This is to certify that the
thesis entitled

Predicting Relative Workload During Construction Activities
Using Multiple Regression Techniques

presented by

Lili Xi

has been accepted towards fulfillment
of the requirements for the

Master of Science degree in Construction Management Program

Major Professor's Signature

Nov 14, 2005

Date

PREDICTING RELATIVE WORKLOAD DURING CONSTRUCTION ACTIVITIES USING MULTIPLE REGRESSION TECHNIQUES

By

Lili Xi

A THESIS

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

MASTER OF SCIENCE

Construction Management Program
School of Planning, Design and Construction

2005

ABSTRACT

PREDICTING RELATIVE WORKLOAD DURING CONSTRUCTION ACTIVITIES USING MULTIPLE REGRESSION TECHNIQUES

By

Lili Xi

In this thesis, the method developed by Abdelhamid (1999) to predict relative workload from in-situ collected sub-maximal oxygen uptake data is redeveloped for 100 experimental subjects from Michigan State University. A relative workload prediction equation (RWP equation) is developed. The standard error of prediction for $\%VO_{2max}$ and VO_{2max} are ±7.6% and ±0.65 liter · min^{-1}, respectively.

In an effort to improve the predictive accuracy of the RWP equation, a number of factors were considered in constructing a multiple linear regression (MLR) model. The prediction capability was best when the Energy of Green's function, relative heart rate, and body surface area were used as predictors. Using the regression model that combined these predictors, the standard error of prediction for $\%VO_{2max}$ and VO_{2max} was ±4.9% and ±0.53 liter · min^{-1}, respectively.

All regression models have been validated using non-steady state oxygen uptake and heart rate data measured for 100 validation subjects. The MLR model provides a robust, efficient and reliable statistical methodology capable of predicting relative workloads from submaximal exercises data collected in-situ. The prediction technique would be critical to the success of many field studies and would greatly enhance work study and exposure/risk assessment methods.

ACKNOWLEDGMENTS

I wish to thank my advisor, Dr. Tariq Sami Abdelhamid, for his encouragement, guidance and kindness during my studies at Michigan State University. I would like to express my gratitude to him for giving me the freedom to pursue this research, and for the financial aid he provided to sponsor my graduate study. In particular, I want to thank him for teaching me how to write research papers and proposals, and for assisting me with the completion of this thesis. From him, I learned how to be a serious researcher and how to take responsibilities and be patient. I am also thankful to Dr. Mohammad Najafi and Dr. Joanne Westphal for their support and assistance during this research.

I am grateful to my parents for taking care of my daughter Kelly for these two years and for providing me moral and spiritual support. Finally, I can have free time to play with her and answer her questions.

I also express my gratitude to Litian He and her husband Huaming Chen, my best friends at MSU, who provided help and encouragement at my most difficult time at MSU. Their friendship helped me to overcome the difficulties I faced when I was pregnant, and when my daughter Kelly was born.

I am grateful to God for all the people around me. I could not have finished this program without their kindness, encouragement and help. I was able to finish this program successfully because of the love of my parents, family, and friends, and the help and encouraging advice from Dr. Tariq. Thanks again to all of you.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDICES

CHAPTER I

INTRODUCTION

I.1 Motivation

Construction work is physically demanding work. The culture of the construction industry has evolved such that contractors rely heavily on hand labor with small, relatively inexpensive and multipurpose tools. This reliance on hand labor may explain why, in the Jobs Rated Almanac ranking of 250 jobs for physical demands, construction trades account for 18 of the worst 50 jobs in the United States (Krantz 2000). The situation is not much different in other parts of the world. In the early '90s, "3K", derived from "Kitsui" (physically hard work), "Kiken" (hazardous) and "Kitanai" (dirty), became a fashionable term in Japan to describe the construction industry (Everett and Saito 1996). Apparently, the construction industry has resigned itself to the notion that a high level of physical effort is an inherent part of doing the work.

