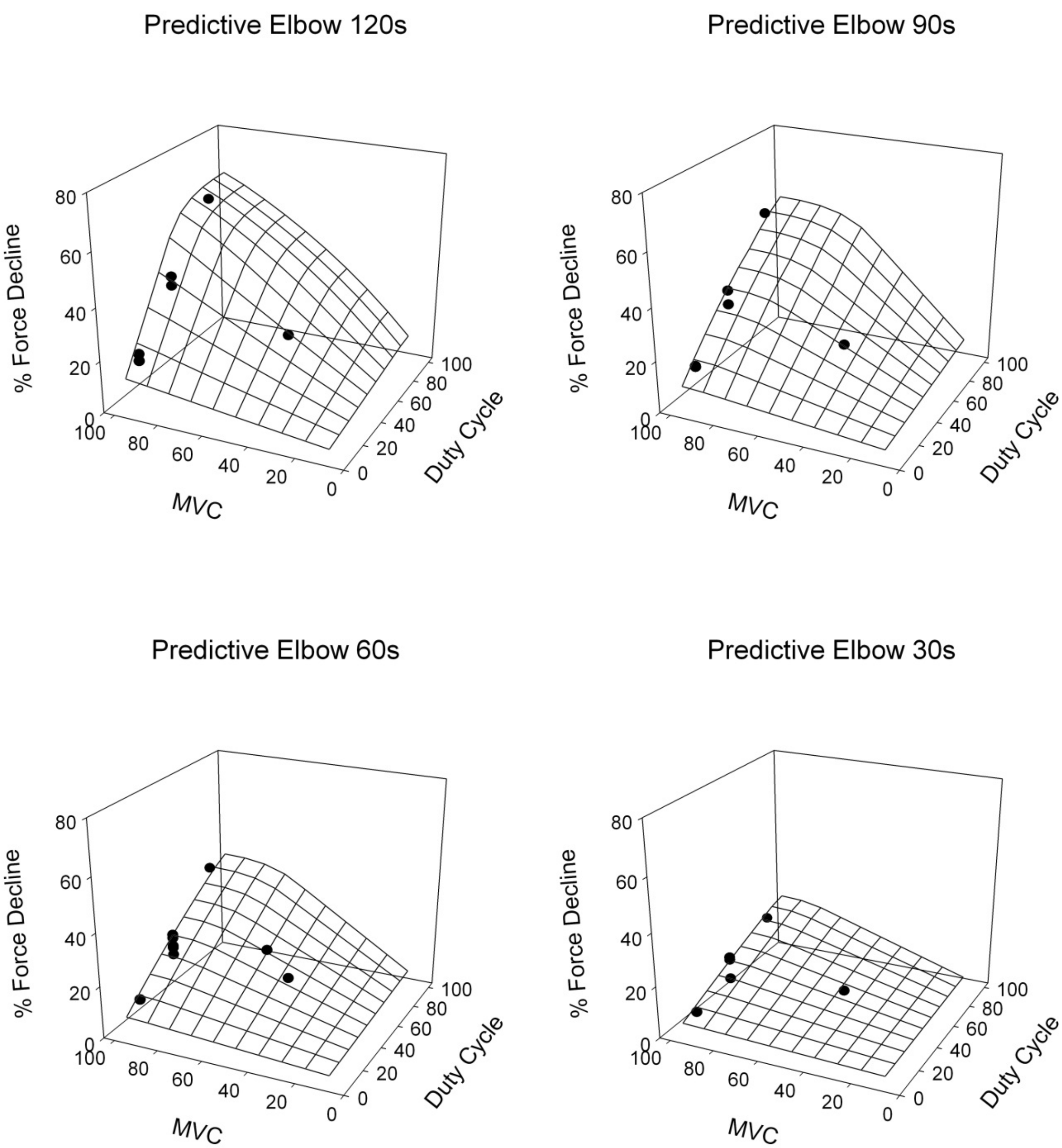

Figure 4- 2: Predictive percent torque decline fatigue response surface for the elbow and the data points found from the meta-analysis at each discrete time point.

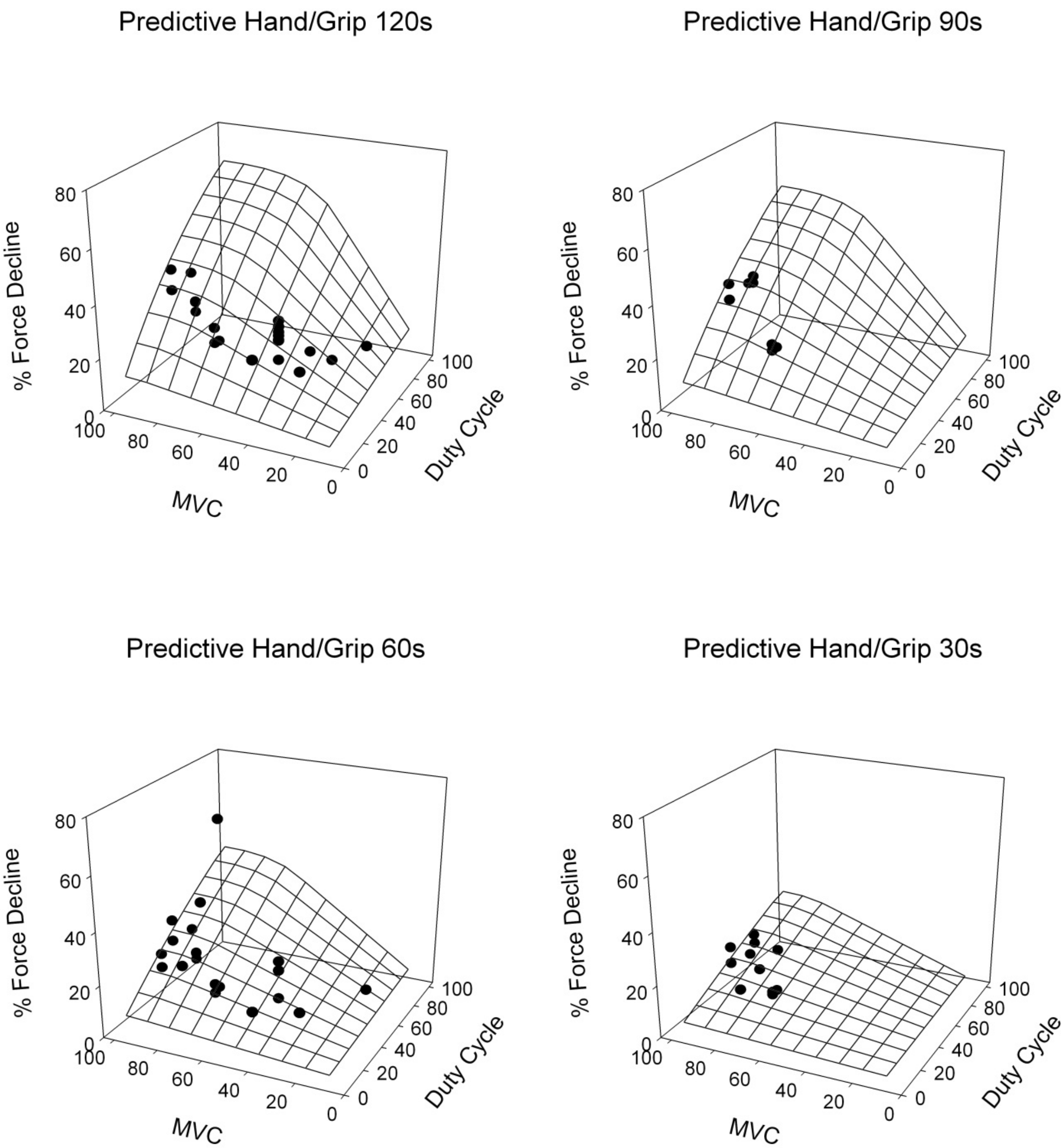

Figure 4- 3: Predictive percent torque decline fatigue response surface for the hand/grip and the data points found from the meta-analysis at each discrete time point.

