The Development and Evaluation of a Cumulative Exposure Integration Method Based on Fatigue Failure Theory

by

Rong Huangfu

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Approved by

Sean Gallagher, Chair, Associate Professor of Industrial and Systems Engineering
Richard Sesek, Associate Professor of Industrial and Systems Engineering
Mark Schall, Assistant Professor of Industrial and Systems Engineering
Jerry Davis, Professor of Industrial and Systems Engineering
Wei Liu, Associate Professor of The Edward Via College of Osteopathic Medicine

Abstract

Cumulative exposure to physical risk factors has been identified as one of the major contributors to the development of workplace musculoskeletal disorders (MSDs). Linear integration methods have been widely used to quantify cumulative spinal loading in the workplace. There is a fundamental assumption behind these methods: the impacts of force and time on the cumulative exposure measure are treated equally. However, evidence from cadaver studies on tendons, ligaments, cartilage, and spinal motion segments suggests a fatigue failure process in the development of MSDs. Under fatigue failure theory, the impact of force is exponentially higher than exposure time in the cumulative damage measure. The aim of this dissertation is to evaluate the linear integration assumption in estimating cumulative damage and to develop and evaluate a novel fatigue failure theory based estimation model for the low back using continuous exposure history.

Thirty male college students were recruited to perform eccentric exercises with the elbow flexors of the non-dominant arm under one of three loading conditions (high, medium, and low force) which all have the same area under the loading curve. Create kinase (CK), resting elbow angle and maximum isometric voluntary contraction (MIVC) were measured before, immediately after the exercise, and in three follow up days (2, 4, and 8 days after the exercise). The relaxed elbow angle and MIVC were significantly reduced in the high force group compared with the other groups. Create kinase results did not show statistical differences among the groups. The results of this experiment suggest that the linear integration method may underestimate the impact of high force loading in estimating cumulative muscle damage.

A fatigue failure based model for estimating low back cumulative damage was developed. In this model, damage for each repetition was estimated using an S-N curve, which was developed based on cadaver study data, and adjusted stress amplitude, which was calculated using rainflow counting and Goodman/Gerber methods. Cumulative damage was estimated by summing the damage from each repetition. Two epidemiology databases that contain exposure data and corresponding health outcomes for the low back were used to evaluate the proposed model. Comparisons with linear and squared integration methods were made. The fatigue failure based model performed best in both databases with the highest odds ratios and the highest number of significant results from the logistic regression tests when compared with the other two methods.

These results suggest that MSDs are potentially the result of cumulative trauma. The proposed fatigue failure theory based model's estimate of cumulative damage was highly associated with negative health outcomes.

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List of Abbreviations

ACGIH American Conference of Governmental Industrial Hygienists

ANOVA Analysis of Variance

ASTM American Society for Testing and Materials

AUMC Auburn University Medical Clinic

BLS Bureau of Labor Statistics

CK Creatine Kinase

HAL American Conference of Governmental Industrial Hygienists Hand Activity Level

IMC Inertial Motion Capture

IMU Inertial Measurement Unit

MIVC Maximum Isometric Voluntary Contraction

MSD Musculoskeletal Disorder

OMC Optical Motion Capture

OSHA Occupational Safety and Health Administration

OWAS Ovako Working Posture Assessment System

PATH Posture, Activity, Tools, and Handling

PEO Portable Ergonomic Observation

QEC Quick Exposure Check

REBA Rapid Entire Body Assessment

RehabWorks East Alabama Medical Center RehabWorks Sports Medicine Outreach

RULA Rapid Upper Limb Assessment

SI Strain Index

TRAC Task Recording and Analysis on Computer

UTS Ultimate Tensile Strength

Chapter 1

Introduction

The Bureau of Labor Statistics (BLS) defines musculoskeletal disorders as "diseases and disorders of the musculoskeletal system and connective tissue due to bodily reaction (e.g., bending, reaching, twisting), overexertion, or repetitive motion" (U.S. Bureau of Labor Statistics, 2016a). Back pain, carpal tunnel syndrome, and rotator cuff syndrome are examples of Musculoskeletal Disorders (MSDs). From 2011 to 2015, MSDs accounted for approximately 31% (Figure 1.1) of the occupational injuries or illnesses cases that involved day(s) away from work (U.S. Bureau of Labor Statistics, 2016b), one of the leading threats to occupational health and well-being.

If one examines nonfatal injury cases involving days away from work reported by BLS for 2015 (U.S. Bureau of Labor Statistics, 2016b), it can be seen that:

- The median number of days lost due to MSD (12) is 50% higher than all other events combined
- More than 32% of MSD cases involved more than 31 days away from work
- Trunk and upper extremity injuries accounted for 79% of all MSD cases (Figure 1.2)

MSDs are a significant component of the cost of occupational injuries and illnesses in the United States. The Occupational Safety and Health Administration (OSHA) estimates that $20 billion a year was spent by employers on direct costs for MSD-related workers' compensation alone and that the indirect costs may be up to $100 billion a year (Occupational Safety and Health Administration, 1999). Estimates by the National Research Council and the Institute of Medicine suggest the costs of low back and upper extremity injuries when measured by compensation costs, lost wages, and lost productivity are between $45 and $54 billion annually (National Research Council and the Institute of Medicine, 2001). A more recent study estimated the direct costs alone of MSDs was around $1.5 billion for the year 2007 based on medical and administrative costs (Bhattacharya, 2014). In addition to the financial impact on the economy, MSDs often impose a significant life change on affected workers who may not be able to return to work or perform simple daily tasks.

More than 70,000 occupational safety professionals in the United States focus on injury prevention in the workplace. One of their primary responsibilities is to understand the potential injury risk for employees completing their daily jobs. Risk assessment tools are often used to quantify the exposure to physical risk

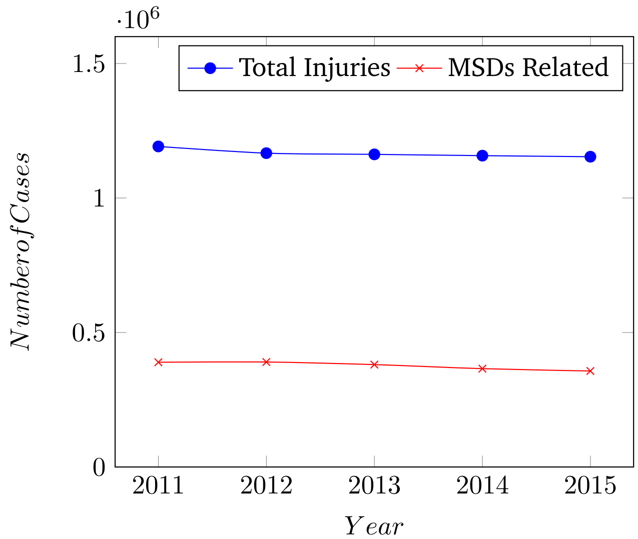

Figure 1.1: Occupational MSDs in 2015 (U.S. Bureau of Labor Statistics, 2016b)

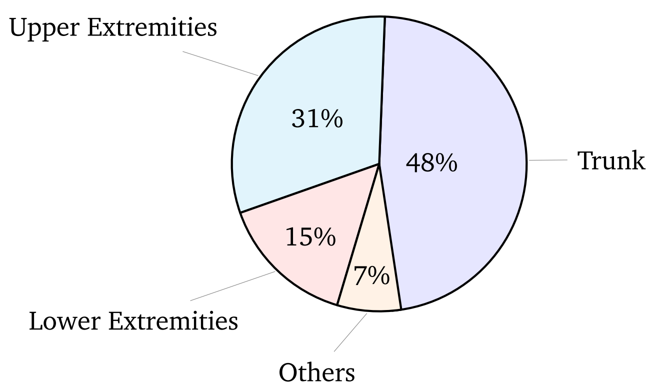

Figure 1.2: Occupational MSDs by body part in 2015 (U.S. Bureau of Labor Statistics, 2016b)

factors (heavy lifting, awkward posture, highly repetitive tasks, etc.). Risk scores generated by these assessment tools are then used to rank the injury risk of the jobs or tasks from high to low. There are several key characteristics of ergonomic risk assessment tools that influence their usefulness to the industry:

- Ease of use: workflow, data collection, and analysis is easy to understand and perform
- Accuracy: accurately capturing and quantifying exposure information
- Validity: validated in linking high-risk scores with a high association of MSD
- Standardization: capable of being used to benchmark across industries

In general, better accuracy and validity may require more complex model logic in the assessment tool ,which in return, would make the tool harder to understand and may require more time in training, data collection, and analysis. However, with advances in technology, the way occupational exposure information is collected and analyzed may soon be changed entirely. This may generate new opportunities for better risk assessment systems that are not only accurate but easy to use.

For example, wearable technology has drawn much attention in the field of occupational injury prevention. By attaching small, lightweight sensors to segments of the human body, motion data can be objectively captured remotely. These types of systems create potential for more complex risk estimation models with better accuracy and validity without sacrificing ease of use thanks to their capability of simplifying the data collection process and ability to collect continuous data with high frequency. With an improved measuring system, potential standardization of occupational exposure categorization could be possible. This standardized measure could enable benchmarking of occupational exposure comparisons across different industries and create a huge benefit in a better understanding of the relationship between exposure and health outcomes.

Traditional risk assessment methods such as the Rapid Upper Limb Assessment (RULA), Rapid Entire Body Assessment (REBA) and the NIOSH Lifting Equation are only capable of dealing with discrete (not continuous) exposure information. These tools were designed to evaluate the worst-case scenario of a job. Each posture and external force combination can only be analyzed individually. No calculation methodologies were provided to estimate cumulative exposure from these tools. In terms of cumulative damage estimation from a continuous exposure history, the low back has been the most studied (Kumar, 1990; Norman et al., 1998; Daynard et al., 2001; Stuebbe, Genaidy, Karwowski, Guk Kwon, & Alhemood, 2002; Sullivan, Bryden, & Callaghan, 2002; Andrews & Callaghan, 2003; Fischer, Albert, McClellan, & Callaghan, 2007; Sutherland, Albert, Wrigley, & Callaghan, 2008; Gallagher, Fischer, Howarth, Albert, & Callaghan, 2011; Callaghan, Howarth, & Beach, 2011; Coenen et al., 2013; Greenland, Merryweather, & Bloswick, 2013; Marras, Ferguson, Lavender, Splittstoesser, & Yang, 2014; Afshari, Motamedzade, Salehi, & Soltanian, 2015). However, these studies have typically used linear integration as a method of assessing the cumulative damage. There is a fundamental assumption behind these linear integration methods widely used in these studies. The impact of force and time (frequency) on the cumulative damage measure were treated equally. This assumption was criticized by Jäger, Jordan, Luttmann, Laurig, and DOLLY Group, 2000 based on a cadaver study that measured cycles to failure for spine segments under different loading conditions. These authors stated that "Higher damage risk results from an increase of the compressive force amplitude than from a corresponding prolongation of time". This finding provides evidence that the linear integration assumption may not be correct.

Recently, Gallagher and Schall Jr., 2017 summarized the evidence suggesting MSDs may be due to a fatigue failure process in musculoskeletal tissues. This evidence included results of in vitro studies performed on tendons, ligaments, cartilage and spinal motion segments. All in vitro studies have shown an exponential relationship between the stress applied and the number of cycles to material failure, supporting fatigue failure theory based relationship (Gallagher & Schall Jr., 2017). This relationship reveals that the impact of force is exponentially higher than the time (frequency) in the cumulative damage measurement. The current widely used linear integration method fails to consider the force-repetition interaction suggested by fatigue failure theory.

Accordingly, the goal of this dissertation is to evaluate the performance of the linear integration method in estimating cumulative damage and to develop and evaluate a fatigue failure based low back cumulative damage estimation model using continuous exposure history. To achieve this goal, the following specific aims will need to be accomplished:

- An eccentric exercise experiment under three different loading conditions with the same area under the loading curve will be performed. The performance of linear integration methods in estimating tissue damage were evaluated by using Creatine Kinase (CK), resting elbow angle and changes in Maximum Isometric Voluntary Contraction (MIVC) measured in this experiment;
- A data processing framework for estimating low back cumulative damage using fatigue failure theory was developed. Case studies were used to demonstrate this framework and describe the cumulative damage outcome;
- The performance of a fatigue failure model was evaluated and compared with linear and squared integration methods using two epidemiology databases.

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Chapter 2

Literature Review

2.1 Work-related Musculoskeletal Disorders

Individual, psychosocial and physical are the main categories of risk factors that contribute to the development of MSDs. The state of health, fitness status and work habits of workers are examples of individual risk factors. These personal and situational differences may lead to different exposure levels for each worker that is exposed to the same job. Psychosocial risk factors include poor social support at work and at home, leisure time-related stressors and pre-existing diseases (Hauke, Flintrop, Brun, & Rugulies, 2011). Physical risk factors that contribute to the development of MSDs, including force, posture, and repetition, have been identified and summarized by Putz-Anderson, Bernard, and Burt, 1997. In the workplace, workers can develop MSDs when lifting heavy objects, when working in awkward postures and highly repetitive tasks. The development of MSDs may be the result of a multifactorial process (Bongers, Ijmker, Van Den Heuvel, & Blatter, 2006).

Ergonomic risk assessment methods, including self-report, observation and direct measurement, have been developed to help practitioners quantify exposure to physical risk factors and estimate the potential risk of injury. In general, the assessment process consists of two major components:

- Quantifying the exposure to physical risk factors
- Estimating risk of injury based on the quantified exposure

By using risk assessment tools, practitioners can quantify the level of risk for a variety of jobs. Resources can be allocated to help develop interventions for these high-risk jobs. This type of job risk assessment can be performed periodically to identify high-risk jobs and also evaluate any improvement resulting from implementing injury intervention controls.

However, there are limitations with the ergonomic risk assessment methods that are currently available to practitioners and researchers. These methods will be discussed, and the potential of a new ergonomic risk estimation method will be proposed subsequently.

2.2 Methods of Quantifying Exposure to Physical Risk Factors

To evaluate the risk associated with the performance of occupational tasks, one must examine both the external load imposed on the body and the effects that this external load causes on the musculoskeletal tissues. Specifically, exposure to physical risk factors (external exposure) can be expressed as biomechanical loading within the body (internal loading) (Winkel & Mathiassen, 1994). The forces experienced by musculoskeletal tissues, results of internal loading, may cause either reversible or irreversible damage to soft tissues which can contribute to the development of MSDs.

The first step towards the understanding of the cause and effect relationship between external exposures and health outcomes is to quantify exposure. Assessment techniques in estimating exposure to physical risk factors can be classified into three (3) categories (Burdorf & Van Der Beek, 1999): Subjective self-report, systematic observation, and direct measurement. The following sections will briefly discuss these three methods.

2.2.1 Subjective Self-Report

Subjective self-report is a method that asks participants about their feelings and attitudes. Surveys or questionnaires are given to participants, which they read, and select a response by themselves without researcher interference.

Self-report questionnaires were used and evaluated in studies (Oberg, Sandsjö, & Kadefors, 1994; Spielholz, Silverstein, & Stuart, 1999; Wiktorin, Karlqvist, & Winkel, 1993; Wiktorin, Hjelm, Winkel, & Köster, 1996) to estimate exposures to physical risk factors including force, posture, and repetition. For example, workers were asked to estimate how much time they spent bending their wrist (Spielholz et al., 1999) and the associated level of perceived force from “very very light” to “very very hard” shown in Table 2.1 on the following page (Borg, 1982).

The benefits of using self-report questionnaires include ease of use, time effectiveness, relatively low cost and the potential for large sample sizes (McDowell, 2006). However, information collected using self-reports is often subject to systematic bias and lack of precision (Burdorf & Van Der Beek, 1999). Compared to video observation and direct measurement, self-report is the least preferred method in estimating posture duration, repetition, movement velocity and hand force (Spielholz, Silverstein, Morgan, Checkoway, & Kaufman, 2001).

Table 2.1: Borg rating of perceived exertion scale (Borg, 1982)

Rating	Description
0	Nothing at all
0.5	Very, very weak
1	Very weak
2	Weak
3	Moderate
4	Somewhat strong
5	Strong
6	
7	Very strong
8	
9	
10	Very, very, strong

2.2.2 Systematic Observation

This method of observation can be either field-based (direct observation at the workplace) or video-based. Practitioners or researchers observe the operation performed by the worker either in person or through the pre-recorded video. Exposure to physical risk factors, which may include information about posture, movement frequency and force, are then recorded by using a checklist or ergonomic risk assessment tool. There are several advantages to using video-based over field-based methods, since videotape allows users to code and review the data, resulting in a more detailed and reproducible evaluation (Spielholz et al., 2001).

Though less accurate and reliable compared to direct measurement (Juul-Kristensen, Hansson, Fallentin, Andersen, & Ekdahl, 2001), observational methods are most frequently used by practitioners (Takala et al., 2010). This is likely because they are relatively easy to use, more flexible, and inexpensive when collecting data in the field (Chiasson, Imbeau, Aubry, & Delisle, 2012). There are a variety of methods have been developed and intended for both practitioners and researchers (Burdorf, 2010; Colombini, 1998; David, Woods, Li, & Buckle, 2008; Hignett & McAtamney, 2000; Keyserling, Stetson, Silverstein, & Brouwer, 1993; Li & Buckle, 2000; McAtamney & Nigel Corlett, 1993; Moore & Garg, 1995; Occhipinti, 1998). Examples of observations methods are shown in Table 2.2 on the next page.

Thirty-two (32) different observational methods assessing biomechanical exposures were evaluated concerning different potential users by Takala et al., 2010. Chiasson et al., 2012 compared the results of eight (8) methods used to evaluate risk factors associated with MSDs using field data. Though there are differences in performance and field of application, they do share some strengths and limitations. The strengths of the tools in these studies are that they are easy to learn and easy to use. The limitations include that they

Table 2.2: Examples of observation methods. Exposures included in the method: posture (P), force (F), duration (D), frequency (Fr), and movements (M) (Takala et al., 2010).

Method (Year)	Target Exposures
Ovako working posture assessment system (OWAS) (1973)	P, F
Revised NIOSH lifting equation (RNLE) (1991)	P, F, D, Fr
Task recording and analysis on computer (TRAC) (1992)	P, F, D, Fr
Rapid upper-limb assessment (RULA) (1993)	P, F, static action
Portable ergonomic observation (PEO) (1994)	P, F, D, Fr, M
Strain index (SI) (1995)	P, F, D, Fr, M
Posture, activity, tools, and handling (PATH) (1996)	P, F, work activity
ACGIH hand activity level (HAL) (1997)	M, F
Quick exposure check (QEC) (1999)	P, F, D, Fr, M

are often time-consuming, only used for static posture, difficult to observe the postures of multiple segments at the same time, only deals with the worst cases, do not support for cumulative assessment and requires well-trained observers (Chiasson et al., 2012; Takala et al., 2010).