A known fact about physically demanding work is that it leads to physical fatigue that may lead to decreased productivity and motivation, inattentiveness, poor judgment, poor quality work, job dissatisfaction, accidents, and injuries (Brouha 1967, Janaro 1982, Injury Facts 2003). Many investigators, dating back to Frederick W. Taylor (the father of Scientific Management) in the early 1900s, have argued that since physical fatigue affects performance, performance can be improved by either identifying and eliminating the causes of physical fatigue or by at least finding ways in which to combat its effects (Aquilano 1968 and Janaro 1982).

Consequently, understanding the physical demands of construction work is of paramount importance in protecting the workforce's safety and health, and to improve productivity. As suggested by Brouha (1967), such understanding is the key to the solution of what a man can do safely.

The most common methods of measuring physical demand are those of measuring the oxygen consumption or oxygen uptake, VO_2 (usually measured in liters of oxygen per minute), during work or exercise, and/or recording the heart rate HR (measured in beats per minute) associated with the performance of an activity. Measured VO_2 has also been used to indirectly estimate energy costs of performing various human activities, which in turn is used to assess potential for physical fatigue.

Earlier studies on the physical demands of construction activities date back to the 1950s and 1960s. These studies were based on work physiology, and energy expenditure values were collected for various trades. These investigations concluded that accurate assessment of construction activities' physiological demands is particularly difficult. This difficulty was attributed to the variety of individual operations involved in one activity, and to the lack of consistency among construction workers in adopting a technique to carry out an activity, let alone its individual operations (Astrand and Rodahl 2003).

Unfortunately, work physiology has been neglected in most contemporary construction workforce research. Abdelhamid and Everett (1999) reversed this situation and demonstrated the feasibility of measuring in-situ physical demands of construction activities for a concrete placing and finishing operation, using work physiology techniques.

Encouraged by these results, a larger study was conducted on construction sites to measure the level of physiological effort at which construction workers work and to evaluate if the effort exceeded physiologically-based standards and limits. Oxygen uptake (VO_2) and heart rate (HR) data for 100 construction workers from 12 different construction trades were collected. Data was collected over a period of 18 months. The trades tested are Asbestos Workers, Bricklayers, Carpenters, Carpet Installers, Cement Finishers, Drywall Installers, Electricians, Glaziers, Ironworkers, Laborers, Pipe Fitters, and Sheet Metal Workers. The results of this study have been published in Abdelhamid and Everett (2002).

The research findings of Abdelhamid and Everett (2002) indicated that the use of any one physiological measurement does not present the entire story regarding the physical workload affecting an individual worker. Wide differences were noted among individual workers' responses to strenuous work. Abdelhamid and Everett (2002) concluded that:

> "Future research should investigate not only the absolute energy expenditure, oxygen uptake, or heart rate for individual workers, but how these values relate to the individuals' maximum values for each measure. Maximum values are difficult, if not dangerous, to measure, but would lead to a better prediction of physical fatigue."

This research is motivated by the need to better understand the physical demands of construction work based on subject-specific measurements. Prior to accomplishing this need, a technique that enables the assessment of subject-specific physical demands needs to be developed.

I.2 Need Statement

Many work physiologists recommend expressing measured oxygen uptake as a percentage of maximum oxygen uptake (VO_{2max}), commonly known as relative workload ($\%VO_{2max} = VO_{2avg}/VO_{2max}$), because it provides a subject-specific workload (Astrand and Rodahl, Bonjer 1971, Rohmert 1973, Kamon 1979, Tomlinson and Manenica 1977). In addition to accounting for individual differences in physiological capacities among workers, relative workload also enables more accurate assessment of potentials of physical fatigue.