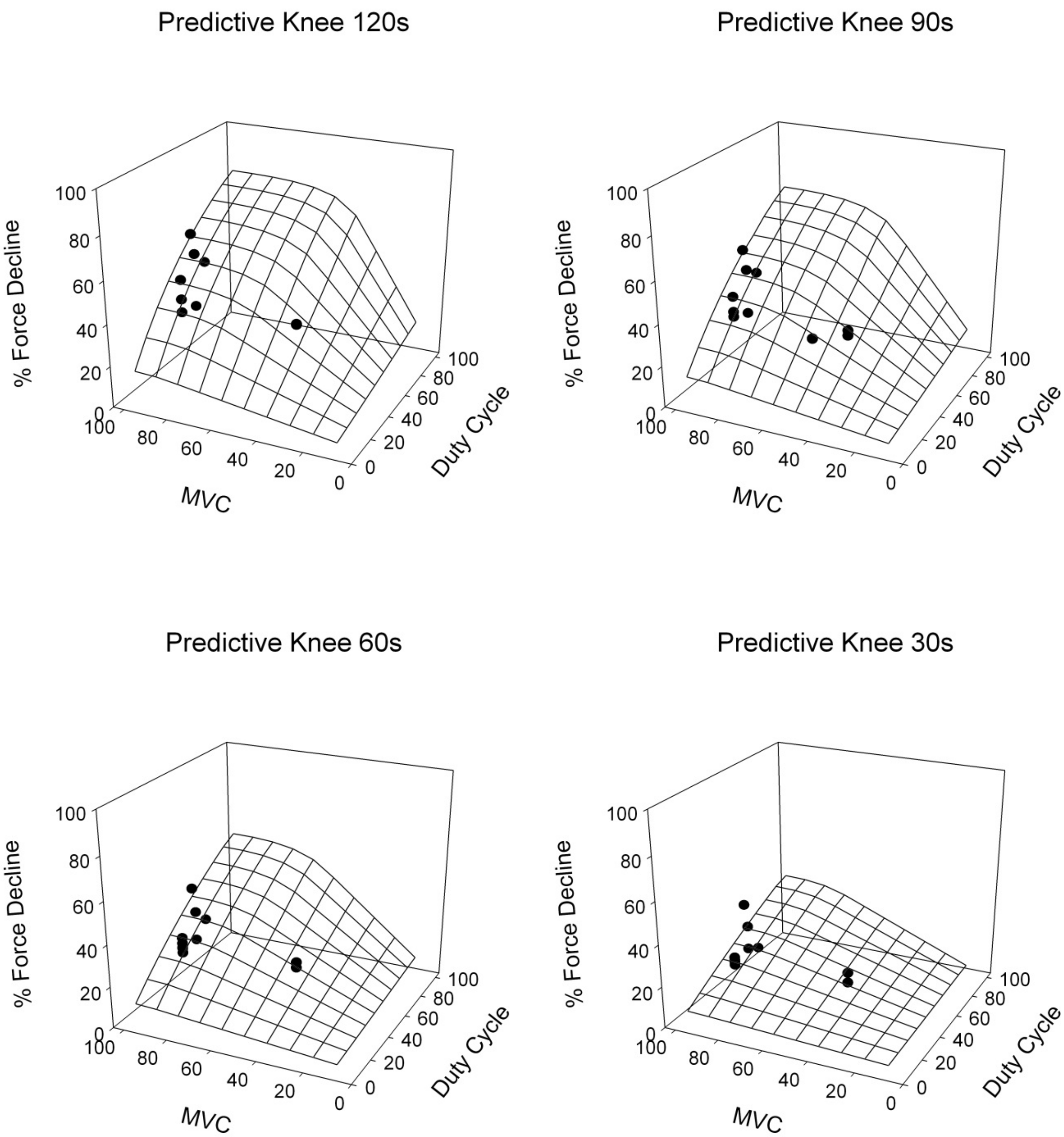

Figure 4- 4: Predictive percent torque decline fatigue response surface for the knee and the data points found from the meta-analysis at each discrete time point.

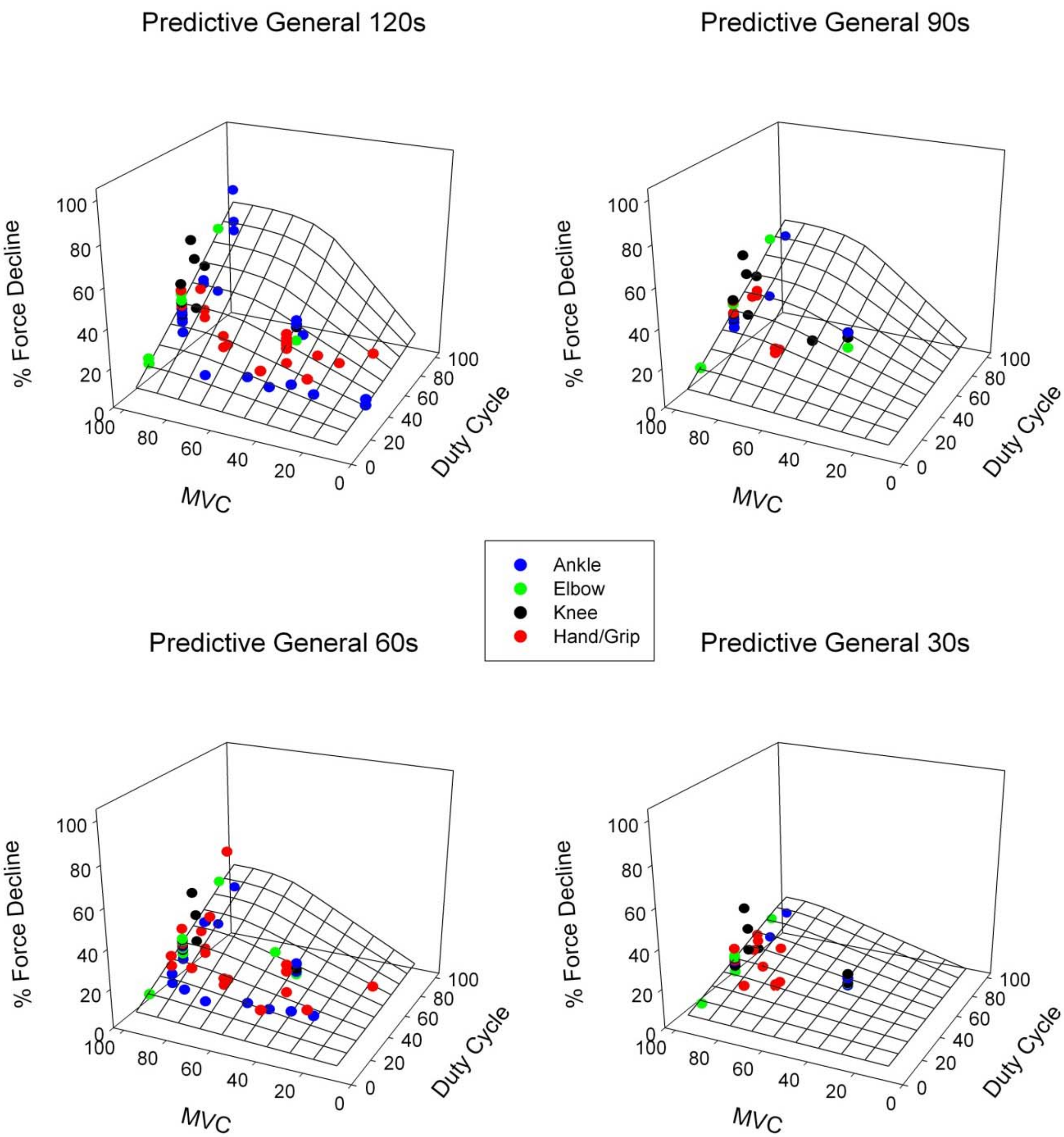

Figure 4- 5: General predictive percent torque decline fatigue response surface and the data points found from the meta-analysis at each discrete time point.

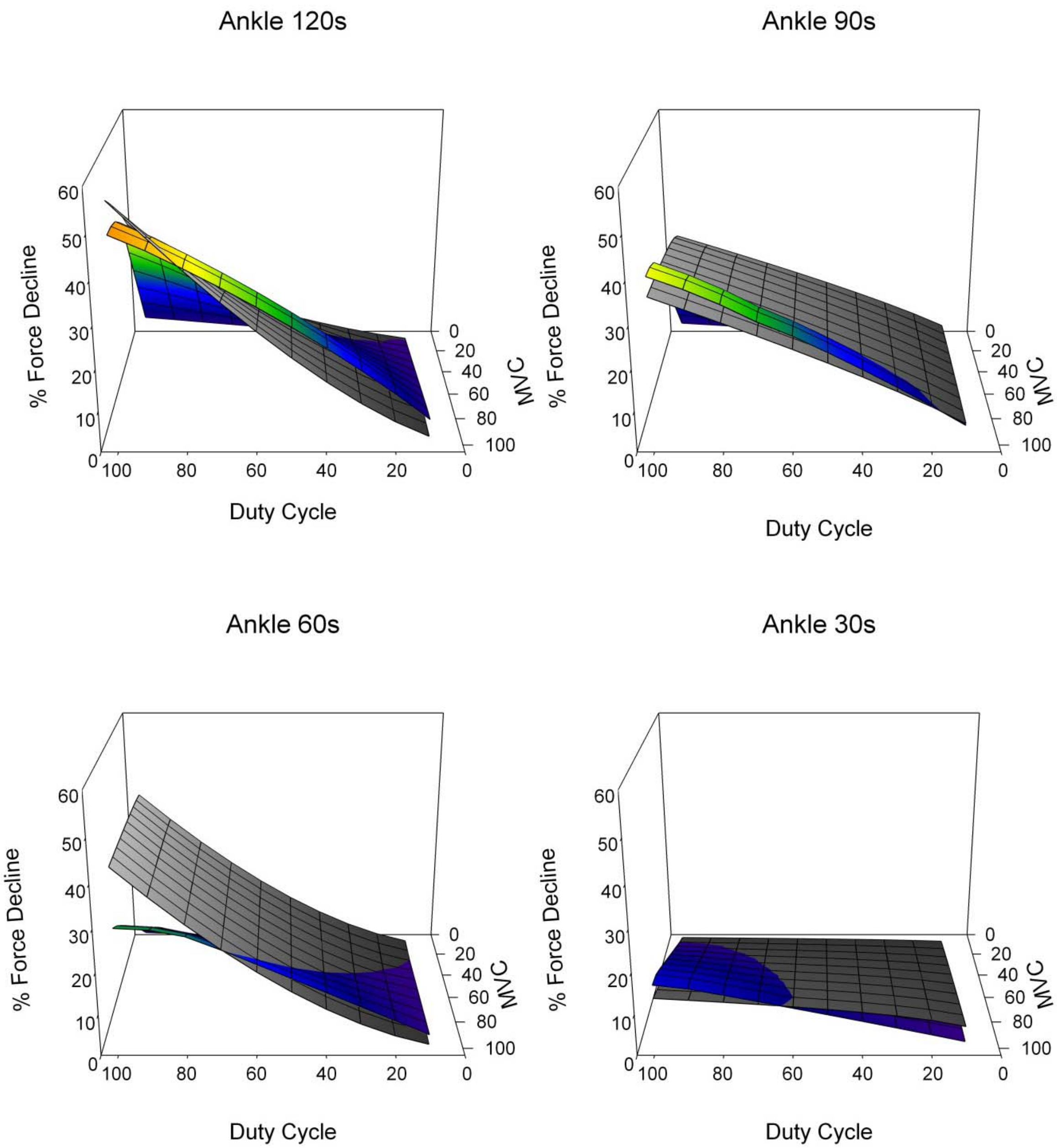

Figure 4- 6: Empirical percent torque decline fatigue response surface (grey) vs. Predictive % decline fatigue response surface (color) at the ankle.