Recently, computer vision has been used to estimate upper limb kinematics and hand activity level (Akkas, Lee, Hu, Yen, & Radwin, 2016; Akkas et al., 2017; Chen, Hu, Yen, & Radwin, 2012; Chen et al., 2015; Radwin et al., 2015). This technology was also applied to assess MSD risk in the construction industry (Li & Lee, 2011). In addition to the 2-D conventional video, Microsoft Kinect^{TM}, which contains an RGB camera and 3D depth sensors, was evaluated and suggested as a potential portable 3-D motion capture system for performing ergonomic assessments in the field (Dutta, 2012). Such a system already has been used as an observational method for assessing postures at work (Diego-Mas & Alcaide-Marzal, 2014) and as a real-time ergonomic assessment system (Haggag, Hossny, Nahavandi, & Creighton, 2013; Martin et al., 2012).

An image processing algorithm was used in these methods to track one or multiple predefined regions of interest, such as the elbow and wrist. Then movement information, such as joint kinematics, of the musculoskeletal system can be calculated. This computer vision technology automates the process of estimating movement speed, duty cycle and exertion time, which saves practitioners and researchers a significant amount of time in identifying elements of exposures to physical risk factors. In addition, this method also provides an objective and relative reliable estimation (Akkas et al., 2017).

Given the nature of video recording, no visual obstructions should be present and relatively stable recordings are required to produce quality results using computer vision. However, it is sometimes challenging to get a clear view of the motion of interest due to the relatively confined areas often present in the industrial environment.

2.2.3 Direct Measurement

The method of direct measurement relies on hardware sensor systems that are attached directly to the subject to capture exposure variables (David, 2005), such as posture and force. A wide range of systems has been developed and applied in occupational ergonomics (Du & Duffy, 2007; Faber, Chang, Kingma, Dennerlein, & van Dieën, 2016; Granata & Marras, 1995; Granata, Marras, & Fathallah, 1996; Hansson, Asterland, Holmer, & Skerfving, 2001; Marras, Fathallah, Miller, Davis, & Mirka, 1992; Radwin & Li Lin, 1993). Examples of direct measurement methods are shown in Table 2.3.

Table 2.3: Examples of direct measurement methods

Technique	Function	Reference
Lumbar motion monitor	Assessment of back posture and motion	Marras et al., 1992
Electronic goniometry	Measurement of angular displacement	Radwin and Li Lin, 1993
Inclinometers	Measurement of segment inclination	Hansson et al., 2001
Optical motion capture	Measurement of 3-D position	Du and Duffy, 2007
Inertial measurement	Measurement of segment orientation	Faber et al., 2016
Electromyography	Estimation of muscle tension	Granata and Marras, 1995
Force plate	Measurement of ground reaction force	Granata et al., 1996

Optical Motion Capture (OMC) is generally treated as the "gold standard" in capturing the three (3) dimensional position of individual segments based on its accuracy: $63 \pm 5\mu m$ for the Vicon-460 system (Windolf, Götzen, & Morlock, 2008). This type of system uses image data captured through cameras in fixed locations to triangulate the 3-D position of the target object between two or more cameras. Data are collected using passive or active markers attached to the target object. Position data with three degrees of freedom for each marker are recorded. Rotational information of an object, such as elbow angle, can be calculated with the data from three or more markers with known relative positions. Thus, human kinematics can be obtained using multiple markers attached to each of the segments. For example, the "Plug-in-Gait" marker set uses forty (40) markers to track the full body kinematics (Vicon, 2006, 2008) which is shown in Figure 2.1 on the next page.

The capture volume of OMC is limited by the number, resolution, and position of the cameras. Generally, six (6) to nine (9) cameras are used to study human movement with a capture volume of approximately $3m \times 3m \times 2m$ (de Vries, Veeger, Baten, & van der Helm, 2009; Kim & Nussbaum, 2014; Latella, Kuppuswamy, Romano, Traversaro, & Nori, 2016; Picerno, Cereatti, & Cappozzo, 2008). OMC is primarily used in a lab environment where the position of cameras can be well controlled. The process of camera calibration, which uses a set of markers with fixed and known relative positions, is required to map the relative position of each camera in the global coordinate system. After the calibration process, the cameras cannot be moved in order

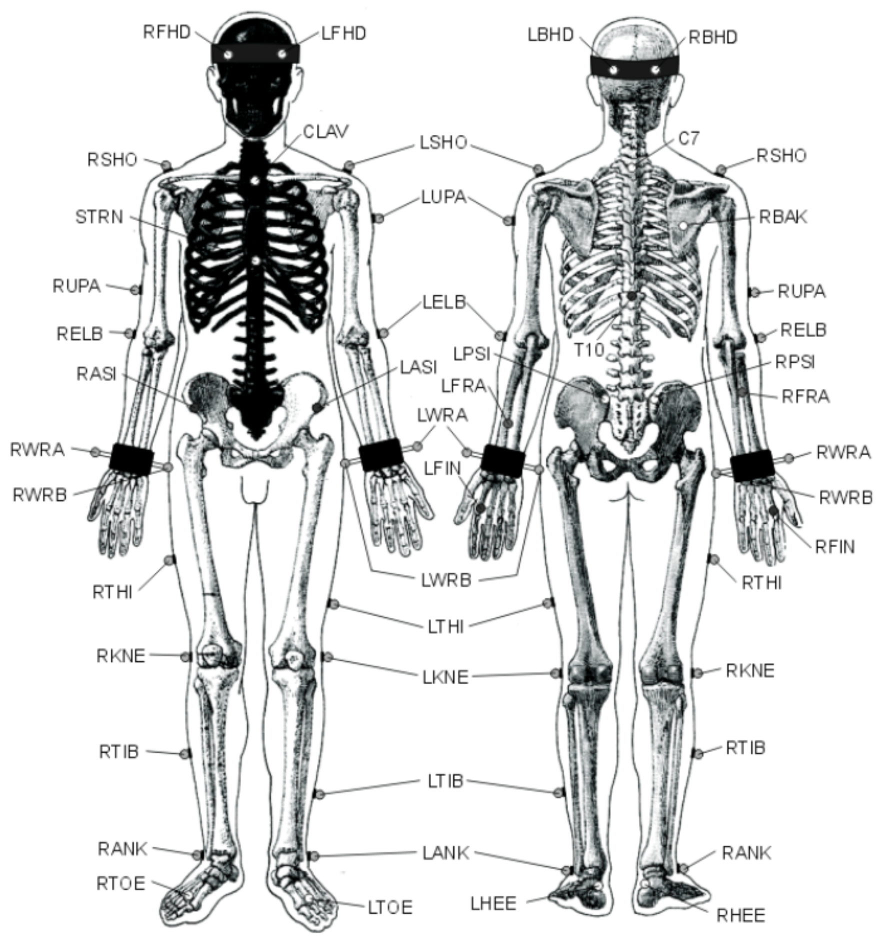


Figure 2.1: Plug-in-Gait marker placement (Vicon, 2006)

to maintain the validity of the calibration and high level of recording accuracy. This requirement limits the application of OMC in field settings.

More recently, Inertial Motion Capture (IMC) has gained attention for estimating human kinematics (de Vries, Veeger, Cutti, Baten, & van der Helm, 2010; Faber et al., 2016; Lebel Karina, Boissy Patrick, Nguyen Hung, & Duval Chrsitian, 2017; Karatsidis et al., 2016; Kim & Nussbaum, 2013; Robert-Lachaine, Mecheri, Larue, & Plamondon, 2017). IMC is an Inertial Measurement Unit (IMU) based system. The IMU is a lightweight, portable and low energy sensor. Data collected by these sensors can be transmitted through a wireless connection to a host computer or stored locally to an Secure Digital (SD) card. These features enable potential applications for estimating human kinematics with a relatively long duration, reasonable quality and good portability outside of a laboratory environment.

By combining data from motion capture and external force measurements, such as force plate and in-shoe force sensors, internal forces experienced by joints and muscles can be estimated using rigid body assumptions or through advanced simulation (Faber, Chang, Kingma, & Dennerlein, 2012; Kim & Nussbaum, 2013; Latella et al., 2016). The traditional method of is using OMC and force plate in a lab environment is considered the gold standard in human kinetics analysis. With advanced technology, new technology like IMC and in-shoe force sensors gain more attention due to the potential benefits of estimating dynamic exposures in the field. Different combinations of these systems have been evaluated against the gold standard (Faber et al., 2012; Koch, Lunde, Ernst, Knardahl, & Veiersted, 2016; Latella et al., 2016; McGill, Marshall, & Andersen, 2013), shown in Table 2.4 on the following page. Faber et al., 2012 proposed a wearable system that consisted of an inertial sensor motion capture system (e.g., Xsens) and shoes with 3-D force transducers based on the performance of the systems that has been evaluated separately (Faber, Kingma, Bruijn, & van Dieën, 2009; Faber, Kingma, Martin Schepers, Veltink, & van Dieën, 2010a; Faber, Kingma, & van Dieën, 2010b). Koch et al., 2016 compared the performance of a foot pressure measurement system (medilogic insoles) in estimating vertical ground reaction force with a force plate. Mean root-mean-square error of 13.9%, 17.7%, and 11.2% were found in the situation of walking, standing, and lifting scenarios respectively. The authors of this study stated that this accuracy level may be adequate for measurement over an entire shift in the occupational environment. This field-based exposure estimation creates the opportunity for a more complex cumulative exposure estimation methodology which may help better understand the relationship between cumulative exposure and work-related MSDs.

Table 2.4: Combinations of motion capture and force sensing system

Motion Capture System	Force Sensing System	Reference
OMC	Force plate	McGill et al., 2013
OMC	In-shoe force sensors	Koch et al., 2016
IMC	Force plate	Latella et al., 2016
IMC	In-shoe force sensors	Faber et al., 2012

2.3 Cumulative Exposure as a Risk Factor

Studies have shown that cumulative exposure to physical risk factors is one of the key contributors to the development of MSDs in the workplace (Kumar, 1990; Norman et al., 1998).

Kumar, 1990 investigated the association between cumulative load and low back pain among 161 institutional aides. A 2-D static biomechanical model was used to estimate the cumulative low back exposure. It was reported that cumulative low back compression was significantly higher ($P < 0.05$) in the group reporting pain compared with the no pain group (Kumar, 1990). Norman et al., 1998 performed a case-control epidemiological study to determine the association between physical loads on the lumbar spine and low back pain. They found that integrated compression (or moment) was significant in distinguishing cases (reported low back pain) from control.

Several other studies also investigated cumulative loading as a risk factor in the development of low back pain (Andrews & Callaghan, 2003; Callaghan, Salewytsch, & Andrews, 2001; Coenen et al., 2013; Daynard et al., 2001; Marras et al., 2014; Jäger et al., 2000; Waters et al., 2006). This evidence strongly suggests the importance of estimating cumulative exposure as a potential predictor of low back pain.

How to capture and quantify cumulative exposure is the first question that must be answered by those whom are interested in understanding the dose-response relationship between exposure and health outcome. Several different methods of capturing and quantifying cumulative exposure are described in the following sections.

2.3.1 Methods in Capturing Cumulative Exposure

Questionnaire

A structured questionnaire was used by Kumar, 1990 to collect exposure information which included: health status concerning MSDs and their type, intensity, duration, and region affected as well as physical stresses at work (postural and activity related). For static postures, joint angles of the wrist, elbow, shoulder, hip, knee, and ankles were measured and recorded from lines drawn on the questionnaire. For dynamic postures, initial and final postures of the tasks were recorded in two dimensions (Kumar, 1990).

Seidler et al., 2001 used structured interviews to collect physical workload including lifting and carrying, working postures, whole body vibration, psychosocial workload, leisure activities, life events, and complaints. Participants were asked to describe the specific objects that were moved followed by questions regarding the weight, frequency, and duration that directly related to the objects (Seidler et al., 2001; Seidler et al., 2003).

Video

Video recording has been widely used to capture posture information for cumulative exposure assessment (Andrews & Callaghan, 2003; Callaghan et al., 2001; Coenen et al., 2013; Daynard et al., 2001; Fischer et al., 2007; Gallagher et al., 2011; Jäger et al., 2000; Mirka, Kelaher, Nay, & Lawrence, 2000; Norman et al., 1998; Stuebbe et al., 2002; Sutherland et al., 2008). Depending on the purpose of the study, recording durations ranged from a few minutes to eight hours with a capture frequency between 3 to 60 Hz. Most of the studies used computer programs to assist manual identification of postural information. A summary of video recording based cumulative exposure assessments for the low back is provided in Table 2.5.

Table 2.5: Summary of cumulative exposure assessment: video recording

Source	Method	Duration	Frame Rate
Norman et al., 1998	Manual (computer-assisted)	2 to 8 hours (typically half shift)	30 Hz
Mirka et al., 2000	Manual (computer-based)	Occupational tasks	30 Hz
Callaghan et al., 2001	Automate (PEAK)	Three lifting tasks	30 Hz
Daynard et al., 2001	Manual track (Norman et al., 1998)	Patient-handling activities	30 Hz
Stuebbe et al., 2002	Manual track	8 hours	10s per 2 minutes
Andrews and Callaghan, 2003	Automate (PEAK)	Three lifting tasks	60 Hz
Fischer et al., 2007	Manual (3DMatch)	Three cycles per task	3 Hz
Sutherland et al., 2008	Manual (3DMatch)	Five cycles per task	30 Hz
Gallagher et al., 2011	Manual (3DMatch)	Three cycles per task	3 Hz
Coenen et al., 2013	Manual	5 to 14 minutes	Not specified

Direct Measurement

Force gauges and transducers have been widely used in field studies to capture external loads acting on the hands (Coenen et al., 2013; Fischer et al., 2007; Gallagher et al., 2011; Norman et al., 1998). Norman et al., 1998 used a force transducer to measure the magnitude of forces acting on hands (Norman et al., 1998). When the device could not be placed between the worker and the work, the worker was asked to estimate the level of hand force and push or pull the transducer against to the side of the workstation. The direction of the force was estimated by a trained observer. Fischer et al., 2007 and Gallagher et al., 2011 measured push, pull and lift force using a force gauge that can capture both the magnitude and 3-D direction of the force.

Postural estimation using direct measurement method has been mainly used in a lab environment (Callaghan et al., 2011; Greenland et al., 2013; Sutherland et al., 2008). An electromagnetic tracking device, which captures position and orientation information, was used to compare the performance in estimating cumulative exposure with a video-based approach by Sutherland et al., 2008. An optical motion capture system using active infrared light emitting markers was used to capture position and acceleration of the upper extremities from simulated lifting tasks in a lab environment by Callaghan et al., 2011. Greenland et al., 2013 used reflective markers to capture two-dimension motion data with a GS-55 digital camcorder (Panasonic) (Greenland et al., 2013).

Custom-made devices were also developed and used for direct measurement of external exposure (Table 2.6). Marras et al., 2014 used a clinical lumbar motion monitor to document the low back kinematic performance in three-dimension at a distribution center (Marras et al., 2014). An inclinometer was used in the field to capture trunk inclination angle during knotting and compacting subtasks of carpet weavers (Afshari et al., 2015).

Table 2.6: Summary of cumulative exposure assessment: direct measurement of posture

Source	Method	Measurement
Sutherland et al., 2008	Electromagnetic tracking device	3-D position and orientation
Callaghan et al., 2011	Infrared light emitting markers	3-D position
Greenland et al., 2013	Reflective markers	2-D position
Marras et al., 2014	Lumbar motion monitor	3-D kinematic
Afshari et al., 2015	Inclinometer	Trunk inclination angle

2.3.2 Spinal Loading Estimation Methods

Biomechanical models ranging from basic two-dimension static models to more complexed three-dimension dynamic models have been used in studies (Table 2.7 on the next page) to estimate the spinal loading for cumulative exposure assessment (Daynard et al., 2001; Kumar, 1990; Mirka et al., 2000; Norman et al., 1998; Sullivan et al., 2002). In general, a rigid segment link models have been used to simplify the modeling of the human skeletal system. For static models, joint reaction force and moment can be calculated following Newton's laws with known joint angles and external forces. For static models, the acceleration of each segment is not considered in the calculation process. Under slow movement condition, the impact of acceleration is relatively small since the magnitude of acceleration is low. For dynamic models, inverse dynamics can be used to estimate joint kinematics through either a "bottom up" or "top down" approach. Acceleration is considered in dynamic models.

In addition to the static and dynamic models, a quasi-dynamic model was used by Daynard et al., 2001 and Norman et al., 1998. Dynamic forces acting on the hands are included in this model while body segment inertial forces are not included (Norman et al., 1998). This model has been shown to generate comparable or higher estimates of spinal loading than dynamic models (McGill & Norman, 1985).

Table 2.7: Summary of biomechanical models used in estimating spinal loading

Source	Model	Calculation Parameter
Kumar, 1990	2-D static	Compressive and shear load
Norman et al., 1998	2-D quasi-dynamic	Compressive, shear load and moment
Jäger et al., 2000	3-D static	Compressive and shear load
Mirka et al., 2000	3-D static	Compressive load
Callaghan et al., 2001	3-D static	Compressive, shear load and moment
Daynard et al., 2001	2-D and 3-D quasi-dynamic	Compressive and shear load
Stuebbe et al., 2002	2-D static	Compressive load
Sullivan et al., 2002	2-D static	Compressive and shear load
Andrews and Callaghan, 2003	2-D static	Compressive and shear load
Fischer et al., 2007	3-D static	Compressive, shear load and moment
Sutherland et al., 2008	3-D static	Compressive, shear load and moment
Gallagher et al., 2011	3-D static	Compressive, shear load and moment
Callaghan et al., 2011	2-D dynamic	Compressive load and moment
Coenen et al., 2013	2-D static	Moment
Greenland et al., 2013	2-D static and dynamic	Compressive load and moment
Afshari et al., 2015	2-D static	Compressive load

2.3.3 Methods of Cumulative Exposure Integration

In order to calculate cumulative loading over a period of time, some integration method is needed. Kumar, 1990 used load over time integration in estimating spinal load:

$$OL = \sum_{i}^{n}(L_i \times t_i) \tag{2.1}$$

where
OL = overall load (compression or shear), $Newton \cdot second\ (N \cdot s)$
L_i = average force of the ith segment of the task (N)
t_i = the duration of the ith segment of the task (s).

Equation (2.1) calculates the overall load for one specific task performed by a worker. To combine different tasks and to calculate cumulative daily overall load, the following equation was used (Kumar, 1990):

$$CDL = \sum_{j}^{n}(OL_j \times F_j) \tag{2.2}$$

where CDL = cumulative daily load, OL_j = overall load for task j, F_j = frequency per day for task j.

Unlike Kumar, 1990, Norman et al., 1998 integrated the peak load for each task over time as the measure of cumulative exposure. In addition, spinal load during the resting time between tasks was incorporated into the algorithm (Norman et al., 1998).

$$Cumulative\ Load_{Total} = \sum_{i}^{n}(PL_i \times t_i \times F_i) + RL \times T \tag{2.3}$$

where
$Cumulative\ Load_{Total}$ = overall cumulative load of all tasks combined ($N \cdot s$)
PL_i = the peak spinal compression load for task i (N)
t_i = the duration of task i (s)
F_i = the frequency per day for task i
n = the number of different tasks performed (i.e. tasks $1\ to\ n$)
RL = the spinal compression load during rest condition (upright standing posture)
T = the total rest time (s).