As the expression for relative workload indicates, once a subject's VO_{2max} is known, the determination of $\%VO_{2max}$ is arithmetically simple. Individuals vary greatly in their respective $V0_{2max}$ values because it can be greatly influenced by genetic factors of age, gender and body dimension, as well as by other factors such as tobacco, alcohol, caffeine usage, climate, and psychological factors. In general, determining VO_{2max} is accomplished through the use of direct (exact) measurement or prediction techniques. Exact measurement of VO_{2max} is impractical for applied research due to its intensive and intricate laboratory procedures as well as the risks it poses for unfit subjects. Prediction techniques offer an attractive alternative with numerous linear and non-linear regression techniques available.

Abdelhamid (1999) developed a new method capable of such prediction. This new prediction methodology was based on the hypothesis that oxygen uptake data are serially dependent, and that by exploiting this dependence, using time series analysis techniques, a regression model between relative workload ($\%VO_{2max}$) and a statistical characteristic of collected oxygen uptake data can be developed.

In Abdelhamid (1999), a time series-based metric called the Energy of Green's function (E_G) was found to be strongly linearly correlated to relative workload ($\%VO_{2max}$). Based on this finding, a simple linear regression model was developed using data from 20 subjects. The regression model had a standard error in predicting $\%VO_{2max}$ and VO_{2max} of $\pm$ 3.4% and $\pm$ 0.5 liter $\cdot$ min^{-1}, respectively.

Using data from five validation subjects, the standard error in predicting $\%VO_{2max}$ and VO_{2max} was $\pm$3.3% and $\pm$0.43 liter $\cdot$ min^{-1}, respectively. The closeness of these errors to those of the regression model indicated that the mean square error of the regression equation is not seriously biased and that it provided an appropriate indication of the predictive capability of the developed regression model.

These initial results are quite promising and establish a starting point for further investigations. A few of the questions that could be explored include the following:

- Is this prediction method suitable for a larger pool of subjects?
- How will adding a subject's height, weight, age, gender, and heart rate affect the accuracy of the regression model?

Answers to the above questions will be very helpful in developing a non-invasive technique for understanding the physical demands of construction work. Therefore, these questions will be further investigated in this research.

I.3 Research Goal and Objectives

This research is motivated by the need to learn more about physical fatigue resulting from work, and how to effectively reduce fatigue and improve work productivity. In order to achieve this, it was clear that a measurement technique had to be developed first. Hence, the goal of this research is to develop a technique for predicting relative workload from sub-maximal physiological data collected in-situ.

The following are the primary objectives of this thesis:

- Validate the simple linear regression model developed in Abdelhamid (1999) for 100 subjects performing a specified exercise regimen.
- Develop and validate a multiple linear regression model to predict the relative workload from sub-maximal oxygen uptake (VO_2).

I.4 Research Scope

This research is an extension of previous work by Abdelhamid (1999) that was aimed at developing a prediction technique for relative workload from in-situ collected data. The primary aim of this research is to improve the accuracy of the simple linear regression model developed by Abdelhamid (1999) through the development of a multiple linear regression model. This research will use data collected from 200 subjects at Michigan State University.

I.5 Thesis Guide

This thesis is divided into five chapters. Chapter I presents the motivation behind this research and the importance of measuring the physical demands of construction work. A need statement is formulated and research goals and objectives are presented along with the scope of the research.

Chapter II presents a background of work physiology and prior research on the physical demands of construction work. Methods of measuring physiological demands by measuring oxygen uptake and/or heart rate are also discussed. The chapter then reviews earlier researches on the methods of predicting relative workload and maximum oxygen uptake.

Chapter III outlines the methodology adopted to accomplish the research goal through a detailed discussion of action items undertaken to achieve the two research objectives. This chapter discusses in more detail the relative workload prediction model developed in Abdelhamid (1999). It also discusses the development of multiple regression models through a hypothetical multiple linear regression model, used to demonstrate the research methodology and the expected results. Lastly, it explains the method used to validate the regression models developed in this research.