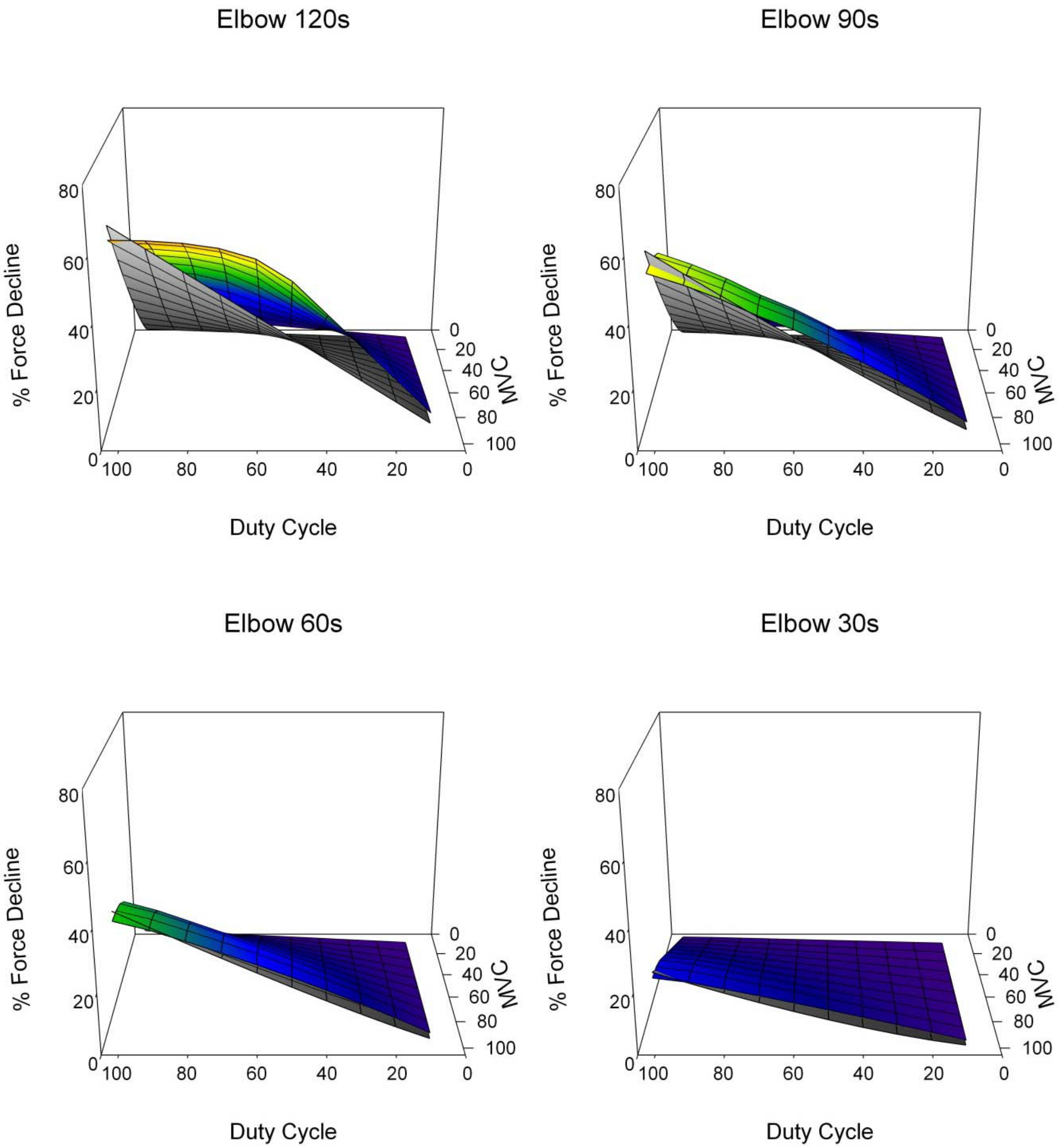

Figure 4- 7: Empirical percent torque decline fatigue response surface (grey) vs. Predictive % decline fatigue response surface (color) at the elbow.

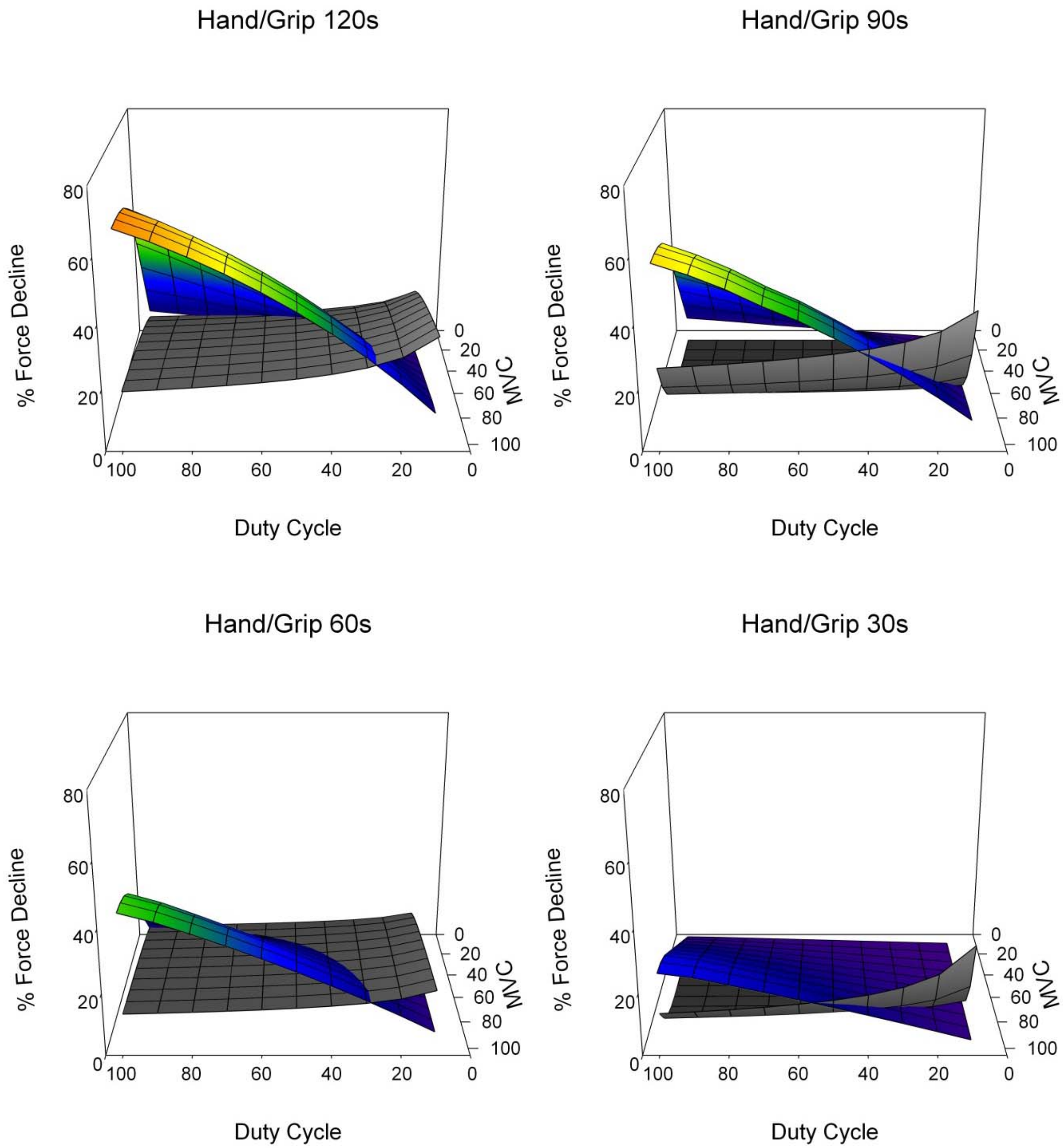

Figure 4- 8: Empirical percent torque decline fatigue response surface (grey) vs. Predictive % decline fatigue response surface (color) at the hand/grip.