Similar to the approach used by Norman et al., 1998, the summation of peak spinal loads for each task multiplied by its duration was used to calculated cumulative spinal load by Daynard et al., 2001. However, spinal loading during rest time was not included.

$$Cumulative\ Spine\ Compression = \sum(PSC_i \times t_i) \tag{2.4}$$

where PSC_i = peak spinal compression for task i, t_i = duration of task i.

In order to understand the performance of different integration methods in estimating cumulative spinal exposure, six (6) different methods were used by Callaghan et al., 2001 to calculate the cumulative loading on L4/L5 and all of them are based on linear integration of load over time:

- Rectangular integration of all frames collected at 30 Hz
- Rectangular integration of data sampled at 5 Hz
- Peak load multiplied by the duration of the task
- Peak load multiplied by work duration and load during upright standing multiplied by rest duration
- Peak load multiplied by the duration of mass on hand
- Lift cycle divided into four components and weight the load accordingly

In addition to the studies discussed above, linear rectangular integration of spinal load over time has been widely used in quantifying cumulative spinal load (Table 2.8 on the next page).

Jäger et al., 2000 discussed a central assumption behind the linear integration of lumbar-disc compression forces over time for cumulative load assessment: the same injury risk is assumed between high

Table 2.8: Additional literature using linear integration method

Source	Model
Stuebbe et al., 2002	$\sum C_i,\ C_i$ = spinal compression for observation i
Sullivan et al., 2002	Rectangular integration
Andrews and Callaghan, 2003	Rectangular integration
Fischer et al., 2007	Rectangular integration
Sutherland et al., 2008	Rectangular integration
Gallagher et al., 2011	Rectangular integration
Callaghan et al., 2011	Rectangular integration
Coenen et al., 2013	Area under the moment curve
Greenland et al., 2013	Area under the curve
Marras et al., 2014	(a) Integration of signal overexertion time (b) Signal peak times the duration of exertion
Afshari et al., 2015	$\sum FC_i \times F_i,\ FC_i$ = compression force for subtasks i F_i = frequency of task i

force-short duration and low force-long duration. These authors stated "Higher damage risk result from an increase of the compressive force amplitude than from a corresponding prolongation of time" (Jäger et al., 2000), as reported by Brinckmann, Biggemann, and Hilweg, 1988. Based on this finding, Jäger et al., 2000 proposed squared and tera-power integration methods.

$$\text{Linear:} \quad \sum (F_i \times t_i)/T \tag{2.5}$$

$$\text{Squared:} \quad \sqrt{\sum (F_i^2 \times t_i)/T} \tag{2.6}$$

$$\text{Tera-power:} \quad \sqrt[4]{\sum (F_i^4 \times t_i)/T} \tag{2.7}$$

where i = time interval, F_i = disc-compression during i, t_i = duration of i, T = shift duration.

Seidler et al., 2001 assessed cumulative exposure by using the modified Mainz-Dortmund dose model to estimate the lumbar disc compression force and then take the square of weights lifted or carried multiplied by the corresponding duration. Each lifting or carrying activity was calculated and summed together to generate the cumulative exposure estimation measure (Seidler et al., 2001).

$$\text{Sum dose for year } = DAYS \times \sqrt{8h \times \sum F_i^2 \times t_i} \tag{2.8}$$

where $DAYS$ = working days per year; t_i = average daily lifting or carrying duration (h);
F_i is defined by:

$F_i = 1,800\ N + 75\ N/kg \times weight\ of\ object\ i\ (kg),$ if lifting with both arms
$F_i = 1,000\ N + 85\ N/kg \times weight\ of\ object\ i\ (kg),$ if carrying in front of or beside the body
$F_i = 1,000\ N + 60\ N/kg \times weight\ of\ object\ i\ (kg),$ if carrying on both sides, shoulder or back
$F_i = 1,700\ N,$ if extreme forward bending

However, from the physics perspective, the squared (Equation (2.6), Equation (2.8)) and tera-powered (Equation (2.7)) algorithm do not fit the classic definition of internal exposure dose that is: units are not in $Newton \cdot sec$ (Waters et al., 2006).

2.4 Fatigue Failure Process in the Development of Musculoskeletal Tissue Damage

2.4.1 Fatigue Failure of Physical Material

Physical materials have a finite functioning life when repetitively stressed. Both high-magnitude stress and cyclic stress can lead to material failure. In high-cycle fatigue situations, an $S - N$ curve is commonly used to describe material performance. This curve shows the number of cycles that lead to material failure under varying loading conditions, generally expressed as stress. As shown in Figure 2.2, higher levels of loading will lead to material failure in fewer cycles while lower levels of stress will last an exponentially larger number of cycles.

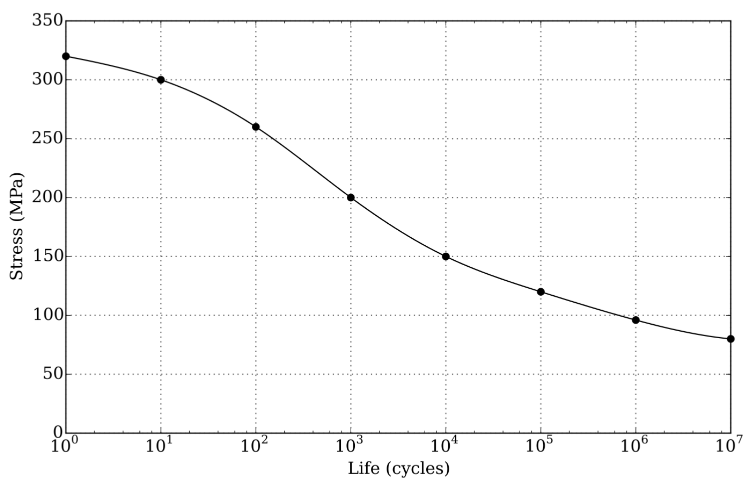


Figure 2.2: S-N curve for Brittle Aluminum with a UTS of 320 MPa (Nicoguaro, 2016)

The traditional application of fatigue failure analysis has been in the evaluation of mechanical components and structures such as aircraft and bridges. Just like other materials, biological tissues (also materials) may experience damage under physical stress and follow the same underlying principles in terms of responding to varying levels of loading conditions.

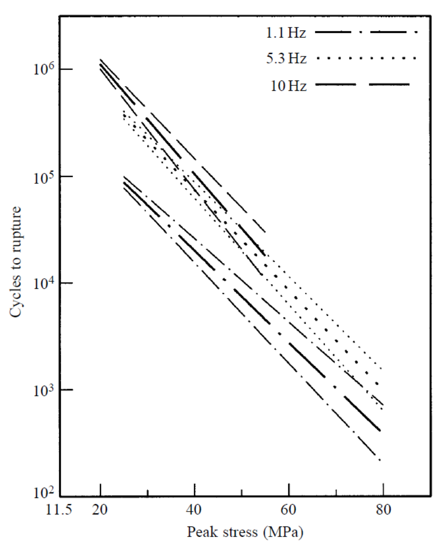
2.4.2 Musculoskeletal Disorder as a Fatigue Failure Process

Gallagher and Schall Jr., 2017 summarized the evidence supporting the fatigue failure process in musculoskeletal tissues. This evidence including vitro studies performed on tendons, ligaments, cartilage and spinal motion segments. As will be described below, all studies have shown an exponential relationship between the stress applied and the number of cycles to material failure (Gallagher & Schall Jr., 2017).

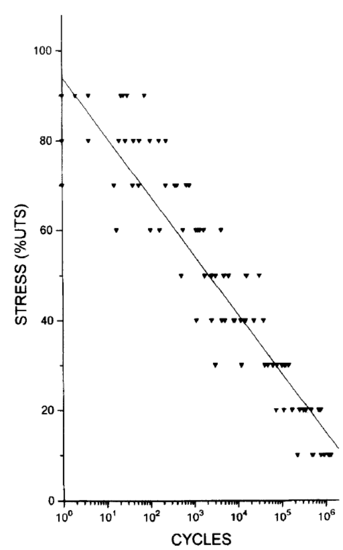
Wang, Ker, and Alexander, 1995 tested 6, 17, and 11 tendon samples (wallaby tail tendons) with the length of 120 mm at 1.1, 5.3, and 10 Hz respectively (Wang et al., 1995). A plot of the number of cycles to rupture against peak stress was drawn based on the testing results (Figure 2.3a). Schechtman and Bader, 1997 reported a similar exponential relationship between cycles to failure and stress based on 90 tendon specimens (human extensor digitorum longus tendons) (Schechtman & Bader, 1997).

$$\text{Wang et al., 1995: } S = 96.5 - 15.8log(N), \text{ estimated by Schechtman and Bader, 1997} \quad (2.9)$$
$$\text{Schechtman and Bader, 1997: } S = 93.98 - 13.13log(N) \quad (2.10)$$

where
N = the number of cycles to failure
S = the stress normalized to a % of the ultimate tensile strength



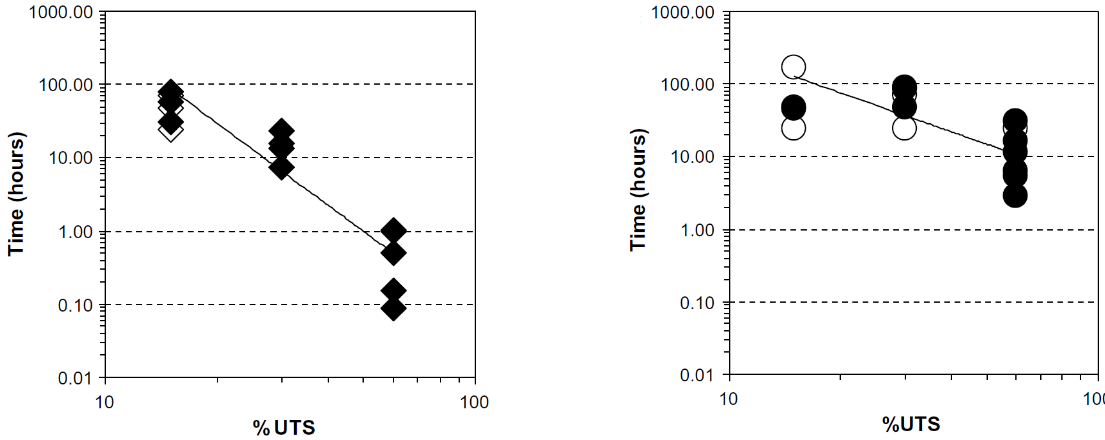
(a) Wang et al., 1995



(b) Schechtman and Bader, 1997

Figure 2.3: Number of cycles prior to rupture (tendon)

Forty-seven (47) medial collateral ligaments from Burgunder rabbits were tested under three different loading conditions by Thornton, Schwab, and Oxland, 2007. Test results were presented using time-to-rupture plots with a clear exponential relationship between percent of ultimate stress (% UTS) and time to rupture (Figure 2.4).

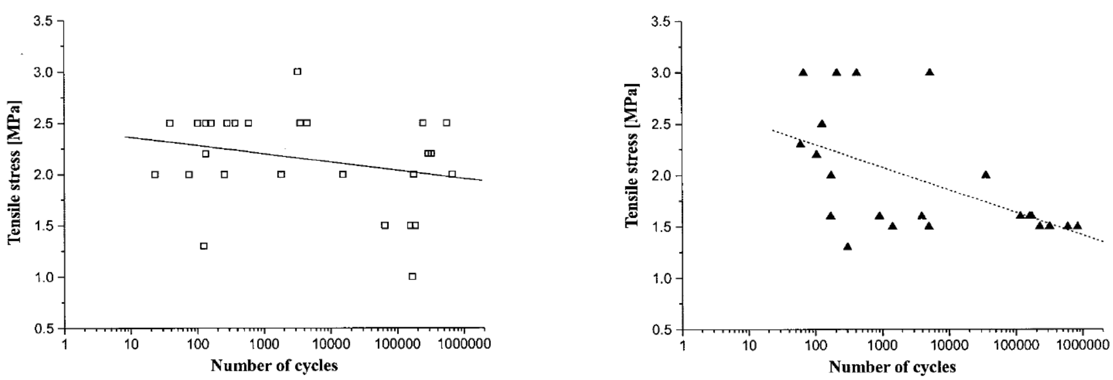


(a) Fatigue

(b) Creep

Figure 2.4: Time-to-rupture under different stress levels (Thornton et al., 2007) (ligament)

Seventy-two (72) tensile specimens from various depths at 16 sites of one knee specimen (cartilage) were tested by Bellucci and Seedhom, 2001. The applied tensile stress against the number of cycles to failure is shown in Figure 2.5.

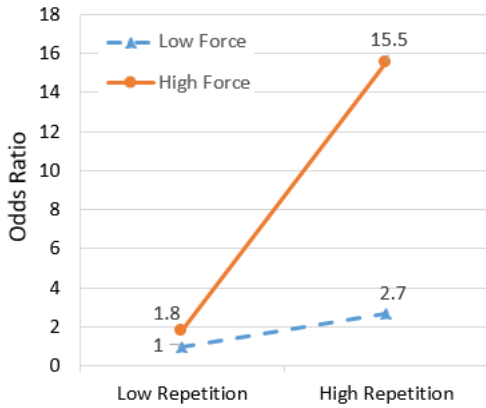


(a) Tested parallel to the collagen fibers

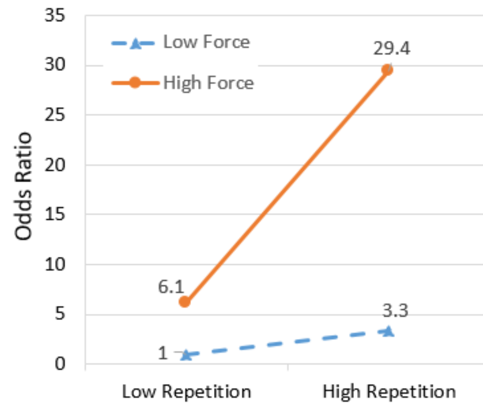
(b) Tested perpendicular to the collagen fibers

Figure 2.5: Cyclic tensile stress vs. number of cycles to failure (Bellucci & Seedhom, 2001) (cartilage)

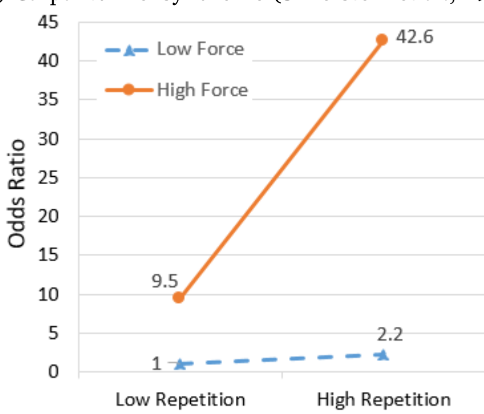
Epidemiological studies, summarized by Gallagher and Heberger, 2013, have examined a force-repetition interaction which strongly suggested a fatigue failure process may be associated with MSD risk (Figure 2.6 on the following page). This pattern has also been found for carpal tunnel syndrome, tendinitis, epicondylitis, hand pain, and low back pain (Armstrong, Fine, Goldstein, Lifshitz, & Silverstein, 1987; Haahr & Andersen, 2003; Nathan, Meadows, & Doyle, 1988; Marras et al., 1993; Silverstein, Fine, & Armstrong, 1987; Thomsen et al., 2007; Zurada, Karwowski, & Marras, 1997).



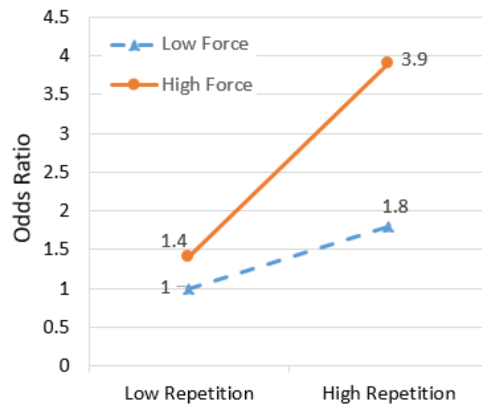
(a) Carpal tunnel syndrome (Silverstein et al., 1987)



(b) Hand-wrist tendonitis (Armstrong et al., 1987)



(c) Low back disorders (Marras et al., 1993)



(d) Lateral epicondylitis (Haahr & Andersen, 2003)

Figure 2.6: Force $\times$ Repetition interaction

Recently, Harris-Adamson et al., 2015 reported the findings based on a large prospective epidemiology study: "forceful repetition" was the loading variable most associated with the development of carpal tunnel syndrome. All this evidence suggests the potential underlying fatigue failure process in the development of MSDs.

2.4.3 The Implication of Fatigue Failure in Cumulative Exposure Assessment

Loadings of musculoskeletal tissues in occupational environments are highly variable. One implication of the fatigue failure theory in assessing cumulative exposure is a validated integration method that has been used in predicting damage accumulation associated with varying loading conditions. The most commonly used model of estimating or predicting damage resulting from spectrum loading is the linear cumulative damage rule (Palmgren-Miner rule) for fatigue life from spectrum load proposed by Palmgren, 1924 and Miner, 1945 (Gallagher & Schall Jr., 2017):

$$c = \sum_{i}^{k} \frac{n_1}{N_1} + \frac{n_2}{N_3} + \cdots + \frac{n_k}{N_k} \tag{2.11}$$

where
c is a constant (often set at 1, but which may vary)
$n_i \cdots$ is the number of loading cycles experienced at force levels at which $N_i \cdots$ cycles would result in material fatigue failure.

When the sum of the right-hand side of the equation (Equation (2.11)) is equal to one, the material would be expected to fail. For different materials, the value of constant c may vary above or below one.