Chapter IV presents results of redeveloping the simple regression model on a larger pool of subjects. Development of the multiple linear regression (MLR) models, with age, height, weight, and heart rate factors is also presented. Statistical properties of the developed regression models are derived and analyzed against the basic assumption upon which the models were constructed. The chapter concludes with a validation of all the regression models on 100 validation subjects. The validation results were used to find the best-fit MLR model.

Finally, Chapter V summarizes the conclusions and contributions of the thesis work. It presents recommendations for future work which will improve accuracy of the MLR model, especially its applicability for construction work. Appendix A discusses time series analysis and serves as a foundation for understanding the conceptual ideas and methods presented in Chapter III and IV. Appendix B provides the raw data for all measurements made in this research. Appendix C describes the experimental protocol setup for data collection during the development and validation experiments in this research.

CHAPTER II

LITERATURE REVIEW

II.1 Energy Expenditure in Humans

Humans typically expend energy through metabolic processing of foodstuffs involving a complicated chain of chemical reactions that take place in various muscle and body tissues. These metabolic processes are central in providing body homeostasis and physical work. Body homeostasis refers to a state of physiological equilibrium produced by maintaining vital functions of various body systems and chemical composition of the human body. Body homeostasis must be maintained regardless of being at rest or at work. At rest, the metabolic processes that guarantee body homeostasis are termed in the literature "basic metabolism" (Astrand and Rodahl 2003). During work, body homeostasis is disturbed and various physiological functions respond to maintain homeostasis and provide the musculoskeletal system with the necessary energy to "operate".

Measuring the energy expended by humans at rest or during work is very important and is the cornerstone of many disciplines branching from human physiology (e.g., exercise physiology and work physiology). The kilocalorie (kcal) is the unit used for measuring energy and it is defined as the quantity of heat necessary to raise the temperature of 1 kilogram (1 liter) of water 1° centigrade (McArdle, Katch, and Katch 1996). It is familiar to dieters as the Calorie, and is equal to about 4 BTUs, 1.162 Watt-hours, or 4186 Joules. There are two main ways to measure the energy humans expend: direct and indirect calorimetry.

II.1.1 Measuring Physiological Demands

Given that metabolic processes that take place in humans result in a production of heat, the metabolic rate is indicated by the rate of heat production. This is the basic idea behind measuring energy expended by humans through directly measuring the heat produced from the metabolic processes. This measuring procedure is therefore termed "direct calorimetry".

Direct calorimetry can only be performed in a human calorimeter, which is an airtight and thermally insulated chamber. A person can literally live in this chamber, while the heat produced from metabolic processes can be accurately measured during rest or work periods. The produced heat is measured by utilizing a heat-measuring device. Many heat-measuring devices for human calorimeters have been developed over the years and are based on different operating principles (McArdle, Katch and Katch 1996).

Measuring energy expenditure using direct calorimetry is extremely accurate. However, human calorimeters are very expensive to build and operate and are obviously not portable. These limitations restrict the use of direct calorimetry to academic research performed in laboratory settings.

Earlier research has demonstrated that the total energy expended by a human can be estimated by measuring the amount of oxygen consumed before, during, and after performance of work or exercise activities. Because oxygen is used and carbon dioxide is produced during energy-yielding reactions, the exhaled air contains less oxygen and more carbon dioxide than the inhaled air. The difference in composition between the inspired and expired air volumes reflects the body's release of energy through aerobic metabolic reactions (McArdle et al. 1996). This technique is referred to as "indirect calorimetry". Indirect calorimetry provides a reasonably accurate, portable, and relatively inexpensive method of measuring energy expenditure compared to direct calorimetry.

Research has shown that for every liter of oxygen consumed 4.83 Kilocalories of energy, on average, are produced. Thus, collected oxygen uptake data may be converted to corresponding energy expenditure by multiplying it by 4.83 kcal per liter of oxygen (Rodahl et al. 1974, McArdle et al. 1971, Astrand and Rodahl 1986). It should be noted that the conversion multiplier varies slightly depending on a physiological attribute termed the "Respiratory Quotient" (McArdle, Katch and Katch 1996).