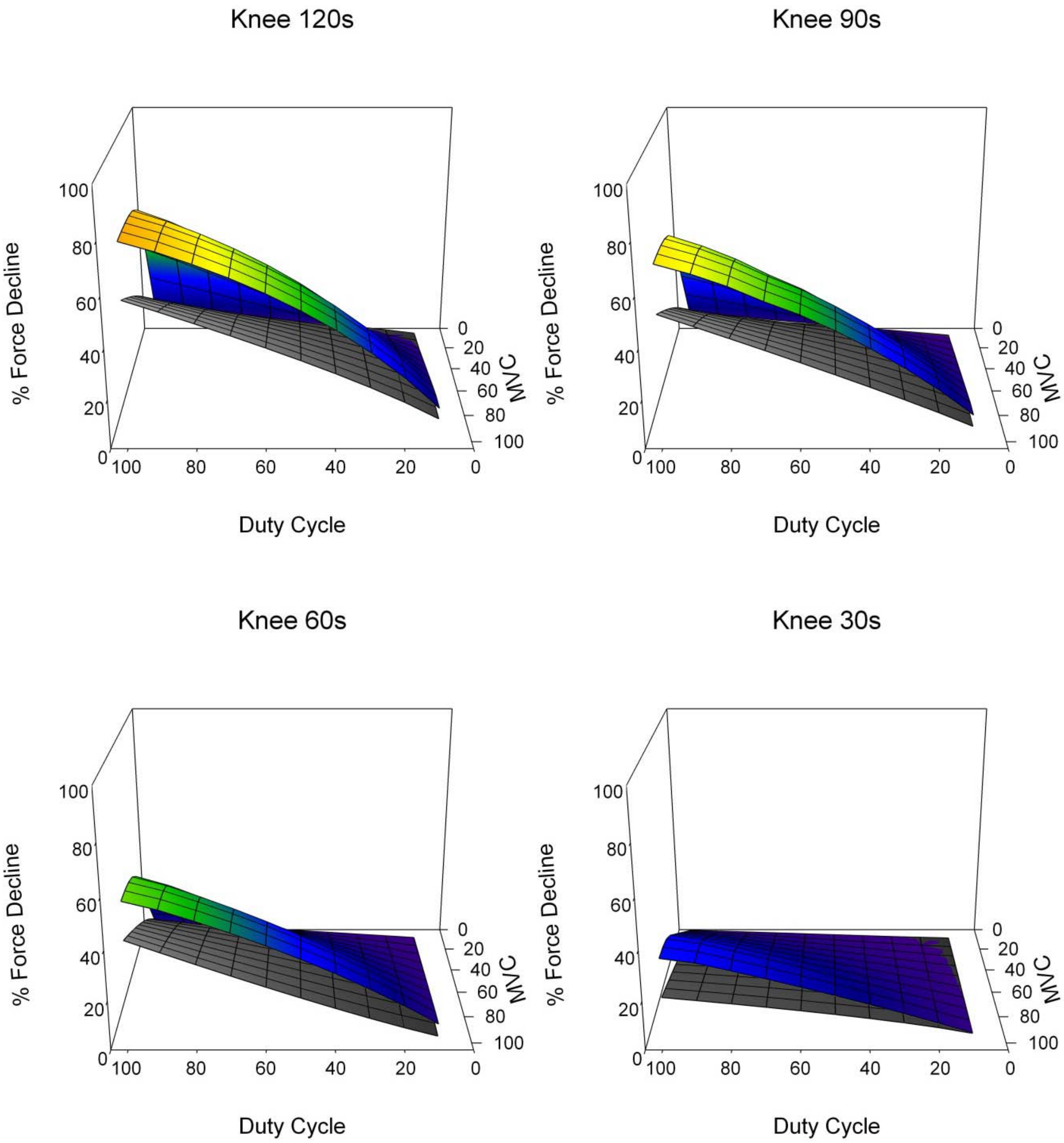

Figure 4- 9: Empirical percent torque decline fatigue response surface (grey) vs. Predictive % decline fatigue response surface (color) at the knee.

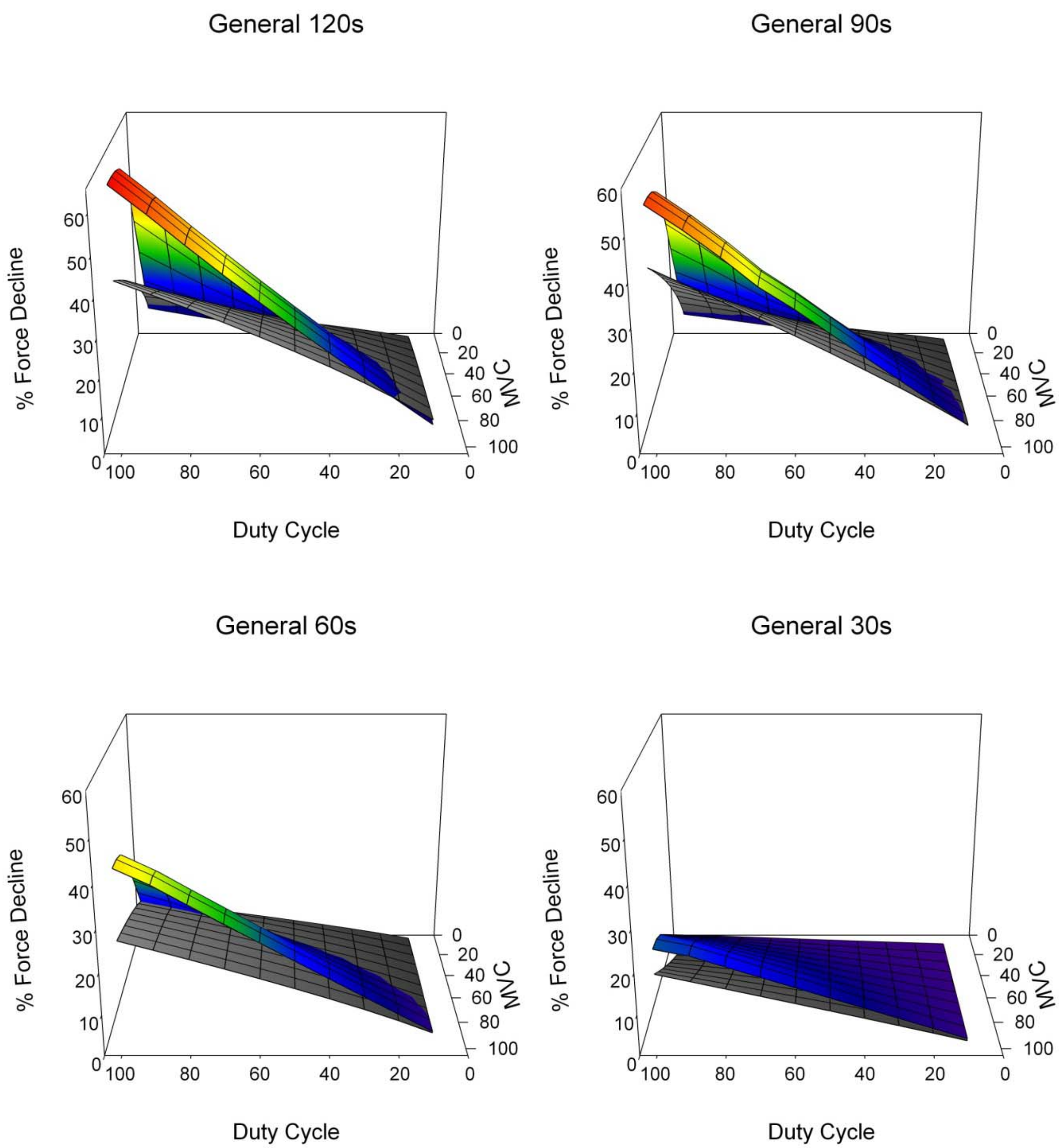

Figure 4- 10: Empirical percent torque decline fatigue response surface (grey) vs. Predictive % decline fatigue response surface (color), general.

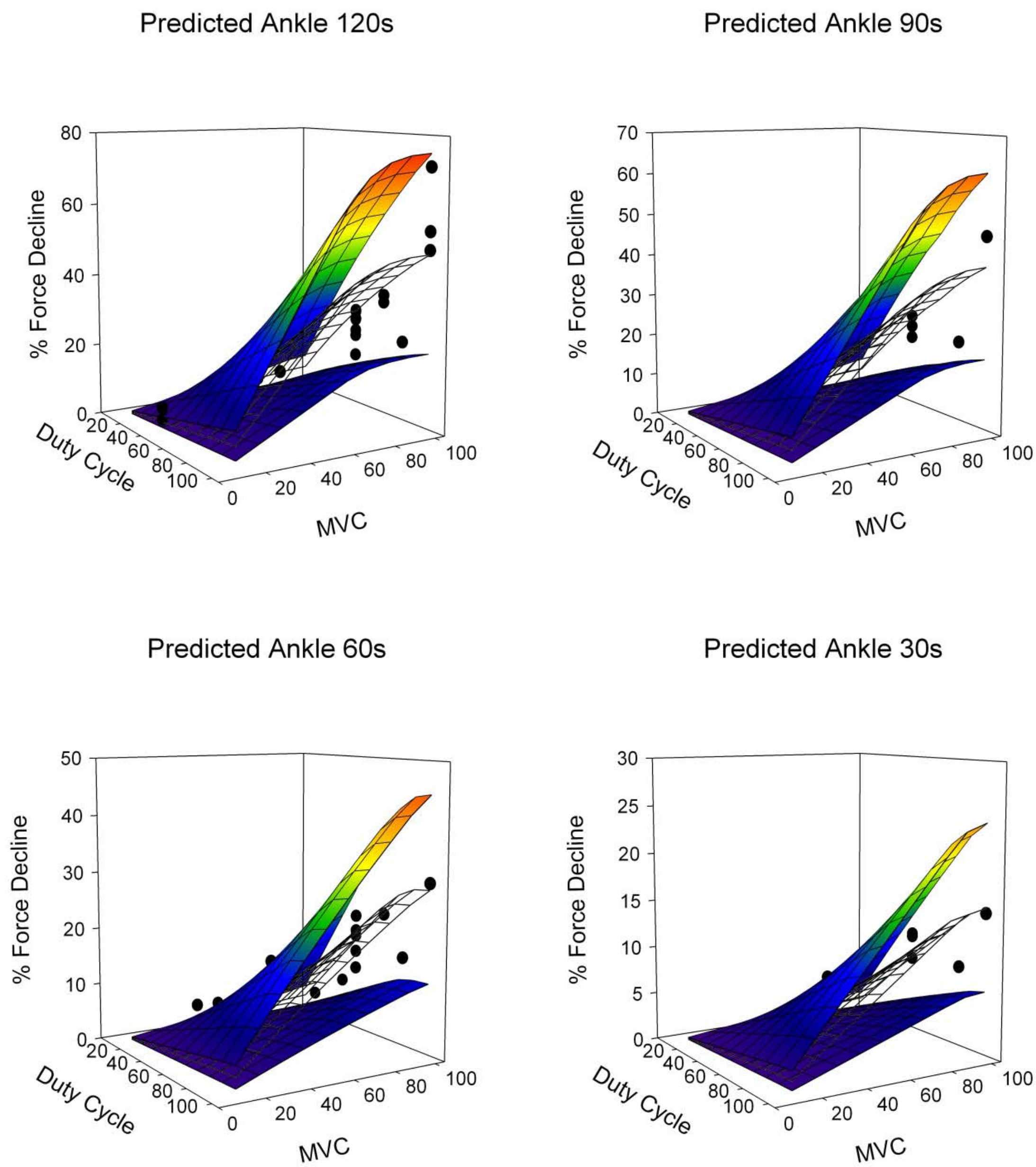

Figure 4- 11: Predicted surface and the 95% CI for the ankle at each discrete time point. Data points from the meta-analysis are also shown.