In order to apply this method, both the stress and the repetition associated with the loading needs to be examined concurrently. For example, suppose a worker performs a task that stresses a tendon at 20 cycles at 60% of Ultimate Tensile Strength (UTS), 100 cycles at 50% UTS and 800 cycles at 40% UTS with assumption that the cycles to failure for 60, 50 and 40% UTS are $1,000$, $10,000$ and $100,000$ cycles, respectively (Table 2.9). Using the Palmgren–Miner technique, the cumulative damage (D_t) is the sum of quotients of the number of cycles experience at each stress level divided by their respective cycles to failure (Equation (2.12)).

$$D_t = \frac{20}{1000} + \frac{100}{10000} + \frac{800}{100000} = 0.02 + 0.01 + 0.008 = 0.038 \tag{2.12}$$

Table 2.9: Example of cumulative damage calculation using Palmgren-Miner rule

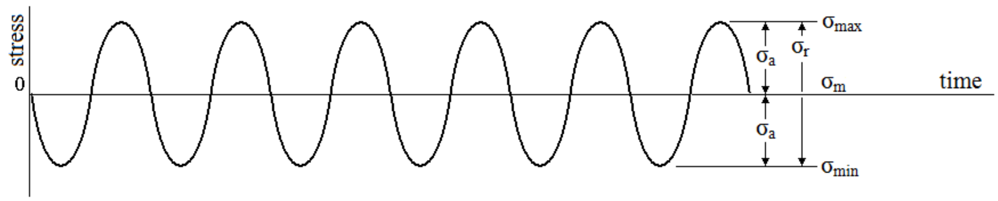
% UTS	Cycles to Failure	Cycles Experienced
60%	1,000	20
50%	10,000	100
40%	100,000	800

The Palmgren-Miner rule often provides a useful estimation of the cumulative fatigue damage in a material; however, it must be understood that it is an approximation. Numerous other factors can impact the development of fatigue failure and these factors can influence the fatigue failure process in a manner not captured by the linear summation approach expressed above. The limitations of this method include:

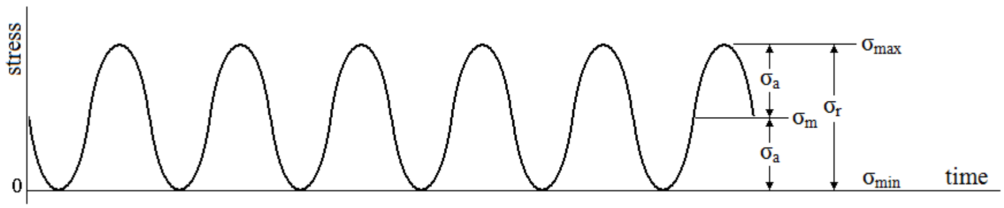
- It fails to recognize the probabilistic nature of fatigue;
- It does not account for the sequence of different loading levels that affect material fatigue life.

The loading pattern on musculoskeletal tissues can vary in many ways. One standard method of performing loading in fatigue failure studies known as completely reversed loading using a sinusoidal loading pattern. This loading pattern represents a loading condition where an object is subjected to alternating tensile and compressive stresses and where the mean stress is 0 (Figure 2.7a on the following page). As described in the figure, σ_a represents the average of the maximum minus the minimum load of the cycle; σ_m represents the mean loading associated with the cycle. Stress ratio (R) and amplitude ratio (A) can be calculated based on $\sigma_{min}, \sigma_{max}, \sigma_a \; and \; \sigma_m$ (Equation (2.13)).

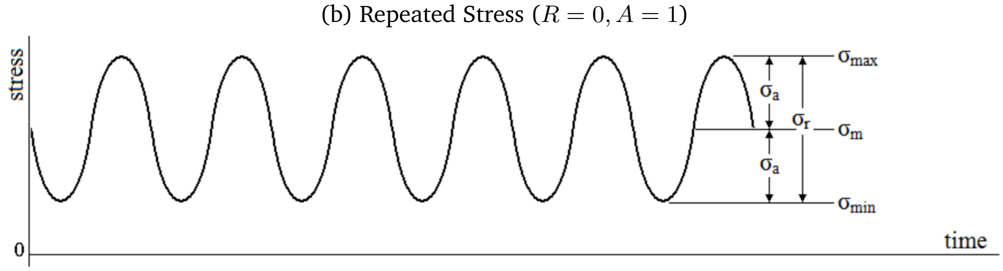
$$R = \frac{\sigma_{min}}{\sigma_{max}}, \quad A = \frac{\sigma_a}{\sigma_m} \tag{2.13}$$



(a) Fully Reversed Sinusoidal Stress ($R = -1, A = \infty$)



(b) Repeated Stress ($R = 0, A = 1$)



(c) Sinusoidal Fluctuating Stress ($R = \infty, A = -1$)

Figure 2.7: Examples of cyclic loading ("Cyclic Loading", 2008)

The standard $S - N$ curve for a physical material is developed assuming a fully reversed loading cycle where $\sigma_m = 0$. When $\sigma_m \neq 0$, certain specific loading conditions known as either repeated stress (Figure 2.7b) or fluctuating stress (Figure 2.7c). Repeated stress is defined as a loading pattern where the minimum stress is zero and cycles to some positive (tensile) or negative (compressive) value. Fluctuating stress is when the minimum stress is non-zero and cycles to stress of larger absolute magnitude. Tendons and ligaments experience similar loading patterns as repeated stress, while spine segments experience similar loading pattern as fluctuating stress. For example, when assessing the spinal loading for a worker lifting boxes, the worker begins the work cycle at a resting position (standing) with a load of approximately 500 N on the spine then repeatedly lifts boxes off the ground which increases the compressive load on the spine (~3,000 N), returning to 500 N when the box is released. So the spine is always experiencing compression that cycles from some non-zero value to a larger amount of stress. Both repeated and fluctuating stresses will result in non-zero mean stress on the tissues, which may shift the fatigue failure curve down, meaning that fewer loading cycles would be needed to reach failure compared to a fully reversed loading condition (Figure 2.8).

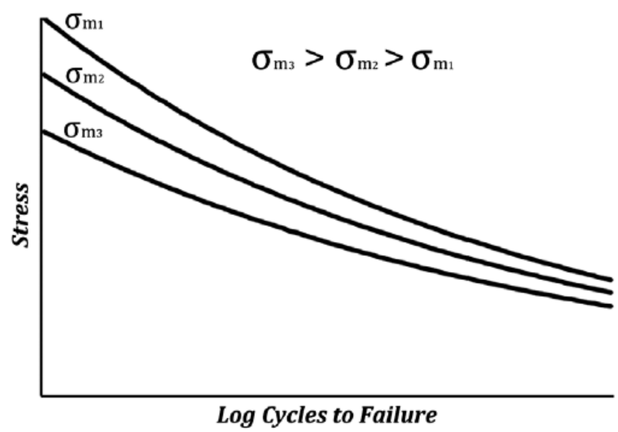


Figure 2.8: The influence of mean stress on S-N curves (Gallagher & Schall Jr., 2017)

The Goodman line (Goodman, 1899) and Gerber criterion (Gerber, 1874) are two methods in fatigue failure theory for calculating safety factors and expected cycles to failure for materials subjected to repeated or fluctuating stress (Figure 2.9). The Goodman criterion is the more conservative of the two. Experimental data on fatigue life of different materials tend to fall between the estimation from these two methods (Stephens & Fuchs, 2001).

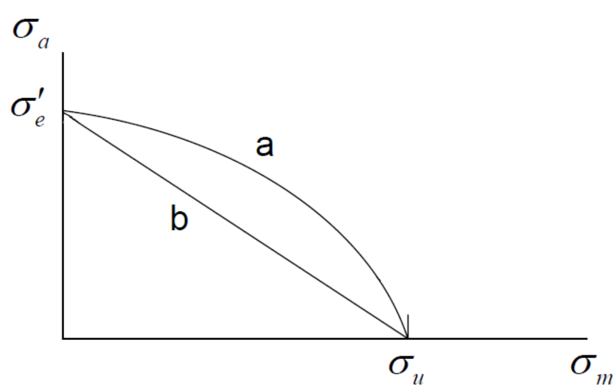


Figure 2.9: Infinite life curve: (a) Gerber; (b) Goodman. σ_u is the ultimate stress, $\sigma_e^{'}$ is the effective alternating stress at failure for a lifetime of 10^6 cycles

In materials science engineering applications, Goodman and Gerber's techniques often used to design materials or parts for 10^6 cycles to failure (considered to be 'infinite life'). These methods can also be used to design material for finite life ($< 10^6$ cycles to failure). Stress amplitude (σ_a) and mean stress (σ_m) would be used to estimated how many cycles would be expected until failure when infinite life conditions are exceeded. Under the completely reversed loading situation, the following equations would be used:

$$N = \left(\frac{\sigma_a}{a}\right)^{\frac{1}{b}} \tag{2.14}$$

$$a = \frac{(f \cdot S_{ut})^2}{S_e} \tag{2.15}$$

$$b = -\frac{1}{3}\log\left(\frac{f \cdot S_{ut}}{S_e}\right) \tag{2.16}$$

where
N = cycles to failure
σ_a = stress amplitude
f = fatigue strength (approximation of the fatigue strength at 10^3 cycles)
S_{ut} = ultimate tensile strength
S_e = stress at the endurance limit

However, in the fluctuating stress situation, σ_a in Equation (2.14) cannot be used since it only applies to completely reversed loading. In the case of fluctuating stress, σ_{rev} represents an equivalent value for completely reversed stress under repeated or fluctuating stress need to be calculated and will replace σ_a in Equation (2.14). Thus, for fluctuating stress conditions (using the Goodman design criterion) the equation for N cycles to failure becomes:

$$N = \left(\frac{\sigma_{rev}}{a}\right)^{\frac{1}{b}} \tag{2.17}$$

where σ_{rev} is:

$$\sigma_{rev} = \frac{\sigma_a}{1 - \frac{\sigma_m}{S_{ut}}} \tag{2.18}$$

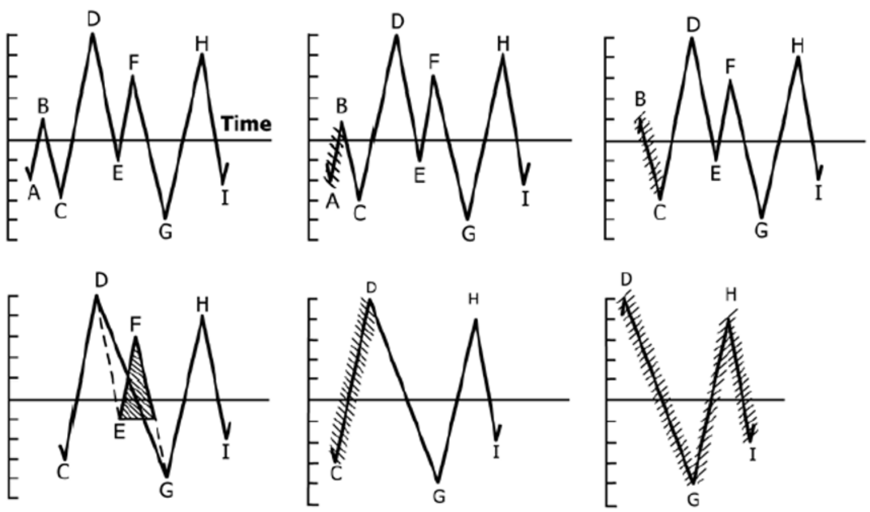
and for the Gerber relation σ_{rev} is:

$$\sigma_{rev} = \frac{\sigma_a}{1 - \left(\frac{\sigma_m}{S_{ut}}\right)^2} \tag{2.19}$$

For discrete exposure information, such as a load value and a number of repetitions (duration of the force exertion), σ_a can be calculated using the magnitude of the load and σ_m is simply the quotient of load divided by the duration of the repetition. The number of repetitions that lead to material failure can be calculated for this pair of exposure information.

For continuous exposure information, for example, an analog stress wave that is collected through a direct measurement device (e.g. EMG or biomechanical simulation). A counting technique is needed to categorize this highly variable type of exposure information to pairs of amplitude and mean stress. One commonly used technique to evaluate highly variable loading patterns in the context of a fatigue failure process is known as 'rainflow analysis' (Matsuishi & Endo, 1968). This method of cycle counting in fatigue analysis has been well documented in American Society for Testing and Materials (ASTM) Standard E1049-85(2017).

The "rainflow" analysis technique takes a continuous exposure history and breaks it down into pairs of mean and range of stress combinations (Figure 2.10). Based on this mean and range of stress profile of a loading history, Goodman and Gerber relationships and the Palmgren–Miner technique can be applied to estimate the amount of cumulative damage in the material of interest. It is important to note that this technique assumes all loads are independent of one another and there are no sequence effects.



Range (units)	Cycle Counts	Events
10	0	
9	0.5	D-G
8	1.0	C-D , G-H
7	0	
6	0.5	H-I
5	0	
4	1.5	B-C , E-F
3	0.5	A-B
2	0	
1	0	

Figure 2.10: Rainflow counting example (ASTM E1049-85-2017)

With the assistance of new technology applied (portable exposure capturing systems) in the field of occupational injury prevention, fatigue failure theory shows great potential in assessing cumulative exposure using continuous exposure history. This new assessment system may help to better understand the relationship between exposure and health outcome and also contribute to the standardization of cumulative exposure quantification. As part of the effort in applying fatigue failure theory in the field of injury prevention, this dissertation: evaluates the performance of current cumulative estimation method (linear integration) in estimating cumulative damage; proposes a fatigue failure based low back cumulative damage estimation model using continuous exposure history; validates and compares this model with other integration method (linear and squared integration) using two epidemiology databases.

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Chapter 3

Evaluating the Linear Integration Method of Estimating Cumulative Tissue Damage in Muscle

3.1 Introduction

MSDs account for a significant portion of the cost of occupational injuries and illness in the United States. Estimates by the National Research Council and the Institute of Medicine suggest the costs of low back and upper extremity injuries when measured by compensation costs, lost wages, and lost productivity are between \$45 and \$54 billion annually (National Research Council and the Institute of Medicine, 2001). A more recent study estimated the direct costs of MSDs was around \$1.5 billion for the year 2007 based on medical and administrative costs (Bhattacharya, 2014). From 2011 to 2015, MSDs accounted for approximately 31% of the occupational injuries or illnesses cases that involved day(s) away from work (U.S. Bureau of Labor Statistics, 2016b), demonstrating that MSDs are one of the leading threats to occupational health and well-being.

Past research has indicated that exposure to cumulative loading is a significant risk factor in the development of musculoskeletal disorders (Kumar, 1990; Norman et al., 1998; Waters et al., 2006; Coenen et al., 2013). Methods used to calculate cumulative loading over time have been summarized by Waters et al., 2006. The general objective of these methods has been to sum the loading exposure for each task, calculated by multiplying the magnitude of the task loading times the task duration and developing an "area under the curve", as exemplified by the following equation (Norman et al., 1998):

$$Cumulative\ Load_{Total} = \sum_{i}^{n}(PL_i \times t_i \times F_i) + RL \times T \tag{3.1}$$

where
$Cumulative\ Load_{Total}$ is the overall cumulative load of all tasks combined (Newton-Seconds, $N \cdot s$);
PL_i is the peak spinal compression load for task i (N);
t_i is the duration of task i (s);
F_i is the frequency per day for task i;
n is the number of different tasks performed (i.e. tasks $1\ to\ n$);
RL is the spinal compression load during rest condition (upright standing posture);
T is the total rest time (s).

An assumption of the "load-integration" cumulative loading model is that short time exposure to high forces will cause a similar level of damage as a relatively long time exposure to low forces. For example, using Equation (3.1), it would be assumed that 20 repetitions of a 1,000 N load held for 2 seconds would lead to identical tissue damage as 4 repetitions of a 5,000 N load held for 2 seconds (both 40,000 $N \cdot s$), given equivalent rest times and loads. The assumption of equivalence of cumulative loads for the example above, however, has been questioned. For example, based on the cadaver study of motion segment fatigue failure conducted by Brinckmann et al., 1988 and Jäger et al., 2000 argued that a doubling of force produces a more injurious response than doubling of exposure time.

More recently, a literature review conducted by Gallagher and Heberger, 2013 revealed a consistent force-repetition interaction regarding MSD risk among different biological tissues. This study indicated that low-force loadings would result in a low rate of tissue damage and high-force loadings will result in a more rapid progression of damage in accordance with fatigue failure theory. Fatigue failure theory (used to predict cumulative damage in materials) uses an altogether different technique for assessing cumulative loading effects. This may explain why using an integrated cumulative low back load, as in a study conducted by Coenen et al., 2013, appears to have underestimated the impact of high force on the risk of low back pain. In fact, these authors added the number of lifts that are larger than 25 kg as an additional risk factor to achieve better prediction of low back pain.

Currently, there are no studies that have directly evaluated different methods of assessing cumulative loading and evaluating which method better predicts the development of musculoskeletal tissue damage resulting from different loading patterns. In order to address this gap, this study examined tissue damage under three different loading conditions (high force-low repetition, medium force-medium repetition, and low force-high repetition) having the same area under the loading curve. The differences of the level of muscle tissue damage (measured using Creatine Kinase (CK), resting elbow angle, and changes in Maximum Isometric Voluntary Contraction (MIVC)) among those three loading conditions suggests how well this integration method fares in assessing cumulative muscle fatigue since the cumulative loads have equal areas under the loading curving. Additionally, this study compared the integration approach to methods used in fatigue failure theory (damage per loading cycle) that may help emphasize the impact of high force in assessing cumulative tissue damage in muscle.

Eccentric muscle exercise provides a basis for examining the impact of different loading patterns on muscle fiber damage, inflammation, and repair in which damaged muscle fibers are nearly completely healed in approximately ten days (Prasartwuth, Taylor, & Gandevia, 2005). The fortunate aspect of eccentric exercise is that the damaged fibers get repaired with new fibers that are stronger and more resistant to damage from subsequent exercise. This eccentric training effect has been demonstrated in both human (Komi & Buskirk, 1972; Newham, Jones, & Clarkson, 1987; Clarkson & Tremblay, 1988) and animal (Faulkner, Opiteck, & Brooks, 1992; Faulkner, Brooks, & Opiteck, 1993) studies. The appearance of CK in blood is generally considered to be an indirect marker of muscle damage and has been frequently used to detect muscle injury and overwork (Clarkson & Tremblay, 1988; Houmard et al., 1990; Olerud, Homer, & Carroll, 1976; Schwane, Johnson, Vandenakker, & Armstrong, 1983; Totsuka, Naganuma, Suzuki, Nakaji, & Sato, 1996). This eccentric training effect and the response of CK in blood provides the opportunity to assess the impact of different loading patterns on musculoskeletal tissues in a manner where tissue damage is reversible and provides a training benefit to participants.

3.2 Methods

3.2.1 Participants

Thirty (30) healthy males between the ages of 20 and 28 were recruited to participate in this study. Inclusion criteria for participants included: those not currently using any medical drugs, dietary supplements, or anabolic steroids, and having no joint, muscular or cardiovascular diseases. Qualified participants must not have performed eccentric exercise on the non-dominant arm bicep (to rule out any training effect) and agreed not to perform eccentric, concentric, or isometric weight training eight weeks before or during the experiment. Informed consent was provided using procedures approved by the Auburn University Institutional Review Board (IRB). Age, body weight, stature, and limb segment length of the participants were collected. Table 3.1 shows a detailed summary of subjects' demographic characteristics.

Table 3.1: Demographic characteristics of the participants

Demographic data	Mean (SD)	Range
Age [years]	22.6 (2.1)	20 - 27
Height [m]	1.79 (0.071)	1.65 - 1.93
Body mass [kg]	79.3 (17.2)	50 - 127
BMI [$kg \cdot m^{-2}$]	24.4 (4.1)	18.4 - 35.2

3.2.2 Experiment Procedures

Participants completed a medical screening form to ensure that they were not experiencing any pain or discomfort in the non-dominant limb that would preclude participation in the study. Then informed consent was obtained. Participants were instructed to avoid exercise of the non-dominant arm during the week prior to and the week following eccentric exercise. Demographic participant data were recorded.