II.1.2 Oxygen Uptake (VO_2) and Heart Rate Measurements

Previous research showed that measuring heart rate (measured in beats per minute) associated with the performance of an activity is another common method for measuring physiological demands. Determining target exercise intensities by heart rate is practical and useful, because it is easily and noninvasively obtained with heart rate monitors during exercise. Many researchers, such as Wyndham et al. (1962), Poulsen and Asmussen (1962), McArdle et al. (1971), Rodehl et al, (1974) have used this approach.

Researchers have found a linear relationship between heart rate and oxygen uptake. As the body performs exercise, there is an increased demand for oxygen to be delivered to the exercising muscles, and this demand is accompanied by an increase in lung and heart function.

In the 1990s, the validity of using this linear heart rate-oxygen uptake relation has been called into question for non-dynamic and discontinuous exertions. Many argued, for example, that a myriad of variables would affect the measured heart rate values and the linear relation obtained for heart rate and oxygen uptake. It has been shown that factors other than work or exercise may lead to increased heart rates. For example, environmental conditions, emotions, fear, previous food intake, body position, muscle groups used, continuity of the work, and whether muscles are acting statically or dynamically (Mass et al. 1989), may all have an effect. Moreover, heart rates vary greatly with individual characteristics such as age and weight. In addition, oxygen consumption is dependent on the intensity of exercise, as well as age, gender, exercise history or habits, hereditary factors and current health status (Lear et al 1999).

These examples indicate that inferences based on the linear relation between heart rate and oxygen consumption may provide an inaccurate measure of metabolic stress on the body. Despite criticism concerning the linear oxygen uptake heart rate relation to predict energy expenditure for various activities, Astrand and Rodahl (2003) have suggested, based on actual experimentation, that:

> "In most cases, the reliability of the conversion is adequate for all practical purposes of field investigation"... "It appears that the use of the recorded heart rate as a basis for the estimation of work load may be acceptable even in many work situation involving arm work or the use of small muscle groups."

The reliability of indirect assessment of VO_2 by measuring HR has mainly been limited to steady-state exercise. It would be a useful technique if it could be found valid for non-steady-state activities, especially for understanding the physical demands of construction work, and assist in developing prediction methods for relative workload measurements.

Bot and Hollander (2000) studied the validity of using heart rate responses to estimate oxygen uptake during varying non-steady activities, such as those found in construction tasks. Dynamic and static exercises engaging large and small muscle masses, and combinations of different muscle groups were conducted in four different experiments. The individual regression equations disclosed significant linear relationships between HR and VO_2 during dynamic, non-steady state arm and leg exercises. Also, during non-steady state activities with different muscle groups significant correlation coefficients (*r*) were established for all subjects. While the *r* values were less compared to those in the steady state conditions, it can still be concluded that estimation of VO_2 by measuring the HR is not limited to steady-state exercise. This conclusion by Bot and Hollander (2000) is encouraging because in most construction activities, the intensity varies constantly and no steady state is reached.

II.1.3 Maximum Oxygen Uptake

The amount of oxygen supplied to a muscle is not unlimited and the limit varies greatly between individuals due to the varying efficiency of peripheral and central processes that occur in our bodies. The maximum supply of oxygen (and of energy) has been reported in terms of the maximum oxygen utilization an individual can achieve and has been termed as maximum oxygen uptake (McArdle et al. 1996). Maximum oxygen uptake or VO_{2max} is defined as the highest oxygen uptake per minute that can be measured during dynamic exercise with large muscle groups.

Another common definition for VO_{2max} (maximal oxygen uptake, maximal aerobic power) is that it's the rate at which oxygen can be used by the body during maximal work. VO_{2max} is directly related to the capacity of the heart to deliver blood to the muscles and is considered a good index of cardio-respiratory fitness and a good predictor of performance capability in aerobic events such as distance running, cycling, cross-country skiing, and swimming.