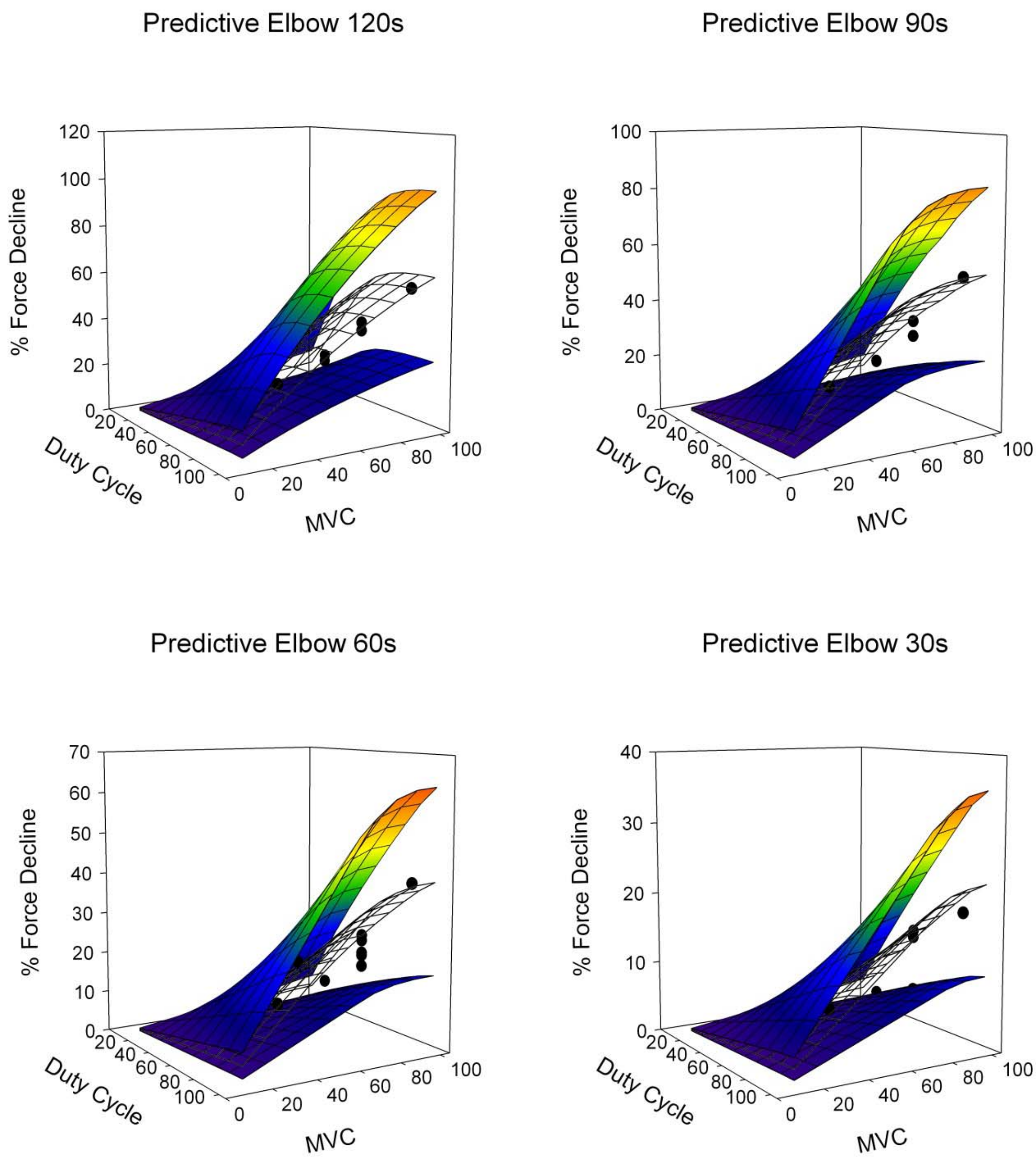

Figure 4- 12: Predicted surface and the 95% CI for the elbow at each discrete time point. Data points from the meta-analysis are also shown.

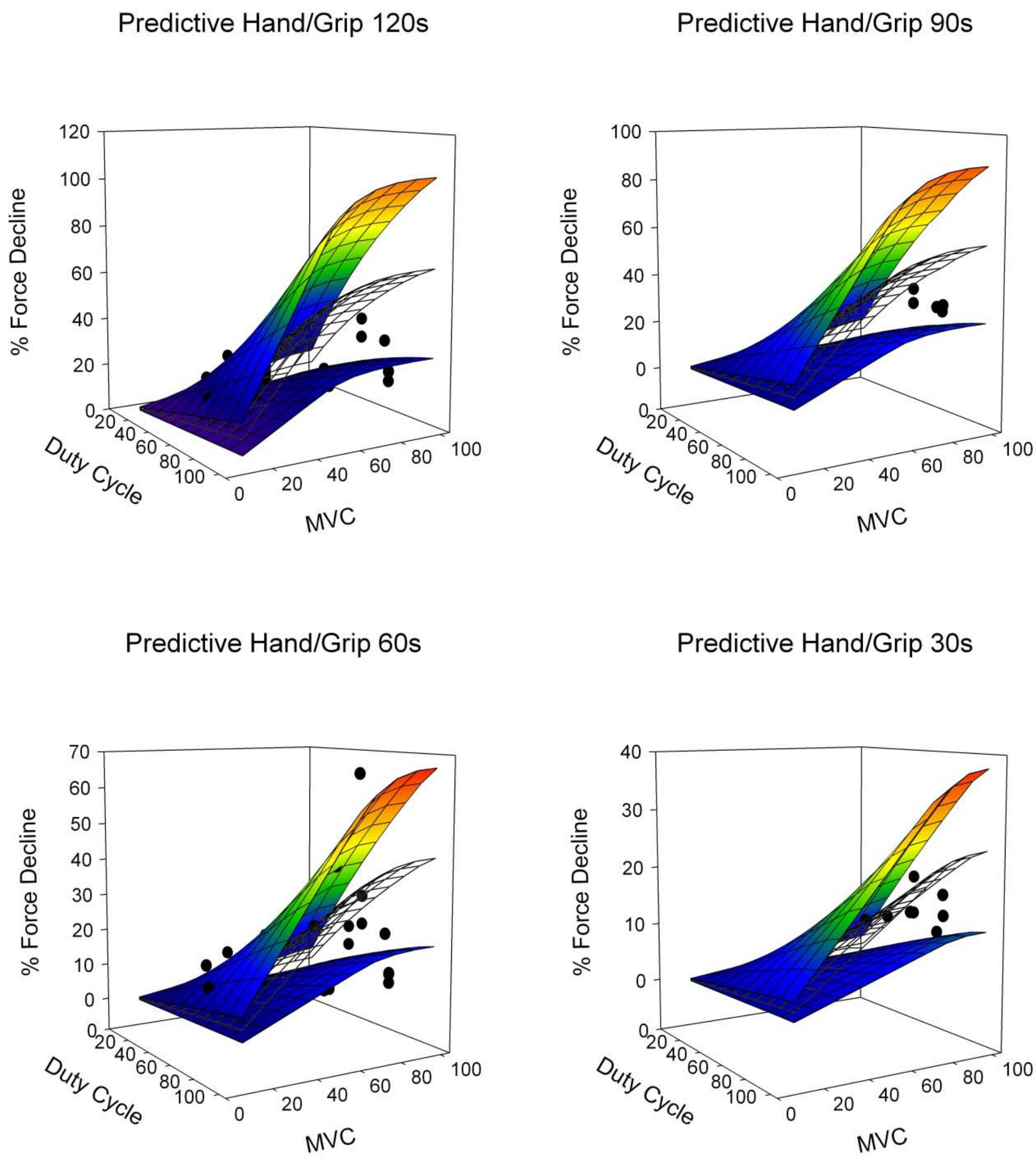

Figure 4- 13: Predicted surface and the 95% CI for the hand/grip at each discrete time point. Data points from the meta-analysis are also shown.