Approximately seven (7) to ten (10) days prior to the eccentric exercise, three (3) MIVCs of the non-dominant arm (at an elbow flexion angle of 90 degrees) were performed by each participant at East Alabama Medical Center RehabWorks Sports Medicine Outreach (RehabWorks). Each MIVC was separated by a rest period of two (2) minutes (Caldwell et al., 1974). The maximum of the three MIVC torques was recorded. Participants were matched using their MIVCs into ten experimental blocks of three participants each. For each block, one of the three types of eccentric exercises was randomly assigned to the participants. Each participant also practiced the timing and precision of performance with the dominant arm during this visit.

At the eccentric exercise day, relaxed elbow angle and MIVC were recorded before and after the eccentric exercise. Based on the testing group each subject was assigned to, subjects would perform the eccentric exercise using the BioDex machine. The total work volume, defined by moment integration over time $(ft \cdot lbs \cdot s)$, was controlled with specific settings in the BioDex machine which would stop moving once the total work volume was reached. Participants then exited the test apparatus and were escorted to the rest area and retained until they felt good enough to leave.

On days 2, 4, and 8 post-exercise, the participants were returned to Auburn University Medical Clinic (AUMC) and RehabWorks for follow-up blood sampling, MIVC trials, and relaxed elbow angle measurements.

Eccentric Exercise

Participants were asked to perform a bout of eccentric exercise with the elbow flexors of the non-dominant arm. The arm started with elbow flexed at approximately 60 degrees elbow included angle (Figure 3.1a) and ended with a 180 degrees elbow angle (elbow fully extended) (Figure 3.1b).

(a) 60 degree

(b) 180 degree

Figure 3.1: Range of motion for the eccentric exercise

There were three types of eccentric exercise with different force and repetition combinations (Table 3.2 on the next page, Figure 3.2 on the following page). These three types of eccentric exercise were randomly assigned to each participant for each of the ten blocks. Each participant was assigned to only one type of eccentric contraction bout, which consisted of sets of 30 eccentric contractions of elbow flexors at 60 degrees per second angular velocity (2 s duration) followed by 8s rest time for each contraction and 2 minutes rest time between each set.

Table 3.2: Three types of eccentric exercise

Types	Moment (% MIVC)	Estimated Repetitions
High force - Low repetition	120	1×30
Medium force - Medium repetition	60	2×30
Low force - High repetition	30	4×30

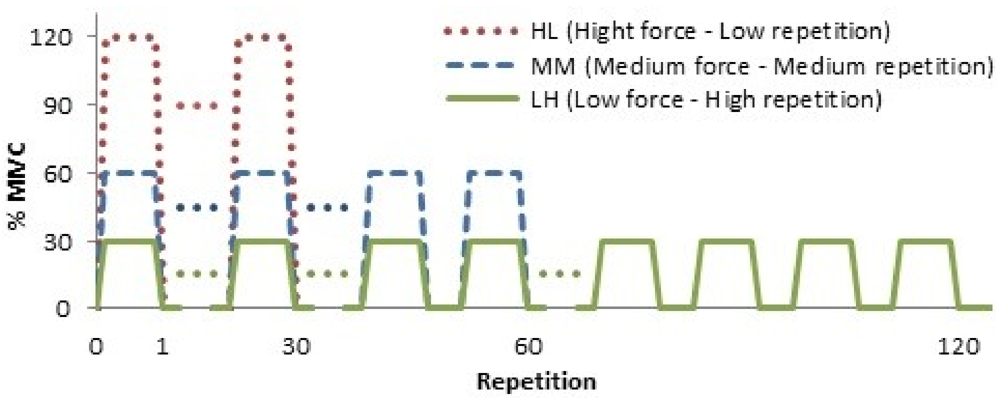

Figure 3.2: Three types of force and repetition combinations

Serum Creatine Kinase Sample Collection

A baseline 5 ml blood sample was taken from each participants' dominant arm antecubital vein on the same day before exercise (Day 0), and 2, 4, and 8 days after exercise. The blood sampling and sample analysis took place at the AUMC. The samples taken before the exercise served as the skeletal muscle micro trauma comparison baseline. The samples taken on the dates post-exercise were used to analyze the possible trending of serum CK level over time.

Maximum Isometric Voluntary Contraction

MIVC is considered to be one of the best methods to quantify the degree and time-course of muscle injury and recovery after exposure to lengthening contractions (Warren, Lowe, & Armstrong, 1999). Participants performed three MIVCs with the elbow flexed at 90 degrees before the eccentric exercise and immediately after the exercise. The maximum MIVC moment was recorded. Each MIVC was separated by a rest period of two (2) minutes (Caldwell et al., 1974). This permits assessment of any deficit in strength and recovery should certain loading force and repetition combination leads to temporary decreases in isometric force capacity due to the temporary muscle fiber damage and subsequent fiber regeneration that occur with eccentric exercise.

Relaxed Elbow Angle

Relaxed elbow angle is an indirect measure of muscle stiffness/soft tissue shortening which has been used in previous studies (Jones, Newham, & Clarkson, 1987; Nosaka, Clarkson, McGuiggin, & Byrne, 1991). This measure is thought to reflect damage to the sarcoplasmic reticulum, resulting in flooding of calcium into muscle cells causing contracture (Cleak & Eston, 1992). Relaxed elbow angle was measured using a goniometer based on three bony landmarks (scapular acromion, humeral lateral epicondyle, and head of ulna) before and after the eccentric exercise on day 0 and also at day 2, 4 and 8.

Biodex Dynamometer System

A Biodex System 4 (Biodex Medical Systems, Shirley, NY, USA) was used for participants to perform the eccentric exercise. This machine provides a well-controlled testing environment to measure moments during the whole process of eccentric exercise. The moment can be easily transformed to force with a known level arm length.

3.2.3 Statistical Analysis

To evaluate the force integration approach, dependent measures were assessed using statistical equivalence testing to determine whether the effects of the three loading conditions on the dependent measures were indistinguishable from another (i.e., that any difference observed is of no practical consequence) (Rogers, Howard, & Vessey, 1993). The confidence interval approach was used to test for equivalency. Equivalence intervals for dependent measures are $\pm 250\ \mu g/L$ for CK (Gao & Gallagher, 2015), a 4-degree decrease in resting elbow angle (Gallagher, Sesek, & Davis, 2014), and a 7.5% difference in isometric strength (Gallagher et al., 2014). A series of Repeated Measures Analysis of Variance (ANOVA) were used to investigate group differences at days 2 and 4, and to calculate the 90% confidence intervals on the pair-wise mean group differences using a Games-Howell post-hoc tests. 90% confidence intervals, obtained from the post-hoc comparisons, were used to test whether the mean group differences reside within the designated equivalence intervals (Rusticus & Lovato, 2011).

3.3 Results

A significant interaction between Loading Group and Day was observed for the percent change in MIVC (Figure 3.3). Tests of simple effects demonstrated that the high force – low repetition (HF-LR) group had a significant decrease in MIVC compared with the other two groups on Days 0, 2, and 4. However, low force – high repetition and medium force – medium repetition group were not statistically different from each other regarding MIVC changes (p ¿ 0.05). As of day 8, all participants recovered to the original state of strength, or slightly above.

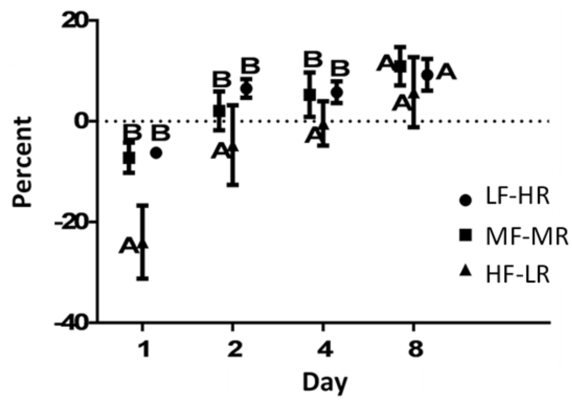

Figure 3.3: Percentage change of MIVC for day 0, day 2, day 4 and day 8

Loading group was found to be a significant main effect on the relaxed elbow angle (p ¡ 0.05) (Figure 3.4). Specifically, high force – low repetition group was statistically different from the low force – high repetition group while medium force – medium repetition group did not show differences when compared with the two groups mentioned above.

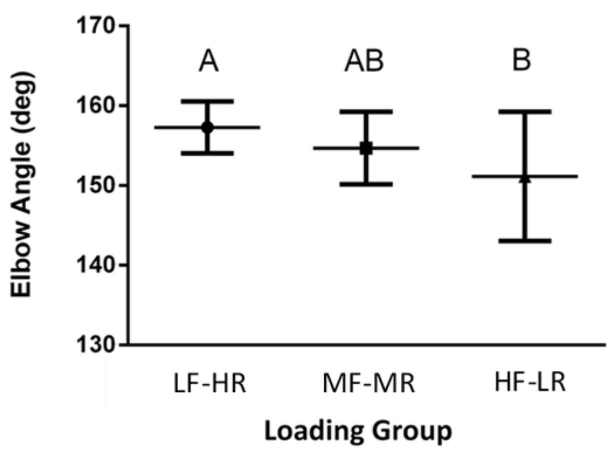

Figure 3.4: Elbow angle plot as a function of loading group

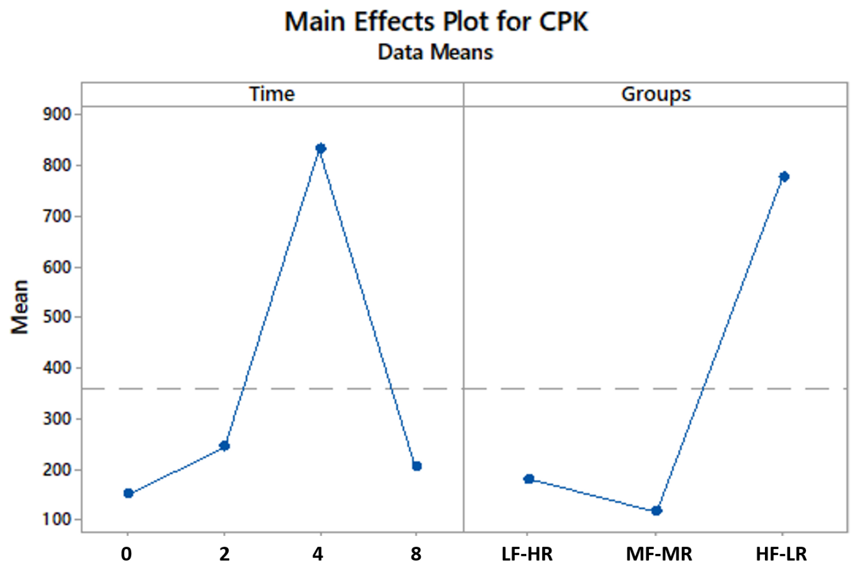

Figure 3.5: Main effects for CK (mean) by time and group

The highest CK for each participant was between day 2 and day 4 in this experiment. The main effect of loading group on the CK response was observed. The high force – low repetition group showed a higher CK response when compared with the other two groups. However, statistical significance was not found among groups.

3.4 Discussion

This study evaluated the integration method (area under the curve) of cumulative loading using an eccentric exercise model. In this study, the three loading groups were designed to have the same work volume (area under the curve). Based on the same area under the curve for all three levels of eccentric exercise, the linear integration approach would suggest the same cumulative loading for all three groups. However, the relaxed elbow angle and the changes in MIVC observed in this study, which were indicators of cumulative muscle damage, were both significantly impacted by the loading groups. This result suggests the linear integration method in estimating cumulative loading may underestimate the impact of high force loading in terms of cumulative muscle damage. This finding may explain that number of lifts $\geq$ 25 kg had additional value in predicting the risk of low back pain found in Coenen et al., 2013 since the linear integration method used in that study potentially underestimated the impact of high force loading in cumulative damage.

The change in relaxed elbow angle is thought to be caused by temporary damage to the sarcoplasmic reticulum resulting from high eccentric loading (Cleak & Eston, 1992). This is believed to cause calcium to flood the muscle cells, leading to a state of contracture leading to the change in resting elbow angle.

Changes in MIVC are considered to be one of the best overall measures of musculoskeletal health and of recovery from sarcomere “popping” that occurs in response to eccentric exercise (Prasartwuth et al., 2005). Results of this dependent variable also indicated that though the area under the loading curve was the same for all three loading groups, the effect in terms of muscle damage was not equivalent.

Though the main effect of high force loading group on creatine kinase response was observed, the statistical analysis did not show significance among the three loading groups. From the experimental design perspective, subjects were instructed not to perform intense sports activities during the experiment period. However, the activities outside of the experimental sessions were not able to be controlled. This condition may potentially introduce noise into the CK responses. In addition, CK responses vary among the general population. Some people have relatively high CK responses while some people may have no CK responses when exposed to the same level of eccentric exercise (Clarkson & Ebbeling, 1988; Kim & Lee, 2015).

According to Gallagher & Schall Jr. (2017), the development of musculoskeletal disorders may be the results of a fatigue failure process. This fatigue failure theory suggests that higher force loading has an exponentially higher damage per cycle loading instead of a linear relationship. The findings from this study are in agreement with this theory in that the linear combination of force and repetition did not appear to result in the same cumulative damage.

3.5 Limitations

Participants were relatively young males without or with limited industry work experience. Though all the participants were instructed not to perform any weightlifting training and competitive sports exercise during the experimentation period, the activity level of the participants was not controlled in this study. This study only included male subjects. The impact of gender differences was not investigated.

3.6 Conclusions

Based on the results of the current study, the following conclusions are drawn:

- Despite an equivalent volume of work (or area under the curve) for the three loading conditions, the relaxed elbow angle (believed to be indicative of transient sarcoplasmic reticulum damage) was significantly reduced in the high force low repetition group compared to the other groups.
- Maximum isometric voluntary contractions were significantly reduced in the high force group. And the changes in MIVC for this group on days 1, 2, and 4 after eccentric exercise suggesting increase transient muscle damage in this group, despite experiencing an equivalent volume of work.

- Creatine kinase results were highly variable between and within groups and did not achieve statistical significance.
- Overall, the results of this experiment suggest that the linear integration method of calculating cumulative loading may underestimate the impact of high force loading in terms of estimating cumulative muscle damage. These results are in line with what would be predicted if damage to musculoskeletal tissues were the result of a fatigue failure process.

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Chapter 4

Applying Fatigue Failure Theory in Estimating Cumulative Low Back Exposure

4.1 Introduction

Cumulative exposure to physical risk factors has been identified as one of the risk factors that contribute to the development of MSDs in the workplace (Kumar, 1990; Norman et al., 1998; Callaghan et al., 2001; Jäger et al., 2000). To better understand the relationship between exposure and health outcome, the ability to quantify cumulative exposure information is critical. Traditionally, practitioners would manually capture exposure information such as posture and forces by observation or video recordings (Burdorf, Rossignol, Fathallah, Snook, & Herrick, 1997; Spielholz et al., 2001). Assessment tools are then used to estimate the level of exposure. With advances in technology over this past decade, continuous measurement of exposure information has become much more accessible and affordable. Practitioners have taken advantage of new technologies to help capture exposure information in the workplace. As a result, large data sets may be generated. There is a need to develop systematic methods for using such information to better understand the relationship between cumulative exposure to physical risk factors and MSDs.

Several different models have been developed to quantify cumulative low back exposure in terms of the moments or compressive forces (Kumar, 1990; Norman et al., 1998; Callaghan et al., 2001; Jäger et al., 2000). One of the estimation methods that has been widely used was a linear integration method (Table 2.8 on page 19).

However, there is a fundamental assumption behind this linear integration method. This assumption is that the impact of force and time (frequency) on the cumulative damage measure is equivalent. This assumption was questioned by Jäger et al., 2000 based on a cadaver study that tested cycles to failure for spine segments under different loading conditions: "Higher damage risk result from an increase of the compressive force amplitude than from a corresponding prolongation of time" (Jäger et al., 2000).

More recently, Gallagher and Schall Jr., 2017 summarized the evidence supporting the fatigue failure process in musculoskeletal tissues. The evidence includes in vitro studies performed on tendons, ligaments, cartilage and spinal motion segments. All studies have shown an exponential relationship between the stress applied and the number of cycles to material failure (Gallagher & Schall Jr., 2017). This relationship reveals the impact of force is exponentially higher than the time (frequency) in the development of cumulative damage. The current widely used linear integration method seems to fail to consider the force repetition interaction.

In recent years, more technology traditionally used in other fields has been introduced to the field of occupational injury prevention. For example, motion capture systems that use inertial measurement units have shown great potential in collecting postural exposure in the field. External force measurement system, such as force sensing insoles and smart gloves, have become more accessible and affordable. This new exposure information capturing system creates great potential in collecting objective data using standardized evaluation systems. This new generation of ergonomics risk evaluation technology shows promise in helping to provide greater insight into cumulative loading compared with traditional risk assessment tools (RULA, REBA, NIOSH Lifting Equation, etc.).

Fatigue failure theory may be ideally suited to leverage the new technology, using a toolbox that has been validated in the science of material engineering. The aim of this study was to develop a systematic data processing framework that uses fatigue failure theory as the core method in estimating cumulative exposure with the ability to use continuous low back loading information captured by modern technology.

4.2 Methods

4.2.1 Data Processing Framework

A data processing framework is presented in Figure 4.1 on the following page. It starts with exposure information including posture and external force. Postural data can be collected by using a motion capture system, manual or computerized video analysis and observation. External forces can be collected through instrumented devices, including force transducers and pressure sensing insoles, direct measurement of contacting object and observational estimation. Using these inputs, simplified or more complex dynamic biomechanical models can be applied to estimate continuous low back stresses such as moments and compression forces.

Rainflow counting techniques can be used to analyze continuous low back loading data and produce a profile of the exposure distribution associated with a number of cycles using estimates of the stress (or force, moment) range, and the mean stress (or force, moment). Damage due to each loading cycle can be estimated and summed as the cumulative damage. Risk estimation can be based on this cumulative damage value. Figure 4.1 on the next page provides a graphic describing this process.