In general, VO_{2max} is accepted as one of the best single indicators of an individual's aerobic fitness. Aerobic fitness is frequently considered the most important aspect of physical fitness. Shephard (1977) defined aerobic fitness as the:

> "ability to maintain the various processes in metabolic exchange as close to the resting state as is mutually possible during the performance of a strenuous and fully learnt task for a moderate time, with a capacity to reach a higher steady rate of working than the unfit and to restore promptly after exercise all equilibrium which were disturbed."

It should be noted, however, that VO_{2max} is only a predisposition for physical performance. A high VO_{2max} does not guarantee good physical performance, since technique and psychological factors may have influenced performance either positively or negatively (Verma 1994).

Research has also shown that this measure is dependent on individual factors (e.g., sex, age, body dimensions, inheritance), environmental factors (e.g., intensity, duration, and technique of exercise), and adaptation through training (Jorgensen 1985).

Astrand (2003) et al., showed in their research on direct measurement of maximal oxygen uptake in 350 individuals ranging in age from 4 to 65 years of age, that there is in both sexes a peak in maximal oxygen uptake at 18 to 20 years of age, followed by a gradual decline. At the age of 65, the mean value is about 70% of what it is for a 25 year-old individual. Maximal oxygen uptake for the average 65-year old man is the same as for a typical 25-year old woman.

Changes in tissue and organ function due to age may explain the decline. As people age, the decline in maximal heart rate is quite evident, and this lower heart rate, coupled with other effects of age, may reduce the individual's maximal cardiac output and hence the oxygen-transporting ability (Astrand and Rodahl 2003).

A study by Astrand (1967b) on 33 building workers (bricklayer, carpenters and laborers) from 30 to 70 years of age showed that the mean heart rate during occupational activity was correlated with the individual's maximal heart rate. For younger subjects, with a maximal heart rate of 185 beats/min, the mean heart rate during occupational activity was 110, while those with a maximum of 150 had a mean of 90 beats/min. Maximal oxygen uptake ranged from 2.2 to 3.6L/min. In general, irrespective of maximal oxygen uptake, each worker used the same percentage of his/her maximum in work operations. In other words, older workers with lower maximal aerobic power kept a slower work tempo than younger ones, but relative load was the same, about 40%. The person with a high maximal heart rate can do a day's work at a higher mean heart rate than a person with a lower maximum, but the relative strain may be the same on the two persons.

Another factor that is important to consider for the determination of maximum oxygen uptake is body fat. Fatty tissue is metabolically fairly inert, but because it can constitute a large proportion of the body weight, it may be important to exclude fatty tissue when evaluating oxygen-transporting capacity (Astrand and Rodahl 2003). This is especially important considering that women's body fat percentage and body dimensions are different from those of men. For example, according to Wilmore (1979), the average North American female at full maturity is approximately 13 cm.

shorter than the average male, 15 to 18 kg lighter in total weight, 18 to 23 kg lighter in lean body weight and considerably fatter, i.e., 25% vs. 15% relative body fat. Hence, it is not surprising that a woman's maximal oxygen uptake per kilogram of gross body weight is a better expression of her potential to move her body than is the maximum related to lean body weight.

II.1.4 Measurement of Maximum Oxygen Uptake

When does a person reach the maximum aerobic power level? If an individual increases the intensity level of exercise, a corresponding increase occurs in heart rate, respiration and oxygen intake, as well as in the activity levels of other parts of the aerobic systems. At some point, however, oxygen intake cannot increase beyond a specific level, even though more work is being performed. At this point, the individual has reached a level that is commonly referred to as maximal oxygen uptake (VO_{2max}). This measure is considered to be the best single indicator of aerobic fitness, because it involves the optimal ability of three major systems of the body (pulmonary, cardiovascular and muscular) to take in, transport and utilize oxygen. The higher an individual's level of maximal oxygen uptake is, the greater the level of physical work that can be performed (Bryant and Peterson 1997).