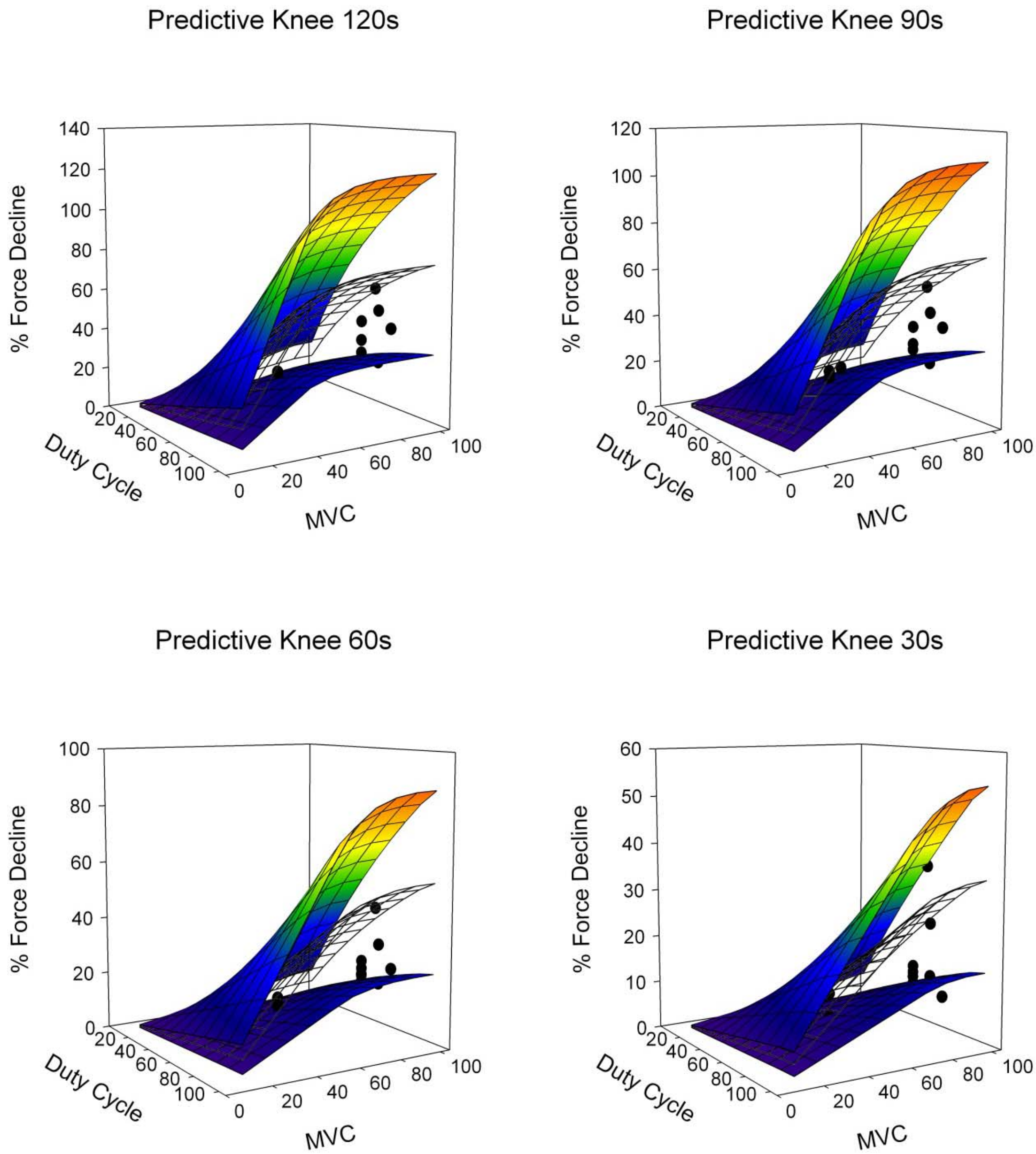

Figure 4- 14: Predicted surface and the 95% CI for the knee at each discrete time point. Data points from the meta-analysis are also shown.

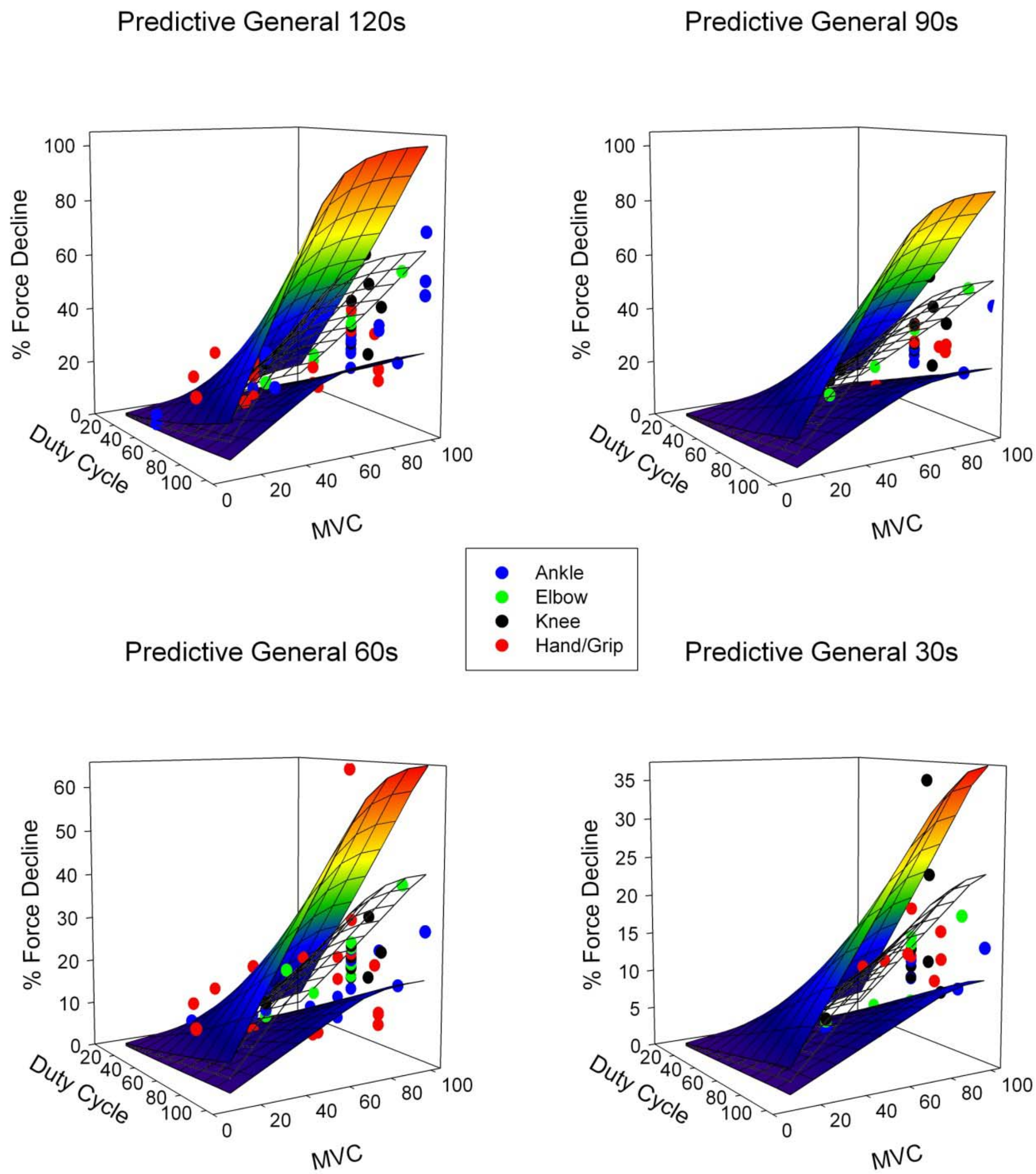

Figure 4- 15: General predicted surface and the 95% CI at each discrete time point. Data points from the meta-analysis are also shown.

CHAPTER 5: CONCLUSION

Review

The goal of this thesis was to further develop models of localized muscle fatigue. First, optimal parameter values were determined for the biophysical muscle fatigue model proposed by Xia and Frey Law, (2008), using empirical intensity-endurance time models of sustained isometric contraction data. Second, new empirical models of torque decay were developed using available data from sustained and intermittent isometric contractions. Third, the biophysical fatigue model was compared to these new models that incorporate rest intervals using the original parameter values. This process provides validation for the fatigue predictions provided by the fatigue model.

This three compartment model was adapted from Liu et al., (2002) to include a controller and alters the ‘flow’ between compartments to create a single loop between the resting, active, and fatigued muscle. The controller allowed the model to be used for sub maximal tasks and the altered flow allowed for recovered muscle (from the fatigued state) to return to the resting state rather than immediately to the active state. This was useful for modeling intermittent contractions which incorporate rest intervals, thus recovering muscle would not be spontaneously activated.

The first aim in the validation process (Chapter 2) was to optimize the F and R parameters to accurately predict intensity-ET curves. This was accomplished by using a grid search optimization process to optimize to a “gold standard” intensity-ET curve (Frey Law and Avin, 2010). We hypothesized the model with the two optimized parameters will be able to reproduce the non-linear intensity-ET relationships found by Frey Law and Avin, 2010. Chapter 2 found that the model was able to reproduce the intensity-ET relationships with the optimal F and R parameters for isometric tasks.

The next aim in the validation process was to validate the model for intermittent tasks. This step required two stages. The first stage was to collect data from literature to create an empirical model to be used as a "gold standard" for comparing the model against (Chapter 3). A meta-analysis was performed searching for percent muscle force decline as a function of duty cycle (DC) and intensity at four discrete time points. Empirical models were created from these data points for each joint that had more than 3 data points (i.e. 3 points are needed to define a plane).

Our hypothesis the empirical model could be developed using DC and MVC to predict the percent toque decline was found to be true. However, the empirical models were created, it was found that most of the data available in the literature, that fit the inclusion/exclusion requirements, was centered on high maximum voluntary contractions (MVCs) (i.e. >50%) and mid DCs (i.e. around 50%). This creates volatility at the extremes of the surfaces.

The final aim was to quantitatively and qualitatively assess the predicted model surfaces against the empirical surfaces (Chapter 4). We hypothesized the optimized F and R parameters for sustained isometric contractions would be valid for intermittent tasks. From this analysis, it was determined that the predicted models, with the optimal F and R parameters, reproduce the empirical models reasonably well and can accurately predict the data found by the meta-analysis. Thus our hypothesis was proven to be correct; however more work may need to be done before this is definitively proven.