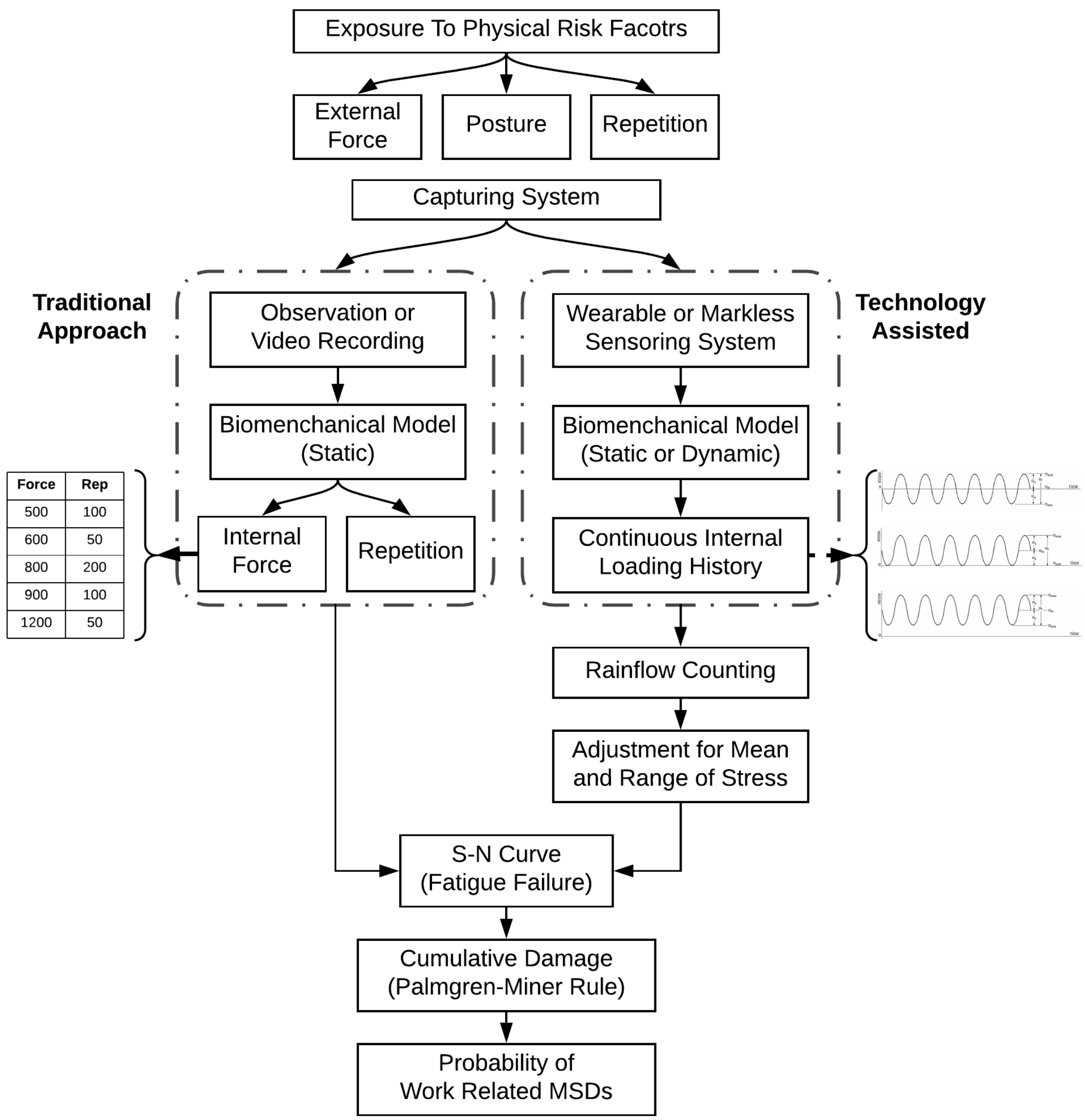


Figure 4.1: Framework for data processing

4.2.2 Low Back Compression Force Estimation

In this study, a simplified biomechanical model developed by Merryweather, Loertscher, and Bloswick, 2009 was used. The compression force estimated by this model has been compared with 3DSSPP and showed a high level of agreement ($R^2 = 0.9649, N = 1559$) (Merryweather et al., 2009).

As shown in Equation (4.1), subject body weight, height, the weight of the external load, torso angle and horizontal distance are used as inputs to estimate low back compression force at the L5/S1 level.

$$F_c = 17.376 \times BW \times H \times \sin\theta + 193.067 \times L \times HB + 7.84 \times (\frac{BW}{2} + L) \tag{4.1}$$

where
F_c = estimated L5/S1 compression force (N)
BW = body weight (kg)
H = height (m)
θ = torso angle with vertical ($degree$)
L = weight of the load (kg)
HB = horizontal distance from the hands to L5/S1 (m)

4.2.3 Rainflow Cycle Counting

Rainflow cycle counting is a well established and applied technique in material fatigue analysis. It generates a loading profile for time history of stresses (force, torque, etc.) by providing the number of times cycles of various sizes occur. Detailed instruction of rainflow cycle counting has been documented in ASTM E1049-85 (2017). Figure 2.10 on page 28 shows an example of the counting method in identifying loading cycles.

Data processing starts with Peak-Valley filtering. The goal of this step is to only keep data points which are reversals in direction/slope of the loading curve. The next step is to characterize the peaks and valleys into pairs that represent repetitions with the amplitude of stresses and mean stresses. Detailed steps are as follows (ASTM E1049-85, 2017): let X be the range under consideration, Y as the range previous of X and S as the start point of the loading history.

1) Read next peak or valley. If out of data, go to Step 6.
2) If there are less than three points, go to Step 1. Form ranges X and Y using the three most recent peaks and valleys that have not been discarded.
3) Compare the absolute values of range X and Y.
   a) If $X < Y$, go to Step 1.
   b) If $X \geq Y$, go to Step 4.
4) If range Y contains the starting point S, go to Step 5; otherwise, count range Y as one cycle; discard the peak and valley of Y; and go to Step 2.
5) Count range Y as one-half cycle; discard the first point (peak or valley) in range Y; move the starting point to the second point in range Y; and go to Step 2.

6) Count each range that has not been previously counted as one-half cycle.

The same technique can be used to analyze the time history of low back compressive loading. To automate the process of cycle counting, a customized program written in Python was developed (Appendix A).

4.2.4 Cycle Loading Damage Estimation

The relationship between the level of stress and cycles to failure for cadaveric lumbar spines was characterized by Gallagher, Sesek, Schall, and Huangfu, 2017 based on two studies (Brinckmann et al., 1988; Gallagher, Marras, Litsky, & Burr, 2005; Gallagher et al., 2007). It revealed a similar exponential relationship (Equation (4.2)) between the level of stress experienced and the number of cycles to failure compared with other material such as metals.

$$N = 902,416 \times e^{-0.162 \times \%US} \tag{4.2}$$

where
N = number of cycles to failure
$\%US$ = percentage of the ultimate strength for a motion segment

The loading pattern for the spine can be categorized as fluctuating stress since the human spine is continuously under a certain level of load due to body weight while at standing and sitting posture. Thus, the stress amplitude and mean stress designed for fully reversed sinusoidal loading need to be adjusted. Therefore, each pair of mean stress and stress range was used to adjust for the revised stress amplitude based on Goodman (Equation (2.18) on page 27) and Gerber (Equation (2.19) on page 27) methods.

This revised stress amplitude was used to represent the stress level for each repetition categorized by the rainflow cycle counting technique. Together with Equation (4.2), the number of cycles to failure for each particular stress amplitude can be estimated. Therefore, damage per each loading cycle can be calculated. Cumulative damage for a series of loading cycles can then be estimated by applying Palmgren-Miner rule (Equation (2.11) on page 24) which is the most commonly used model of estimating or predicting damage resulting from spectrum loading.

4.2.5 Case Studies

To demonstrate the fatigue failure based model output and to compare it with the linear integration cumulative loading estimation method, two case studies were developed. Two lists of jobs with different force and frequency combination were used (Table 4.1 on the next page and Table 4.2 on the following page).

Case Study I

- Mono-task (one force level for each job)
- Same repetition for all force levels (360 repetitions per hour)
- Compressive force range from 500 N to 2000 N (increment of 100 N)

Table 4.1: Case study I job list

Job ID	Force (N)	Frequency (per hour)	Job ID	Force	Frequency (per hour)
I-1	500	360	I-9	1300	360
I-2	600	360	I-10	1400	360
I-3	700	360	I-11	1500	360
I-4	800	360	I-12	1600	360
I-5	900	360	I-13	1700	360
I-6	1000	360	I-14	1800	360
I-7	1100	360	I-15	1900	360
I-8	1200	360	I-16	2000	360

Case Study II

- Mono-task (one force level for each job)
- Same "area under the loading curve" (equivalent to 1000N at 180 repetitions per hour)
- Compressive force range from 500 N to 1500 N (increment of 100 N)

Table 4.2: Case Study II job list

Job ID	Force (N)	Frequency (per hour)	Job ID	Force	Frequency (per hour)
II-1	500	360	II-7	1100	164
II-2	600	300	II-8	1200	150
II-3	700	257	II-9	1300	138
II-4	800	225	II-10	1400	129
II-5	900	200	II-11	1500	120
II-6	1000	180			

In this study, the ultimate strength was estimated at 6,000 N for an 'average' spine (Brinckmann et al., 1988). The resting load was estimated at 294 N for an 'average' person (weight 75 kg) calculated by using the biomechanical model (Equation (4.1) on page 51). Each repetition was simulated with a duration of 5 seconds. An example of the simulated spine loading is provided (Figure 4.2 on the following page). For job I-4, the compressive force is 800 N and the frequency is 360 per hour. So, for every 10 seconds, the spine loading was 800 N for 5 seconds and then at resting load of 294 N for the rest of the 5 seconds.

Cumulative damage was calculated for each job using both fatigue failure based model and the linear integration method. For fatigue failure model, the calculation process as followed:

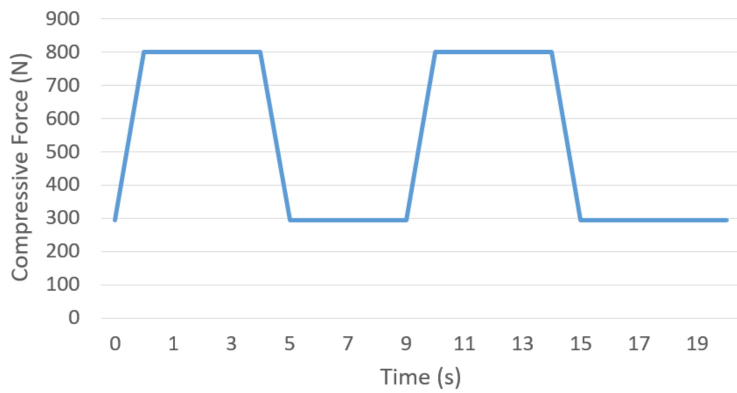


Figure 4.2: Example of simulated spine loading (Job ID: I-4)

- The simulated loading history was processed by rainflow counting to generate range and mean compressive force for each repetition
- The stress magnitude was then adjusted based on the range and mean force using Goodman and Gerber methods
- This revised stress amplitude was then used to calculate damage per each loading cycle by applying Equation (4.2) on page 52
- Linear summation was then used to combine all the repetitions and generate one cumulative damage value

For the linear integration method, the estimation method presented by Norman et al., 1998 was used. Equation (2.3) on page 18 was used to calculate cumulative damage measure based on the compressive force for each repetition, resting force, and duration under each force level.

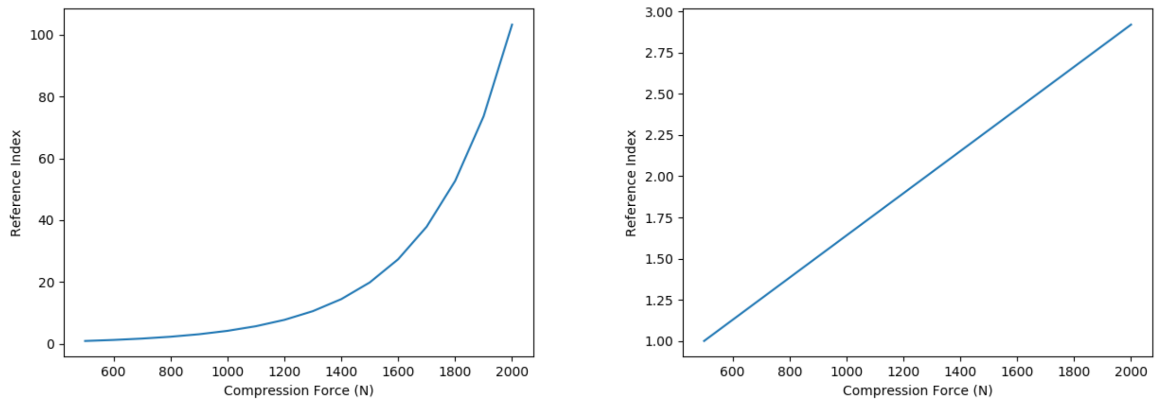
Since the cumulative damage measures calculated from fatigue failure model and linear integration model was in a different unit (percentage of total fatigue failure and newton hour respectively), cumulative damages for job I-1 and job II-1 were used as the reference value. All other cumulative damages were divided by the reference value (defined as 'Reference Index') to enable comparison between method.

4.3 Results

4.3.1 Case Study I

This case study kept frequency the same between the two methods while changing the compression force levels. Cumulative damage under different force level were calculated. Because of the different cumulative damage estimation units between the fatigue failure and the linear integration method, cumulative damage at 500 N compressive force was used as the reference for comparison.

As shown in Figure 4.3a, the fatigue failure based method showed an exponential relationship between the level of compressive force and estimated cumulative damage measure. On the other hand (Figure 4.3b), the linear integration based method showed a linear relationship between force and cumulative damage.



(a) Fatigue Failure Method

(b) Linear Integration Method

Figure 4.3: Cumulative damage estimated under different force levels

4.3.2 Case Study II

This case study kept the "area under the loading curve" the same for all force level and frequency combinations. As shown in Figure 4.4 on the next page, though compressive forces are different, the linear integration method was not able to differentiate high and low force conditions. On the other hand, fatigue failure based methods treat the impact of force on cumulative damage exponentially higher than the impact of time or frequency. More specifically, cumulative damage at 1,500 N and 120 repetitions per hour was more than six times the damage at 500 N and 360 repetitions per hour based on fatigue failure based estimation method.

4.4 Discussion

The model developed in this study was designed with the capability to accommodate low back compressive force history generated from different biomechanical models using different exposure capturing systems. Thus, it provides flexibility in terms of the scope of cumulative damage estimation. In other words, it can deal with more complex, fully dynamic biomechanical models using full-body motion capturing systems and also be able to utilize data generated from peak loading estimation from a static biomechanical model.

The biomechanical model used in this study also provides the capability of taking personal characteristics (height and weight) into consideration. Additional adjustment for personal characteristics can be added

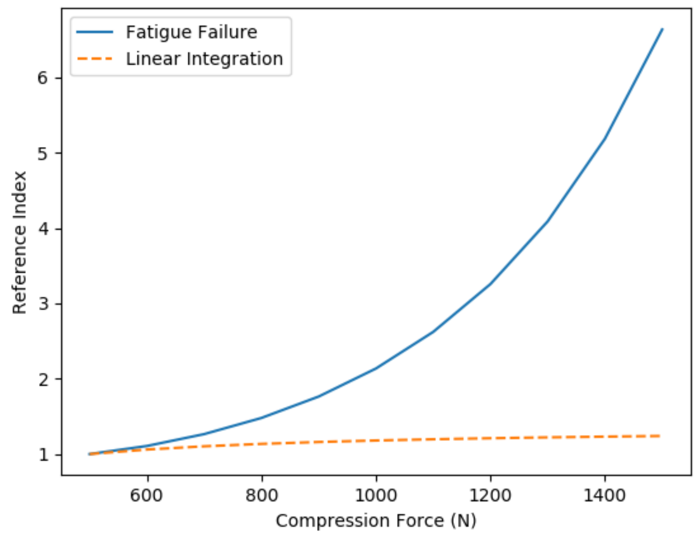


Figure 4.4: Estimated cumulative damage with same "area under the loading curve"

by changing the ultimate strength of the spine. However, currently, more studies are still needed to better understand that relationship.

4.5 Limitations

A simplified biomechanical model was used to estimate low back compressive force which may not represent the actual internal forces. A more complex biomechanical model could be used to achieve better estimation. Limited personal characteristics were included in the model. Age, gender, height, and weight were not included in the estimation model. Average spine strength was used (6,000 N). However, personal characteristics can be added to the model. For example, height and weight can be applied in the biomechanical model when estimating internal forces. Additionally, age and gender can be used to adjust spine strength. Rainflow counting was used in categorizing loading profile. The impact of sequence and rest time was not considered in this model.

4.6 Conclusions

A fatigue failure based cumulative low back damage estimation framework was developed. It uses low back continuous loading, captured by motion capture and external force capture system and a simplified biomechanical model, as an input and generates cumulative damage estimation as an output. The model used the rainflow counting method to create a loading profile for the low back. The number of cycles to failure under different loading conditions is used to estimate damage per cycle for each low back load. The linear summation is then used to estimate the total cumulative damage of the low back.

Case studies were performed to demonstrate the property of this model when compared with traditional linear integration methods. This model applied fatigue failure theory in estimating cumulative damage. With the same amount of repetition, a higher force would result in exponentially higher cumulative damage estimates while the linear integration method would be a linear relationship between force and cumulative damage. When keeping the "same area under the curve" (force * repetition kept the same), fatigue failure based model would show higher level of cumulative damage as force increase while linear integration method would not show significant differences.

In summary, this study presents a new cumulative low back damage estimation method for continuous low back loading based on fatigue failure theory. It enables the use of continuous exposure information captured by portable motion capture and force sensing system as input to estimate cumulative damage to better quantify exposure to physical risk factors that contribute to the development of MSDs.

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Chapter 5

Evaluation of the Fatigue Failure-Based Cumulative Low Back Exposure Estimation Method

5.1 Introduction

The linear integration methods have been widely used in estimating cumulative low back damage (Kumar, 1990; Norman et al., 1998; Callaghan et al., 2001; Jäger et al., 2000). As discussed in the previous chapter, the assumption behind this integration method was questioned by Jäger et al., 2000 based on a cadaver study (Brinckmann et al., 1988). The need for a better estimating method became apparent. The squared integration method was then proposed by Jäger et al., 2000. The intention was to give more weight to force than the time when calculating cumulative damage by squaring force. However, this squared integration method was merely a mathematical equation without scientific basis in explaining the potential relationship between this model and the mechanism underlying the development of work-related MSD.

Fatigue failure theory, proposed by Gallagher and Schall Jr., 2017, may be one of the mechanisms that contribute to the development of work-related MSD. It reveals that the impact of force is exponentially higher than the time (frequency) in the development of cumulative damage. Though this method showed promise in the capability of providing a better estimation of cumulative damage that lead to work-related MSD, the calculation process seems too complex to be handled manually. An automated data processing framework has been proposed and developed in the previous chapter intended to address this issue. The next step before confident usage of this methodology would be the validation of this model.

This study aimed to evaluate this fatigue failure based low back cumulative damage estimation model using two epidemiology databases (an LMM database and an automotive database). Linear and squared integration methods were also used in estimating low back cumulative damage. The performance of those three methods was compared based on their ability to differentiate high-risk vs. low-risk jobs.

5.2 Methods

5.2.1 Experimental Databases

LMM Database

The LMM database described by Marras et al., 1993 and presented in Zurada et al., 1997 was used in this study. This database collected low back exposure information, which included peak moment and repetition rate, for 235 mono-task manufacturing jobs. The peak moment and frequency of each exertion was simulated into a continuous loading curve. The health outcome for each of the jobs was categorized as low-risk or high-risk jobs. Low-risk jobs were defined as those having no injuries and no turnover for the preceding three-year period, while high-risk jobs were those having at least 12 injuries per 200,000 hours of exposure. There are 124 low-risk jobs and 111 high-risk jobs in this database.