In the field of exercise physiology, when limiting factors for VO_{2max} are discussed, it is usually with reference to human subjects, without metabolic disease, undergoing maximal whole-body exercise, at sea level. Under these conditions, it is the ability of the cardio-respiratory system (i.e. heart, lungs, and blood) to transport O_2 to the muscles, that limits VO_{2max}, not the ability of muscle mitochondria to consume O_2 (Bassett et al. 2000).

Exact techniques for the determination of VO_{2max} require rigid and standardized criteria to ensure that a true maximum has been reached. These techniques are commonly performed on treadmills or cycle ergometers (CE) using an exercise protocol that involves a gradual increase in the workload until the subject reaches complete exhaustion and can no longer perform the exercise. Excellent discussions on exact techniques to determine VO_{2max} can be found in Astrand and Rodahl (2003), Kilbom (1995), and McArdle et al. (1996).

But exact measurement of VO_{2max} requires well-equipped laboratory settings and special equipment, and may be dangerous for unfit or untrained subjects. The limitations of exact measurement have inspired the development of prediction techniques to determine VO_{2max}. Examples of widely used prediction techniques are the walking test (Cooper 1968, Kline et al. 1987), endurance runs (Cooper 1968, Verma 1994), the step test (as referenced in McArdle, Katch, and Katch 1996), nomograms (Astrand 1960, Astrand and Rodahl 2003), and linear and non-linear regression equations (Verma 1994).

Most of these prediction techniques use submaximal exercise tests to predict maximal oxygen uptake (VO_{2max}) from an individual's heart rate at a certain submaximal workload. Maximal oxygen uptake is then predicted using an established regression equation (Astrand 1956, ; Asmussen and Molbeck 1959, Maritz et al. 1961, and Margaria et al. 1965). The submaximal tests are useful for estimating aerobic fitness without undue stress to the subjects, and are more suited to the elderly or individuals with known diseases. Submaximal tests are also more easily, inexpensively and rapidly administered to larger numbers of subjects (ACSM 1995).

However, some researchers (Davies 1968, Glassford et al. 1965, Rowell et al. 1964, McArdle et al 1996) have pointed out serious limitations in the predictive accuracy of using heart rate during submaximal work to evaluate VO_{2max}. The percentage error in prediction values has been reported to be between 15-20%.

As summed in the classic textbook of work physiology by Astrand and Rodahl (2003) the reliability of predicting maximal oxygen uptake from the submaximal heart rate response to a given rate of exercise has to be studied in more detail.

One method of predicting an individual's maximal oxygen uptake by use of nomogram (P.O.Astrand and Ryhming 1954) has been critically studied over the years. The standard error of this method for predicting maximal oxygen uptake from submaximal exercise tests was 10% in individuals of the same age, but up to 15% in subjects of different ages when the age correction factor of maximal oxygen uptake was applied.

The validity of the nomogram has also been tested in other laboratories. In some cases, there has been good agreement with other methods, but in other cases, it has resulted in underestimations. Therefore it is suggested by Astrand and Rodahl (2003) that an evaluation of the maximal effect of the oxygen uptake based on studies at submaximal work rates or oxygen uptake should be done with great caution, especially when persons of different age groups are considered.

To increase the accuracy of prediction, attempts have been made by Hermiston and Faulkner (1971) and Mastropaolo (1970) to include more physiological variables in the prediction equation. Predictive accuracy was further improved by Verma et al. (1977) by using a non-linear formula for estimating VO_{2max} from cardio-respiratory strains. Jessup et al. (1974) made an attempt to predict VO_{2max} from some physiological as well as anthropometrical variables, and obtained a high multiple correlation between observed and estimated VO_{2max}. Verma et al. (1980) suggested a multiple linear regression equation for predicting VO_{2max} from anthropometric variables. The equation has been considered a simple approach for predicting VO_{2max} based on anthropometrics variables only.