Limitations

While this thesis showed that the model can accurately predict the fatigue response surfaces (i.e. % decline as a function of DC and intensity), it should be noted that this study had some limitations. The first limitation is the F and R parameters were optimized to isometric intensity-ET curves, and then used to predict % decline surfaces. The better approach would have been to use the F and R parameters to predict intermittent intensity-ET curves. This approach was unfeasible due to the lack of ET data at low intensities and DCs. This is due to ETs being greater than an hour, and no researcher has kept a subject performing a task for that long due to the immense amount of time that would be required and likely discomfort or boredom of the subjects. Thus large amounts of data for intermittent intensity-ET curves were not available. Percent force decline data at four discrete time points was then chosen, since initial searches found more data than the initial search for intermittent intensity-ET curves.

Although intensity-ET relationships are the current “standard” for assessing muscle fatigue; the relative torque decline surfaces for intermittent tasks that were developed in this thesis provide further insight into what occurs at the muscle level (i.e. decline in muscle force production) during intermittent work cycles. This insight could provide a new method for developing rest-work cycles or job rotation cycles in industry.

The second limitation of this validation effort was most of the data available in the literature, that fit the inclusion/exclusion requirements, was centered on high maximum voluntary contractions (MVCs) (i.e. >50%) and mid DCs (i.e. around 50%). Having all the data around a small section of the grid created volatility at the extremes of the surfaces; which caused some of the surfaces to vary away from the predicted shape of the fatigue response surface (e.g. Figure 4-9). This volatility in the surfaces highlights the need for more research to be done around the entire range of DCs and MVCs, so a more accurate response surface can be created for use independently and/or as a gold standard for comparison.

The last limitation of this study was length of the four discrete time points (i.e. 30, 60, 90, 120 seconds). The model is meant to be used as an ergonomic tool for predicting muscle fatigue due to a work task. Unfortunately work tasks often last longer than 120 seconds. These four time points were chosen based on the available data, to maximize our ability to generate empirical surfaces. However, it was found that even at these short time periods there was a relatively small amount of data points available. Ideally a wider range of time points (e.g. up to 30 minutes) would be used.

Future Work

Even with the limitations of the validation process, this thesis has provided validation to the model proposed by Xia and Frey Law, (2008) for isometric tasks, and for short intermittent tasks (i.e. <120 seconds). Future research is needed to determine the relative torque decline at the extremes of the surfaces (i.e., low intensities or DCs) over a longer time period. This will allow for development of more practical empirical models of torque decline as a function of task intensity and DC that may be useful as ergonomic tools in and of themselves. In addition it will provide the needed data to validate the biophysical model against longer time points using a more accurate response surface.

REFERENCES

Allman, B.L. and Rice, C.L., 2003. Perceived exertion is elevated in old age during an isometric fatigue task. Eur J Appl Physiol 89, 191-197.

Alway, S.E., 1991. Is fiber mitochondrial volume density a good indicator of muscle fatigability to isometric exercise? J Appl Physiol 70, 2111-2119.

Armatas, V., Bassa, E., Patikas, D., Kitsas, I., Zangelidis, G. and Kotzamanidis, C., 2010. Neuromuscular differences between men and prepubescent boys during a peak isometric knee extension intermittent fatigue test. Pediatric Exercise Science 22, 205-217.

Bemben, M.G., Massey, B.H., Bemben, D.A., Misner, J.E. and Boileau, R.A., 1996. Isometric intermittent endurance of four muscle groups in men aged 20-74 yr. Medicine and Science in Sports and Exercise 28, 145-154.

Bemben, M.G., Tuttle, T.D., Bemben, D.A. and Knehans, A.W., 2001. Effects of creatine supplementation on isometric force-time curve characteristics. Medicine and Science in Sports and Exercise 33, 1876-1881.

Bendall, J.R., 1952. Effects of the "marsh factor" on the shortening of muscle fibre models in the presence of adenosine triphosphate. Nature 170, 1058-1060.

Benwell, N.M., Mastaglia, F.L. and Thickbroom, G.W., 2007. Differential changes in long-interval intracortical inhibition and silent period duration during fatiguing hand exercise. Experimental Brain Research 179, 255-262.

Benwell, N.M., Mastaglia, F.L. and Thickbroom, G.W., 2007b. Changes in the functional mr signal in motor and non-motor areas during intermittent fatiguing hand exercise. Experimental Brain Research 182, 93-97.

Benwell, N.M., Sacco, P., Hammond, G.R., Byrnes, M.L., Mastaglia, F.L. and Thickbroom, G.W., 2006. Short-interval cortical inhibition and corticomotor excitability with fatiguing hand exercise: A central adaptation to fatigue? Experimental Brain Research 170, 191-198.

Bigland-Ritchie, B., Cafarelli, E. and Vollestad, N.K., 1986. Fatigue of submaximal static contractions. Acta Physiol Scand 128, 137-148.

Bigland-Ritchie, B., Furbush, F. and Woods, J.J., 1986b. Fatigue of intermittent submaximal voluntary contractions: Central and peripheral factors. J. Appl. Physiol 61, 421-429.

Birtles, D.B., Minden, D., Wickes, S.J., Puxley, K.P.M., Llewellyn, M.G.A., Casey, A., Rayson, M.P., Jones, D.A. and Newham, D.J., 2002. Chronic exertional compartment syndrome: Muscle changes with isometric exercise. Medicine and Science in Sports and Exercise 34, 1900-1906.

Birtles, D.B., Rayson, M.P., Casey, A., Jones, D.A. and Newham, D.J., 2003. Venous obstruction in healthy limbs: A model for chronic compartment syndrome? Medicine and Science in Sports and Exercise 35, 1638-1644.

Burnley, M., 2009. Estimation of critical torque using intermittent isometric maximal voluntary contractions of the quadriceps in humans. Journal of Applied Physiology 106, 975-983.

Bystrom, S. and Sjøgaard, G., 1991. Potassium homeostasis during and following exhaustive submaximal static handgrip contractions. Acta Physiol Scand 142, 59-66.

Chaffin, D.B., Andersson, G.B.J. and Martin, B.J. (2006). Occupational biomechanics. Hoboken, John Wiley & Sons, Inc.

Charlton, I.W. and Johnson, G.R., 2001. Application of spherical and cylindrical wrapping algorithms in a musculoskeletal model of the upper limb. Journal of Biomechanics 34, 1209-1216.

Chung, L.H., Callahan, D.M. and Kent-Braun, J.A., 2007. Age-related resistance to skeletal muscle fatigue is preserved during ischemia. Journal of Applied Physiology 103, 1628-1635.

Denavit, J. and Hartenberg, R.S., 1955. A kinematic notation for lower-pair mechanisms based on matrices. Journal of Applied Mechanics 77, 215-221.

Desailly, E., Sardain, P., Khouri, N., Yepremian, D. and Lacouture, P., 2010. The convex wrapping algorithm: A method for identifying muscle paths using the underlying bone mesh. Journal of Biomechanics 43, 2601-2607.

Ding, J., Wexler, A.S. and Binder-Macleod, S.A., 2003. Mathematical models for fatigue minimization during functional electrical stimulation. Journal of Electromyography & Kinesiology 13, 575-588.

Ditor, D.S. and Hicks, A.L., 2000. The effects of age and gender on the relative on the relative fatigability of the human adductor pollicis muscle. Can. J. Physiol. Pharmacol. 78, 781-790.

Duchateau, J. and Hainaut, K., 1985. Electrical and mechanical failures during sustained and intermittent contractions in humans. Journal of Applied Physiology 58, 942-947.

Egana, M. and Green, S., 2007. Intensity-dependent effect of body tilt angle on calf muscle fatigue in humans. European Journal of Applied Physiology 99, 1-9.

El Ahrache, K., Imbeau, D. and Farbos, B., 2006. Percentile values for determining maximum endurance times for static muscular work. International Journal of Industrial Ergonomics 36, 99-108.

Fimland, M.S., Helgerud, J., Knutsen, A., Ruth, H., Leivseth, G. and Hoff, J., 2010. No effect of prior caffeine ingestion on neuromuscular recovery after maximal fatiguing contractions. European Journal of Applied Physiology 108, 123-130.

Frey Law, L.A. and Avin, K.G., 2010. Endurance time is joint specific: A modelling and meta-analysis investigation. Ergonomics 53, 109-129.

Fujimoto, T. and Nishizono, H., 1993. Involvement of membrane excitation failure in fatigue-induced by intermittent submaximal voluntary contraction of the 1st dorsal interosseous muscle. Journal of Sports Medicine and Physical Fitness 33, 107-117.

Fulco, C.S., Cymerman, A., Muza, S.R., Rock, P.B., Pandolf, K.B. and Lewis, S.F., 1994. Adductor pollicis muscle fatigue during acute and chronic altitude exposure and return to sea-level. Journal of Applied Physiology 77, 179-183.

Fulco, C.S., Rock, P.B., Muza, S.R., Lammi, E., Braun, B., Cymerman, A., Moore, L.G. and Lewis, S.F., 2001. Gender alters impact of hypobaric hypoxia on adductor pollicis muscle performance. Journal of Applied Physiology 91, 100-108.

Gandevia, S.C., 1992. Some central and peripheral factors affecting human motoneuronal output in neuromuscular fatigue. Sports Medicine 13, 93-98.

Gandevia, S.C., 2001. Spinal and supraspinal factors in human muscle fatigue. Physiological Reviews 81, 1729-1771.

Garg, A., Hermann, K., Schwoerer, B. and Kapellusch, J., 2002. The effects of maximum voluntary contraction on endurance times for the shoulder girdle. International Journal of Industrial Ergonomics 30, 103-113.

Gatton, M., Pearcy, M. and Pettet, G., 2001. Modelling the line of action for the oblique abdominal muscles using an elliptical torso model. Journal of Biomechanics 34, 1203-1207.

Gonzales, J.U. and Scheuermann, B.W., 2007. Absence of gender differences in the fatigability of the forearm muscles during intermittent isometric handgrip exercise. Journal of Sports Science and Medicine 6, 98-105.