Automotive Database

This database was from an epidemiological study examining MSD outcomes from a large automotive manufacturer. Data were analyzed from a database consisting of 667 manufacturing jobs. It includes historical injury data for the analyzed jobs as well as symptom interviews for 1022 participants (Sesek, 1999).

The automotive database consists of data collected from six different plants. Only jobs with well-defined lifting activities were included in this analysis (administrative jobs or jobs that did not have well-defined tasks were not analyzed). Subject data used for this study was limited to reports of discomfort assessed by ratings of perceived discomfort and anonymized injury reports for the job on which the subject worked. Negative health outcomes were defined as self-reported LBP and LBP-related medical visits reported for the subject's job. Symptoms were categorized into one of five categories (Sesek, 1999):

1) "Job-related symptoms": symptoms originated on the subject's job
2) "Job aggravated": symptoms aggravated by the subject's current job, but not originating on job
3) "No change or improvement in subject symptoms" while on the job, but symptoms not originating on the job
4) "Symptom improvement on the job": symptoms not originating on the present job and improving
5) No symptoms present

Symptoms were self-reported via structured interview both on the day of the subject interview and retrospectively for the previous year. Case definitions included various combinations of symptoms and LBP-related injuries on the job in the previous year. Controls were subjects lacking job-related symptoms and/or working on jobs with no LBP-related reports of injury in the previous year. Based on different low back pain case/control definitions, two subsets with 302 and 274 subjects, were analyzed, as discussed in further detail below. These low back health outcome case and control definitions were:

1) LBP in the Last Year (Categories 1 & 2) vs. No LBP in the Last Year (Categories 4 & 5)
2) LBP in the Last Year (Category 1 only) vs. No LBP in the Last Year (Category 5 only)

5.2.2 Low Back Compression Force Estimation

A simplified biomechanical model (Equation (4.1) on page 51) was used to estimate low back compression force based on peak moment input from the databases. Force estimation was based on an 'average' person with the weight of $75kg$, the height of $1.7m$ and trunk flexion angle of $10°$ with reference to the vertical direction. In this study, the ultimate strength was estimated at $6,000N$ for an 'average' spine (Brinckmann et al., 1988). The resting load was estimated at $294N$ for an 'average' person (weight $75kg$) calculated by using the biomechanical model (Equation (4.1) on page 51). Each repetition was simulated with a duration of 5 seconds. An example of the simulated spine loading is provided in chapter 4 (Figure 4.2 on page 54).

5.2.3 Cumulative Exposure Estimation Methods

Several different estimation methods were used to quantify cumulative low back exposure. These include the widely used linear integration method (Norman et al., 1998), squared integration method (Jäger et al., 2000) and a fatigue failure theory based method (Gallagher & Schall Jr., 2017).

Linear Integration

Norman et al., 1998 evaluated the relative importance of different exposure measures (peak spine loads, hand loads, trunk kinematics and cumulative spine loads) of low back as predictors for reported low back pain. The authors found that cumulative biomechanical variables are important risk factors that related to the reporting of low back pain (Norman et al., 1998). The cumulative spine loads were estimated by integrating the peak load for each task over time (Equation (2.3) on page 18). The spinal load during rest time between tasks was also incorporated into the algorithm (Norman et al., 1998).

Squared Integration

Jäger et al., 2000 discussed the assumption behind the linear integration of lumbar-disc compression force over time for cumulative load assessment, specifically that the same injury risk is assumed between high force-short duration and low force-long duration. "Higher damage risk result from an increase of the compressive force amplitude than from a corresponding prolongation of time" (Jäger et al., 2000) was reported by Brinckmann et al., 1988. Based on this evidence, Jäger et al., 2000 proposed a squared integration method (Equation (2.6) on page 19). This method gives force more weight than time by squaring the force when calculate cumulative loading.

Fatigue Failure based Method

The fatigue failure model developed in chapter 4 was used in this study. There are four key component of this fatigue failure theory based method: 'S-N' curve, rainflow cycle counting, stress amplitude adjustment, and Palmgren-Miner rule. The calculation process is described as followed:

- The simulated loading history for each job was processed by rainflow counting to generate range and mean compressive force for each repetition
- The stress magnitude was then adjusted based on the range and mean force using Goodman and Gerber methods
- This revised stress amplitude was then used to calculate damage per each loading cycle by applying Equation (4.2) on page 52
- Linear summation was then used to combine all the repetitions and generate one cumulative damage value for each job

5.2.4 Statistical Analysis

Cumulative damages estimated by all three methods were arranged in ascending order and were separated into deciles with counts of cases (high-risk jobs as defined by the database). Binary logistic regression was used to determine the significance of the models, the goodness of fit, and the deviance explained by cumulative measures (R^2_{DEV}), which is a maximum likelihood analogue to the coefficient of determination used in ordinary least squares models (Agresti, 2002). Odds ratios were used to examine whether differences were present among the various deciles of risk. Cut point (50th percentile of cumulative damage measure) analysis was also performed.

5.3 Results

5.3.1 Results Using the LMM Database

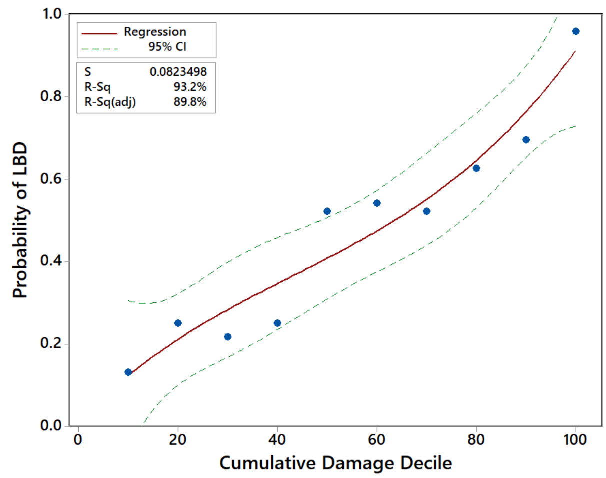
All three methods showed good capability in terms of differentiating high-risk vs. low-risk jobs as shown (Table 5.1 on the following page) based on the cut point at 50th percentile based on cumulative damage measures. The fatigue failure based method showed the highest odds ratio of 7.54 while linear and squared integration methods were 5.38 and 6.91 respectively.

Table 5.1: Results of cut point analysis at 50th percentile of cumulative damage

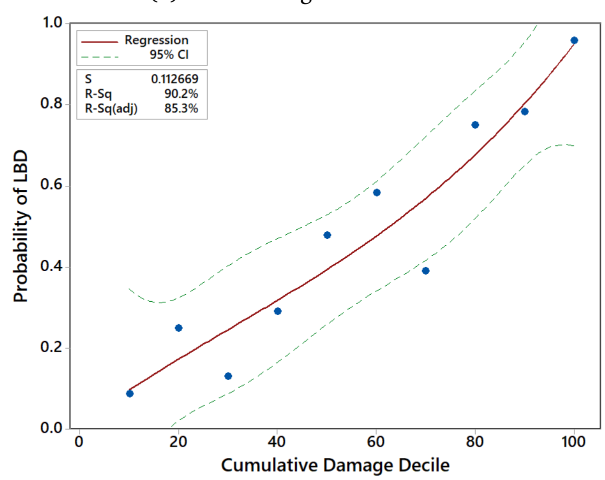
Method	p-value	Odds Ratio	95% CI
Fatigue Failure	< 0.001	7.54	(4.22, 13.46)
Linear Integration	< 0.001	5.38	(3.08, 9.41)
Squared Integration	< 0.001	6.91	(3.89, 12.27)

For the logistic regression analysis of the deciles of cumulative damage measures for the three methods, the fatigue failure based method showed the highest R^2 in explaining the variance. The relationship between cumulative damage measures in deciles and the probability of low back health outcome defined by the LMM database were plotted in Figure 5.1 on the next page.

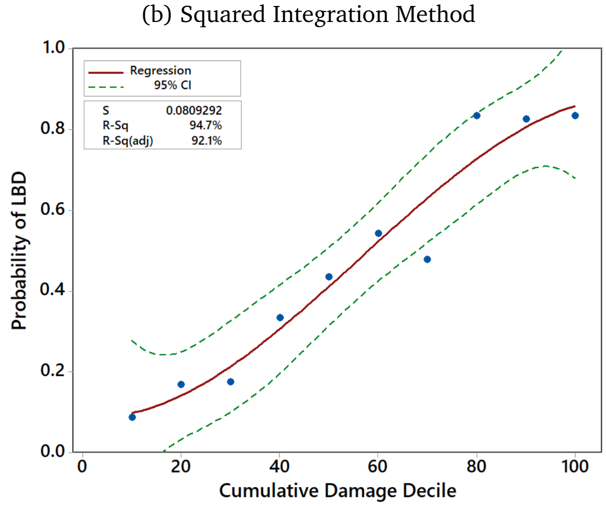
Odds ratio analyses between each decile of risk per cumulative damage estimates for all three methods were performed (Table 5.2, Table 5.3, and Table 5.4). The fatigue failure based model has the greatest number of paired comparisons that was significantly different from each other (30 out of 45) while the linear integration based model was 29 out of 45 and squared integration based model was 27 out of 45. Results showed that the fatigue failure model was better in identifying jobs with medium risk (40th to 70th percentile), while linear integration model was only able to separate jobs between high (50th to 90th percentile) and low-risk level (10th to 40th percentile). The squared integration model did not show consistency in differentiating high-risk jobs with high exposure and low-risk jobs with low exposure. For example, the 60th percentile of cumulative damage was significantly different from 40th percentile and below, while the 70th percentile was not significantly different from 40th and 20th percentile. In other words, the squared integration model did better in identifying medium risk levels compared with the linear integration method. However, it was not significant enough to differentiate the risk of middle range exposure from high or low cumulative damage measures.



(a) Linear Integration Method



(b) Squared Integration Method



(c) Fatigue Failure Method

Figure 5.1: Relationship between the cumulative measure and the probability of LBD from the LMM database (Marras et al., 1993; Zurada et al., 1997)

Table 5.2: Odds ratios between deciles of risk per cumulative damage estimates based on the fatigue failure method

	Cumulative Damage Deciles								
	20	30	40	50	60	70	80	90	100
10	2.1 (0.3, 12.8)	2.2 (0.4, 13.5)	5.3* (1.0, 28.2)	8.1* (1.5, 42.8)	12.4* (2.4, 65.1)	9.6* (1.8, 50.9)	52.5* (8.6, 319.0)	49.9* (8.2, 303.9)	52.5* (8.6, 319.0)
20		1.1 (0.2, 4.8)	2.5 (0.6, 9.8)	3.8* (1.0, 14.9)	5.9* (1.5, 22.6)	4.6* (1.2, 17.7)	25.0* (5.5, 114.1)	23.8* (5.2, 108.8)	25.0* (5.5, 114.1)
30			2.4 (0.6, 9.4)	3.7 (0.9, 14.2)	5.6* (1.5, 21.5)	4.4* (1.1, 16.9)	23.8* (5.2, 108.8)	22.6* (4.9, 103.7)	23.8* (5.2, 108.8)
40				1.5 (0.5, 5.0)	2.4 (0.7, 7.6)	1.8 (0.6, 6.0)	10.0* (2.5, 39.3)	9.5* (2.4, 37.5)	10.0* (2.5, 39.3)
50					1.5 (0.5, 4.9)	1.2 (0.4, 3.8)	6.5* (1.7, 25.2)	6.2* (1.6, 24.0)	6.5* (1.7, 25.2)
60						0.8 (0.2, 2.4)	4.2* (1.1, 16.2)	4.0* (1.0, 15.4)	4.2* (1.1, 16.2)
70							5.5* (1.4, 21.0)	5.2* (1.3, 20.1)	5.5* (1.4, 21.0)
80								1.0 (0.2, 4.4)	1.0 (0.2, 4.6)
90									1.1 (0.2, 4.8)

* represent risk deciles that are significantly different from one another.

Table 5.3: Odds ratios between deciles of risk per cumulative damage estimates based on the linear integration method

	Cumulative Damage Deciles								
	20	30	40	50	60	70	80	90	100
10	2.2 (0.5, 10.2)	1.9 (0.4, 8.9)	2.2 (0.5, 10.2)	7.3* (1.7, 31.4)	7.9* (1.8, 33.8)	7.3* (1.7, 31.4)	11.1* (2.6, 48.2)	15.2* (3.4, 68.6)	153.3* (14.8, 1,593.6)
20		0.8 (0.2, 3.2)	1.0 (0.3, 3.7)	3.3* (1.0, 11.2)	3.5* (1.0, 12.1)	3.3* (1.0, 11.2)	5.0* (1.4, 17.3)	6.9* (1.9, 24.7)	69.0* (7.6, 625.9)
30			1.2 (0.3, 4.7)	3.9* (1.1, 14.2)	4.3* (1.2, 15.2)	3.9* (1.1, 14.2)	6.0* (1.7, 21.8)	8.2* (2.2, 31.1)	82.8* (8.9, 773.0)
40				3.3* (1.0, 11.2)	3.5* (1.0, 12.1)	3.3* (1.0, 11.2)	5.0* (1.4, 17.3)	6.9* (1.9, 24.7)	69.0* (7.6, 625.9)
50					1.1 (0.3, 3.4)	1.0 (0.3, 3.2)	1.5 (0.5, 4.9)	2.1 (0.6, 7.0)	21.1* (2.4, 183.3)
60						0.9 (0.3, 2.9)	1.4 (0.4, 4.5)	1.9 (0.6, 6.4)	19.5* (2.3, 168.3)
70							1.5 (0.5, 4.9)	2.1 (0.6, 7.0)	21.1* (2.4, 183.3)
80								1.4 (0.4, 4.6)	13.8* (1.6, 120.4)
90									10.1* (1.1, 89.9)

* represent risk deciles that are significantly different from one another.

Table 5.4: Odds ratios between deciles of risk per cumulative damage estimates based on the squared integration method

	Cumulative Damage Deciles								
	20	30	40	50	60	70	80	90	100
10	3.5 (0.6, 19.5)	1.6 (0.2, 10.4)	4.3 (0.8, 23.6)	9.6* (1.8, 50.9)	14.7* (2.8, 77.5)	6.8* (1.3, 36.0)	31.5* (5.6, 175.9)	37.8* (6.5, 218.9)	241.5* (20.4, 2,861.6)
20		0.5 (0.1, 2.1)	1.2 (0.3, 4.4)	2.8 (0.8, 9.4)	4.2* (1.2, 14.4)	1.9 (0.6, 6.7)	9.0* (2.4, 33.2)	10.8* (2.8, 41.9)	69.0* (7.6, 625.9)
30			2.7 (0.6, 12.3)	6.1* (1.4, 26.4)	9.3* (2.2, 40.2)	4.3* (1.0, 18.7)	20.0* (4.4, 91.9)	24.0* (5.0, 115.0)	153.3* (14.8, 1,593.6)
40				2.2 (0.7, 7.4)	3.4* (1.0, 11.3)	1.6 (0.5, 5.3)	7.3* (2.0, 26.1)	8.7* (2.3, 32.9)	55.9* (6.3, 497.6)
50					1.5 (0.5, 4.8)	0.7 (0.2, 2.3)	3.3 (1.0, 11.2)	3.9* (1.1, 14.2)	25.1* (2.9, 218.2)
60						0.5 (0.1, 1.5)	2.1 (0.6, 7.3)	2.6 (0.7, 9.3)	16.4* (1.9, 142.5)
70							4.7* (1.3, 16.2)	5.6* (1.5, 20.5)	35.8* (4.1, 313.4)
80								1.2 (0.3, 4.7)	7.7 (0.8, 69.5)
90									6.4 (0.7, 59.6)

* represent risk deciles that are significantly different from one another.

5.3.2 Results from the Automotive Database

Continuous logistic regression and cut point analyses were performed for all three integration methods under two different case/control definitions (see Table 5.5 to Table 5.8). The adjusted cut point analysis was also performed based on site, age (> 40 vs. ≤ 40), gender, and BMI (> 30 vs. ≤ 30). The fatigue failure based estimation method performed best (p ¡ 0.05 in all eight statistical analyses). The squared integration method performed close to the fatigue failure based method. The p-value, though still in the statistically significant range (p ¡ 0.05), was higher compared with the fatigue failure model. For the linear integration based method, only one statistically significant difference (p = 0.049) was found among all analyses which showed relatively poor performance in associating cumulative damage with the health outcome. The site was found to be significant in both continuous logistics regression and cut point analyses while age, gender, and BMI were not statistically significant.

Table 5.5: Continuous logistics regression analysis (LBP last year 4/5 vs. 1/2)

	p-value of different estimation methods		
	Fatigue Failure	Linear	Squared
Unadjusted			
Cumulative Damage	0.012*	0.155	0.036*
Adjusted			
Cumulative Damage	0.010*	0.171	0.039*
Site	0.017*	0.014*	0.014*
Age	0.632	0.708	0.572
Gender	0.402	0.515	0.48
BMI	0.464	0.534	0.433

Table 5.6: Continuous logistics regression analysis (LBP last year 5 vs. 1)

	p-value of different estimation methods		
	Fatigue Failure	Linear	Squared
Unadjusted			
Cumulative Damage	0.004*	0.182	0.034*
Adjusted			
Cumulative Damage	0.004*	0.094	0.027*
Site	0.021*	0.011*	0.018*
Age	0.258	0.320	0.235
Gender	0.712	0.854	0.840
BMI	0.274	0.302	0.237

Table 5.7: 50th percentile cut point analysis (LBP last year 4/5 vs. 1/2)

	p-value of different estimation methods		
	Fatigue Failure	Linear	Squared
Unadjusted			
Cumulative Damage	0.021*	0.202	0.063
Adjusted			
Cumulative Damage	0.022*	0.099	0.021*
Site	0.014*	0.009*	0.007*
Age	0.762	0.736	0.607
Gender	0.487	0.459	0.501
BMI	0.404	0.502	0.415

Table 5.8: 50th percentile cut point analysis (LBP last year 5 vs. 1)

	p-value of different estimation methods		
	Fatigue Failure	Linear	Squared
Unadjusted			
Cumulative Damage	0.025*	0.142	0.093
Adjusted			
Cumulative Damage	0.021*	0.049*	0.027*
Site	0.016*	0.008*	0.008*
Age	0.374	0.365	0.281
Gender	0.901	0.779	0.907
BMI	0.213	0.271	0.228

5.4 Discussion

In this study, the new fatigue failure based cumulative exposure estimation model developed in the previous chapter was evaluated using two epidemiological databases. The cumulative damage measure generated by the model showed significant association with low back health outcome in both epidemiological databases. When compared with linear and squared integration methods, the fatigue failure based model performed best among the three in all statistical testing scenarios.

For the LMM database, all the jobs contained only one task with force as the dominant driving factor that was associated with the low back health outcome. Therefore, the linear and squared methods were statistically significant in the logistics regression. However, decile analysis revealed that linear and squared methods lacked the ability to differentiate medium to low-risk jobs while fatigue failure based method showed better performance in the low-risk region.