Hagberg, M., 1981. Work load and fatigue in repetitive arm elevations. Ergonomics 24, 543-555.

Hamada, T., Sale, D.G., MacDougall, J.D. and Tarnopolsky, M.A., 2003. Interaction of fibre type, potentiation and fatigue in human knee extensor muscles. Acta Physiologica Scandinavica 178, 165-173.

Hill, A.V., 1938. The heat of shortening and the dynamic constants of muscle. Proceedings of the Royal Society of London Series B-Biological Sciences 126, 136-195.

Huijgens, J.M.M., 1981. A model for quantifying static load, incorporating muscle fatigue. in Buskirk, W.C. (Eds.), Biomechanics symposium. Boulder, CO, American Society of Mechanical Engineers**:** 97-99.

Hunter, S.K., Ryan, D.L., Ortega, J.D. and Enoka, R.M., 2002. Task differences with the same load torque alter the endurance time of submaximal fatiguing contractions in humans. J Neurophysiol 88, 3087-3096.

Iridiastadi, H. and Nussbaum, M.A., 2006. Muscle fatigue and endurance during repetitive intermittent static efforts: Development of prediction models. Ergonomics 49, 344-360.

Iridiastadi, H. and Nussbaum, M.A., 2006b. Muscular fatigue and endurance during intermittent static efforts: Effects of contraction level, duty cycle, and cycle time. Human Factors 48, 710-720.

Jakobi, J.M., Rice, C.L., Curtin, S.V. and Marsh, C.D., 2000. Contractile properties, fatigue and recovery are not influenced by short-term creatine supplementation in human muscle. Experimental Physiology 85, 451-460.

Johnson, M.A., Polgar, J., Weightman, D. and Appleton, D., 1973. Data on the distribution of fibre types in 36 human muscles: An autopsy study. Journal of the Neurological Sciences 18, 111-129.

Jubeau, M., Muthalib, M., Millet, G.Y., Maffiuletti, N.A. and Nosaka, K., 2012. Comparison in muscle damage between maximal voluntary and electrically evoked isometric contractions of the elbow flexors. Eur J Appl Physiol 112, 429-438.

Katayama, K., Amann, M., Pegelow, D.F., Jacques, A.J. and Dempsey, J.A., 2006. Effects of artial oxygenation on quadriceps fatigability during isoated muscle exercise. Am J Physiol Regul Integr Comp Physiol 292, 1279-1286.

Kent-Braun, J.A. and Ng, A.V., 1999. Specific strength and voluntary muscle activation in young and elderly women and men. Journal of Applied Physiology 87, 22-29.

Kent-Braun, J.A., Ng, A.V., Doyle, J.W. and Towse, T.F., 2002. Human skeletal muscle responses vary with age and gender during fatigue due to incremental isometric exercise. Journal of Applied Physiology 93, 1813-1823.

Kent-Braun, J.A., Sharma, K.R., Weiner, M.W. and Miller, R.G., 1994. Effects of exercise on muscle activation and metabolism in multiple sclerosis. Muscle & Nerve 17, 1162-1169.

Lanza, I.R., Russ, D.W. and Kent-Braun, J.A., 2004. Age-related enhancement of fatigue resistance is evident in men during both isometric and dynamic tasks. Journal of Applied Physiology 97, 967-975.

Liu, J., Brown, R. and Yue, G., 2002. A dynamical model of muscle activation, fatigue, and recovery. Biophysical Journal 82, 2344-2359.

Liu, J.Z., Zhang, L., Yao, B., Sahgal, V. and Yue, G.H., 2005. Fatigue induced by intermittent maximal voluntary contractions is associated with significant losses in muscle output but limited reductions in functional mri-measured brain activation level. Brain Research 1040, 44-54.

Ma, L., Chablat, D., Bennis, F. and Zhang, W., 2009. A new simple dynamic muscle fatigue model and its validation. International Journal of Industrial Ergonomics, 211-220.

Ma, L., Chablat, D., Bennis, F., Zhang, W., Hu, B. and Guillaume, F., 2011. A novel approach for determining fatigue resistance of different muscle groups in static cases. International Journal of Industrial Ergonomics 41, 10-18.

Manenica, I., 1986. A technique for postural load assessment. in Corlett, N., Wilson, J. and Manenica, I. (Eds.), *The ergonomics of working postures*. Londres, Taylor & Francis.

Marion, M.S., Wexler, A.S. and Hull, M.L., 2010. Predicting fatigue during electrically stimulated nonisometric contractions. Muscle & Nerve 41, 857-867.

Mazzini, L., Balzarini, C., Colombo, R., Mora, G., Pastore, I., De Ambrogio, R. and Caligari, M., 2001. Effects of creatine supplementation on exercise performance and muscular strength in amyotrophic lateral sclerosis: Preliminary results. Journal of the Neurological Sciences 191, 139-144.

Monod, H. and Scherrer, J., 1965. The work capacity of a synergic muscluar group. Ergonomics 8, 329-338.

Muthalib, M., Jubeau, M., Millet, G.Y., Maffiuletti, N.A., Ferrari, M. and Nosaka, K., 2010. Biceps brachii muscle oxygenation in electrical muscle stimulation. Clinical Physiology and Functional Imaging 30, 360-368.

Ng, L.J., Sih, B.L. and Stuhmiller, J.H., 2011. An integrated exercise response and muscle fatigue model for performance decrement estimates of workloads in oxygen-limiting environments. Eur J Appl Physiol.

Ordway, G.A., Kearney, J.T. and Stull, G.A., 1977. Rhythmic isometric fatigue patterns of elbow flexors and knee extensors. Research Quarterly 48, 734-740.

Petersen, K., Hansen, C.B., Aagaard, P. and Madsen, K., 2007. Muscle mechanical characteristics in fatigue and recovery from a marathon race in highly trained runners. Eur J Appl Physiol 101, 385-396.

Pitcher, J.B. and Miles, T.S., 1997. Influence of muscle blood flow on fatigue during intermittent human hand-grip exercise and recovery. Clinical and Experimental Pharmacology and Physiology 24, 471-476.

Rohmert, W., 1960. Determination of the recovery pause for static work of man. Internationale Zeitschrift Fur Angewandte Physiologie, Einschliesslich Arbeitsphysiologie 18, 123-164.

Rose, L., Ericson, M. and Ortengren, R., 2000. Endurance time, pain and resumption in passive loading of the elbow joint. Ergonomics 43, 405-420.

Russ, D.W. and Kent-Braun, J.A., 2003. Sex differences in human skeletal muscle fatigue are eliminated under ischemic conditions. Journal of Applied Physiology 94, 2414-2422.

Russ, D.W., Towse, T.F., Wigmore, D.M., Lanza, I.R. and Kent-Braun, J.A., 2008. Contrasting influences of age and sex on muscle fatigue. Medicine and Science in Sports and Exercise 40, 234-241.

Sato, H., Ohashi, J., Iwanaga, K., Yoshitake, R. and Shimada, K., 1984. Endurance time and fatigue in static contractions. J Hum Ergol (Tokyo) 13, 147-154.

Sejersted, O.M. and Sjøgaard, G., 2000. Dynamics and consequences of potassium shifts in skeletal muscle and heart during exercise. Physiol Rev 80, 1411-1481.

.
Shahidi, A.V. and Mathieu, P.A., 1995. Endurance time characteristics of human ankle dorsiflexors and plantarflexors. Eur J Appl Physiol Occup Physiol 71, 124-130.

Sjøgaard, G., 1986. Intramuscular changes during long-term contraction. in Corlett, N., Wilson, J. and Manenica, I. (Eds.), *The ergonomics of working postures*. Londres, Taylor & Francis.

Stackhouse, S.K., Stevens, J.E., Lee, S.C., Pearce, K.M., Snyder-Mackler, L. and Binder-Macleod, S.A., 2001. Maximum voluntary activation in nonfatigued and fatigued muscle of young and elderly individuals. Physical Therapy 81, 1102-1109.

Stein, R.B., 1974. Peripheral control of movement. Physiol Rev 54, 215-243.

Tachi, M., Kouzaki, M., Kanehisa, H. and Fukunaga, T., 2004. The influence of circulatory difference on muscle oxygenation and fatigue during intermittent static dorsiflexion. European Journal of Applied Physiology 91, 682-688.

Taylor, J.L., Allen, G.M., Butler, J.E. and Gandevia, S.C., 2000. Supraspinal fatigue during intermittent maximal voluntary contractions of the human elbow flexors. Journal of Applied Physiology 89, 305-313.

Van Der Helm, F.C.T., 1994. A finite element musculoskeletal model of the shoulder mechanism. Journal of Biomechanics 27, 551-569.

Van Der Helm, F.C.T., Veeger, H.E.J., Pronk, G.M., Van Der Woude, L.H.V. and Rozendal, R.H., 1992. Geometry parameters for musculoskeletal modelling of the shoulder system. Journal of Biomechanics 25, 129-144.

Vigouroux, L. and Quaine, F., 2006. Fingertip force and electromyography of finger flexor muscles during a prolonged intermittent exercise in elite climbers and sedentary individuals. Journal of Sports Sciences 24, 181-186.

Visser, B. and van Dieen, J.H., 2006. Pathophysiology of upper extremity muscle disorders. J Electromyogr Kinesiol 16, 1-16.

Wood, D.D., Fisher, D.L. and Andres, R.O., 1997. Minimizing fatigue during repetitive jobs: Optimal work-rest schedules. Human Factors 39, 83-101.

Xia, T. and Frey Law, L.A., 2008. A theoretical approach for modeling peripheral muscle fatigue and recovery. Journal of Biomechanics 41, 3046-3052.

Yang, J., Marler, R., Kim, H., Arora, J.S. and Abdel-Malek, K. (2004). Multi-objective optimization for upper body posture prediction. American Institute of Aeronautics and Astronautics., 1-18.