For the automotive database, each job consisted of multiple tasks with highly variable force combinations. The linear integration method failed in identifying high-risk vs. low-risk jobs for all the health outcome definitions except one condition (p-value of 0.049 in Table 5.8). This may be because the linear integration method does not take the interaction of force and repetition into consideration. In other words, 1,000 N exposure for 5 seconds was treated the same for 200 N exposure for 25 seconds. On the other hand, there was an exponential relationship between cycles to failure and level of loading in the fatigue failure-based method.

It is worth noting that the squared integration method showed much better performance compared to the linear integration method. It performed similarly to the fatigue failure method in the logistics regression analysis, though with a less significant p-value. This could be explained by the intention of "punishing" the high force over time by taking the square of the force which aligns with fatigue failure theory.

5.5 Limitations

Two epidemiological databases were developed without the intention to be used for fatigue failure based model evaluation. The exposure information was not captured as a continuous measurement. Assumptions were made to be able to use this information to simulate the continuous loading of the low back. No personal characteristics (age, gender, height, weight, etc.) were included in estimating cumulative damage. Average spine strength was used (6,000 N) as the ultimate strength in the model without adjusting for individual differences. Rainflow counting was used in categorizing loading profile. The impact of sequence and rest time was not considered in this model.

5.6 Conclusions

Based on the results of this study, the following conclusions are drawn:

- The cumulative damage measure generated by the fatigue failure model showed significant relationship for low back health outcome in both epidemiological databases.
- Compared with linear and squared integration methods, the fatigue failure based model was the best among the three in all statistical testing scenarios performed in this study.
- The proposed fatigue failure theory based model's estimate of cumulative damage was highly associated with negative health outcomes.

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Chapter 6

The Role of Fatigue Failure Theory in Occupational Injury Prevention

6.1 Introduction

Cumulative exposure to physical risk factors (force, posture, repetition, etc.) is one of the contributors to the development of MSDs (Kumar, 1990; Norman et al., 1998; Andrews & Callaghan, 2003; Callaghan et al., 2001; Coenen et al., 2013; Daynard et al., 2001; Marras et al., 2014; Jäger et al., 2000; Waters et al., 2006). As workers perform manual material handling tasks, external forces create moments and stresses on the human body. To support the completion of work task and keep internal balance, tissues inside human body experience a higher level of loading (compression, tension and/or shear) than when one is under a resting condition. This increased loading may pose damage to human tissues and potentially lead to tissue function loss (an MSD). The quantification of cumulative internal loading due to external exposures is the basis to develop a better understanding of the relationship between external exposure and the development of MSDs. In this dissertation, a fatigue failure based data processing framework was developed which estimates the low back cumulative damage based on continuous compressive loading history. Validation of this model using two epidemiological databases showed promising results in estimating injury risks when compared to traditionally used integration methods (linear and squared integration).

In this chapter, a conceptual model that describes how external exposure may lead to tissue damage (and potentially MSDs) was constructed. This model will be used to discuss the role of fatigue failure theory in the understanding of MSD development and how it may impact the direction in developing injury intervention strategies.

6.2 Model Description

This model (Figure 6.1 on the following page) consists of six major components: external exposure (e.g., manual material handling), subsequent internal exposure (compressive, tensile and shear loading), tissue damage decision tree, damage intervention, tissue repair, and personal characteristics. Components of the model and model logic are described in this section.

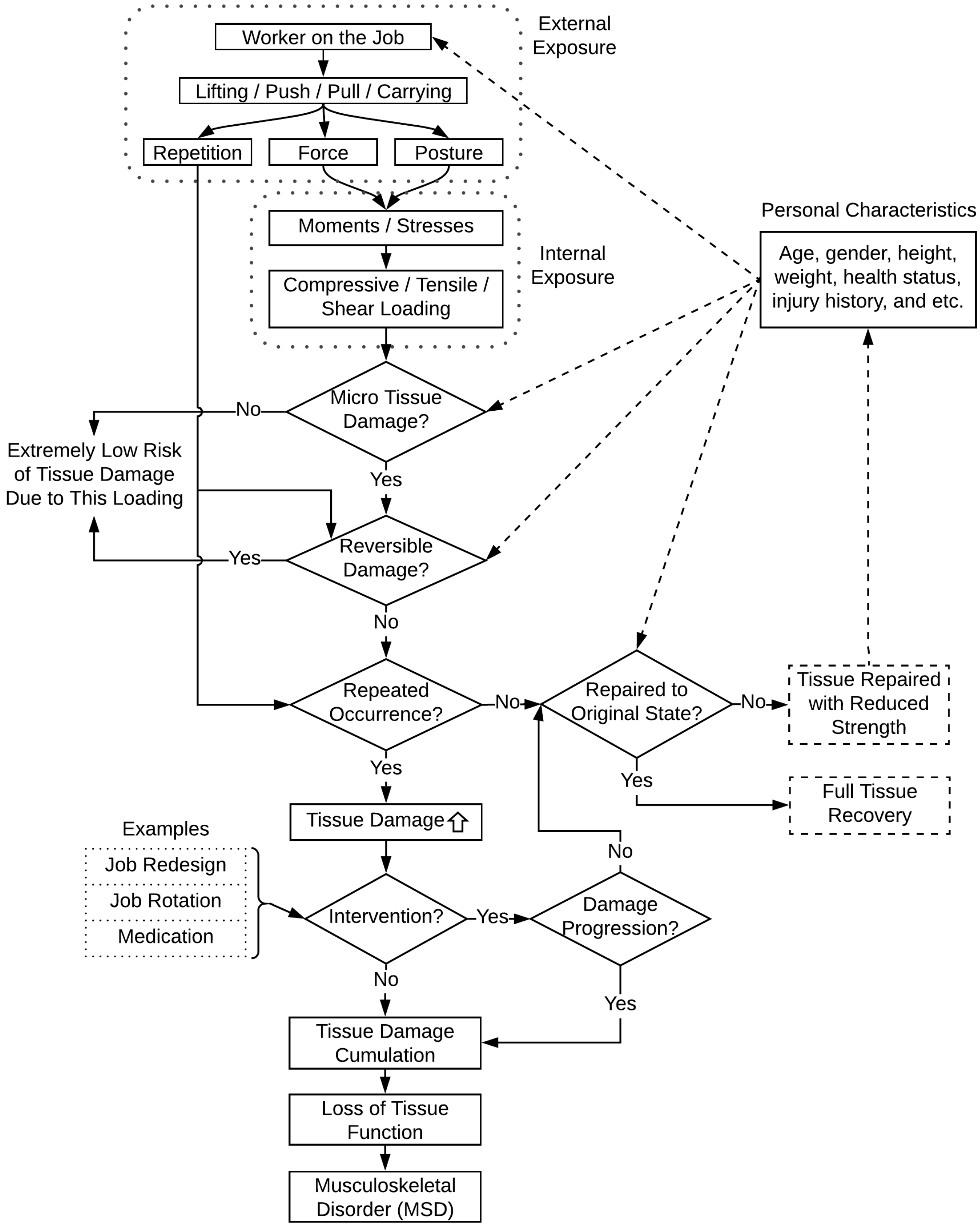

Figure 6.1: A conceptual model of MSD development due to external exposure

External Exposure

External exposure defined in this model was based on manual material handling tasks which include lifting/lowering, pushing/pulling and carrying. When workers are engaged in these types of activities, external loads (boxes, parts, cart, etc.) that are handled by workers create moments and stresses acting on the human body. Depending on the nature of the task, workers may be required to adjust posture to support the completion of tasks. These manual material handling tasks are typically repeated multiple times throughout the entire work shift. In general, these external exposures are observed as the external force (primarily hand force), the posture of the worker and the repetition of the task.

Internal Exposure

The external force (hand force) and posture of the worker create moments and stresses on the human body structure. To support completion of physical tasks and maintain balance of the body, tissues inside the body experience higher levels loading when compared to the body in a resting condition (sitting or lay down). The internal loading can be compressive, tensile, shear or the combination of the three. Biomechanical models are used to estimate internal structure loading based on observed external exposure (external forces and postures).

Tissue Damage Decision Tree

While under mechanical stress, a weak section of the tissue may experience stress concentration. Depending on the magnitude of the stress and the ultimate strength of the material, this stress concentration may or may not result in micro tissue damage. If the magnitude of the stress is low enough or the strength of the material is high enough, there may not be any damage to the stressed tissue. If the load surpasses the no-damage threshold, physical tissue damage could potentially occur. Biologic tissue, which differs from other types of material, has the potential to repair itself. However, the capability of healing is limited. If the rate of damage occurring is higher than the tissue's healing ability, the micro tissue damage may progress. As the micro damage accumulates, tissue damage can be observed.

Damage Intervention

Damage intervention can potentially reduce damage accumulation or reduce the damage to a reversible level. In the model, a few intervention methods used in the workplace are included as examples. Engineering controls, such as job redesign, are the preferred way to reduce external exposure which in return reduce internal load. Job rotation is an administration control which does not reduce the level of external exposure.

It redistributes the exposure to other workers. Medication may be introduced to workers to help improve the health status and support the healing process in the body. If no intervention is introduced, the accumulation of irreversible damage can lead to tissue damage and the potential for loss of tissue function at a macro level (development of an MSD).

Tissue Repair

The ability to repair (or heal) for different biological tissues varies. Muscle, which contains a large quantify of soft tissue and high density of blood vessels, has greater ability to repair and regenerate itself than cartilage which has very limited blood and nutrition supply. For certain levels of damage, the human body can repair it to the original state which has the same strength property. However, if it exceeds a certain threshold, the repaired tissue will have a reduced strength property. But, in some cases, strength can actually increase after repair. However, this is outside the scope of this dissertation.

Personal Characteristics

Personal characteristics play a significant role in the development of MSDs when exposed to physical risk factors. For example, the same job or task can present varying risk for different people each with their own height, weight, strength, etc. In other words, with the same job, the external exposure and result internal loads will differ among people due to varying personal characteristics. In addition, the stress level that would introduce micro tissue damage is different from person to person since ultimate tissue strength varies among people. These personal characteristics can also influence the healing capability which would make the stress level for irreversible damage different among people. Additionally, personal characteristics do not always remain constant. For example, the tissue strength would impact at what level of stress damage occurs. Then, the tissue healing capability determines if the damaged tissue can be repaired to the original state and level of strength. This updated strength will again impact the stress level at which damage happens. This personal characteristic has an impact on the damage development process and will also be influenced by the result of it. This illustrates the dynamic property of personal characteristics.

6.3 Discussion

The estimation of cumulative damage using fatigue failure theory is based on three major inputs: the level of stress applied to the material of interest, the S-N curve and the ultimate strength of this material. Figure 6.2 on the next page is an example of an S-N curve. This curve describes the exponential relationship between the level of stress experienced by the material and the number of cycles that would lead to material failure under this stress level.

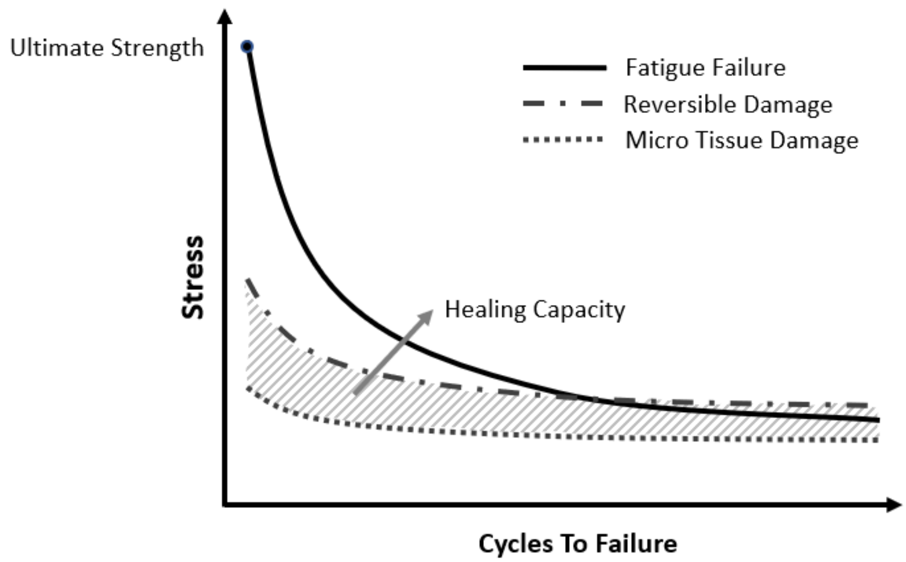

Figure 6.2: Fatigue failure S-N curve

When the stress level remains at a relatively low level (below the stress level for micro tissue damage), the material can experience quite large numbers (almost infinite) of loading cycles until it fails. In other words, under this level of stress, the damage produced by the cyclic loading is negligible. As stress level increase over the micro tissue damage line but below the reversible damage line in the graph, the damage is no longer negligible and it may cause tissue damage. However, since biological tissue has a certain level of healing capability, some amount of damage to the tissue is tolerable by the body. If the stress continues to increase beyond the reversible damage line, the damage caused to tissue cannot be fully repaired by the human body. If no injury intervention is introduced, the tissue damage would accumulate and lead to tissue function loss.

Ultimate strength plays an important role in terms of estimating the fatigue failure damage. Since ultimate strength varies among different materials and people, for the same level of stress, the level of damage could be quite different. This feature of the fatigue failure model provides a great opportunity for individualized injury risk assessment which consider personal characteristics.

Though there is limited knowledge of the fatigue failure property of human tissues available, this model provides the opportunity not only to quantify the cumulative damage and study the association with work-related MSDs but the potential to identify a threshold for stress level that will not cause harmful effect on human body.

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Chapter 7

Conclusions and Future Research

7.1 Conclusions

The goal of this research was to evaluate the performance of the current linear integration methods in estimating cumulative damage; to develop a fatigue failure based low back cumulative damage estimation method using continuous loading history; and to validate the developed model using two two epidemiology databases. The major conclusions of this research are as follows:

1. The performance of the linear integration methods in estimating tissue damage was evaluated using CK, resting elbow angle and changes in MIVC measured in an eccentric exercise experiment under three different loading conditions with the same area under the loading curve. These conclusions included:

   (a) The linear integration methods were widely used in estimating cumulative damage of low back.

   (b) The relaxed elbow angle and the changes in MIVC were significantly impacted by the loading groups which were designed to produce the same work volume (area under the loading curve).

   (c) The result suggests that the linear integration method of calculating cumulative loading may underestimate the impact of high force loading in terms of estimating cumulative muscle damage.

2. A fatigue failure based cumulative low back damage estimation framework was developed. It took low back continuous loading as input and generated cumulative damage estimates as output. The model used a rainflow counting method to create low back loading profile. The number of cycles to failure was applied under different loading condition (S-N curve) to estimate damage per cycle for each low back load. A linear summation of damage was then used to estimate the total cumulative damage of the low back. Case studies were performed to demonstrate the property of this model when compared with the traditional linear integration methods. These conclusions included:

   (a) This model applied fatigue failure theory to the estimation of cumulative damage. With the same amount of repetition, a higher force would result in exponentially higher cumulative damage estimates while the linear integration method would be a linear relationship between force and cumulative damage.

(b) When keeping the “same area under the curve” (force * repetition kept the same), fatigue failure based model still shows exponentially higher cumulative damage as force increases while the linear integration methods maintain more or less the same level of cumulative exposure estimation.

3. The fatigue failure based cumulative low back damage estimation model developed in this research was evaluated using two epidemiological databases. Additional analysis using linear and squared integration methods were also performed. These conclusions included:

   (a) The cumulative damage measure generated by the fatigue failure model shows a significant relationship (continuous logistics regression, $p < 0.05$) with low back health outcome in both epidemiological databases.

   (b) When compared with the linear and squared integration method, the fatigue failure based model is best (lowest p-value) among the three in all statistical testing scenarios performed in this study.

   (c) The proposed fatigue failure theory based model’s estimate of cumulative damage was highly associated with negative health outcomes.

7.2 Future Research

1. As suggested by fatigue failure theory, loading patterns (means and ranges of stress) may impact the level of fatigue damage. In this research, the loading pattern was considered when calculating cumulative damage. However, the methodology used was developed in material engineering on metal material. The difference between biological and metal material may impact the damage response due to different loading pattern. Studies that investigate damage responses from different loading patterns on biological tissue would be very beneficial to better adjusting damage estimation in the model.

2. The exposure information from the two epidemiological databases used in this research was collected with limited technical assistance (e.g., motion capture sensors, etc.). The data were collected without the intention for the type of analysis performed in this research. Because of that, one of the limitations was that the continuous loading history was simulated from the database. The simulated exposure history may not accurately represent the loading experienced by the operators. Additional epidemiology study based on continuous loading history is needed to validate this model.

3. In this research, personal characteristics were not included in the internal force estimation nor in the exposure and health outcome relationship analysis. However, personal characteristics would impact the internal force and also the ultimate strength of the biological tissue which in return would impact

the estimating of cumulative tissue damage and the estimation of the probability of occupational injury. A study that includes personal characteristics in estimating cumulative exposure could, in theory, provide better results in associating damage measures with health outcomes.

7.3 Summary

How to quantify cumulative exposure to physical risk factors is the first question that needs to be answered for any study that are interested in better understanding the relationship between exposure and occupational health outcome. This research evaluated the linear integration method that is most widely used in estimating low back cumulative exposure. The assumption behind this integration method was challenged by the results of this study: with controlled "area under the loading curve", the high force low repetition combination resulted in higher muscle damage than the low force high repetition group. This finding showed agreement with fatigue failure theory that there is an exponential relationship between the level of stress experienced and the number of cycles leads to material failure. In other words, high force exposure would result in exponentially higher damage compared with relatively lower force exposure. A low back cumulative damage estimation method using continuous loading history was developed based on fatigue failure theory. This method was validated using two epidemiological databases. Though the current estimation method used simulated loading history without considering personal characteristics, the development of this method was the first attempt toward the next generation of automated ergonomic risk assessment with this cutting-edge theory.

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Appendices

Appendix A

Python Code for Rainflow Counting

```
def rainFlow(dataList):
    d = dataList

    range_ls = []
    mean_ls = []
    cycle_ls = []  # count as one cycle or half cycle

    while len(d) > 3:
        base_length = len(d)
        for i in range(len(d)):
            p0, p1, p2 = d[i], d[i+1], d[i+2]
            dif1, dif2 = abs(p1-p0), abs(p2-p1)

            if dif1 <= dif2:
                p_range = dif1
                p_mean = (p0 + p1) / 2.0

                range_ls.append(p_range)
                mean_ls.append(p_mean)

                if i == 0:     # count as half cycle if include the start point
                    cycle_ls.append(0.5)
                    del d[0]
                else:
                    cycle_ls.append(1)
                    del d[i:i+2]
            else:
                pass

        if len(d) == base_length:
            print ("Cycle Counting Failure, current data length: " + str(len(d)))
            break
        else:
            pass
    return range_ls, mean_ls, cycle_ls
```