Although some of the methods based on physiological variables have achieved maximum precision for predicting VO_{2max}, these may not be of practical use in a field situation for selecting personnel suitable for certain kinds of service and industrial work, and for sports. This is due to the laborious and time-consuming procedures required for measuring the physiological variables involved in the predictions. In addition, the external validity of these techniques has been a topic of debate, i.e., whether the maximum oxygen uptake obtained from these techniques will be similar to that during the actual activity under evaluation.

Wertheim et al. (2002) performed a study on the measurement of maximal oxygen uptake in moving environments. The study pointed out that in previous studies on physical fatigue during simulated ship movements, the apparent exhaustion of subjects after experimentation suggested that oxygen consumption, the traditional index of physical workload, expressed as a percentage of peak oxygen consumption (VO_{2max}), and measured in a separate graded exercise test (GXT), underestimates workload in a moving environment.

They mentioned that the GXT tests were carried out in a stationary environment, as is standard practice. To explain the underestimation, they hypothesized that VO_{2max}

might have been less if the GXT had been carried out in a moving environment. Their study employed three experimental tests of this hypothesis, performed with a ship motion simulator aboard a ship at sea. In all three experiments, VO_{2max} was indeed significantly reduced, the difference being between 6 and 10%, when the GXT was carried out in a moving environment. Theoretical reasons for this phenomenon are discussed and investigated, but a clear explanation is still lacking.

Though an explanation of the motion-induced decrease of VO_{2amx} was not given by Wertheim et al., their research on maximum oxygen uptake under a moving environment advanced research technologies for simulating a real dynamic situation for measurement of VO_{2max}. It addressed the issue of how to measure or predict VO_{2max} from an angle closer to real world conditions.

In sum, most of the methods for measuring or predicting VO_{2max} are generally non-invasive and provide quick results, but are not necessarily the most accurate. Some provide highly accurate results, but require the presence of a well-equipped laboratory and trained personnel. Hereinafter some of these methods of predicting VO_{2max} are reviewed in more detail.

A. HR-VO_2 Linear Relationship

The most popular method for predicting VO_{2max} is the HR-VO_2 linear relationship. With an assumption of maximum heart rate, a corresponding value of oxygen uptake, using the linear relationship, is developed between the two. This value is assumed to be the VO_{2max}. The linear relationship has been explained in more detail in section II.1.2. Therefore only some different views about this method will be mentioned here.

Several researchers argued that this method has an error of up to 8 percent (McArdle et al. 1996). The ACSM (1995) have reported variability of HR_{max} of up to 10-12 beats per minute in normal subjects when using the popular formula: HR_{max} = 220 – age. This suggests that HR may not be a valid measure of VO_{2max}. Researchers have also argued that this method is only accurate for light to moderate workloads, because at heavier workloads there is a larger than expected increase in the VO_2 per unit increase in HR.

B. Time Series Analysis

As previously mentioned, Abdelhamid (1999) developed a method capable of directly predicting relative workload from in-situ collected sub-maximal oxygen uptake data without the need to determine maximum oxygen uptake. A statistical analysis technique called time series analysis was used to model oxygen uptake data. The methodology is based on the hypothesis that oxygen uptake data are serially dependent, and that by using time series analysis techniques, a regression model between relative workload and statistical characteristics of collected oxygen uptake data can be developed.

The result is a special kind of regression model, termed AutoRegressive Moving Average model, ARMA(p,q). After arriving at an adequate ARMA(p,q) for the observed time series, the Green's function "G_j" was derived and used to make inferences about the system that produced the data – the human body, in this case. The Green's function "G_j" was the strongest candidate because, by definition, it quantitatively summarized how a system responded to disturbances and described the system's resistance to changes from a state of equilibrium.

Using the time series analysis package ITSM 2000 version 7.0 (Brockwell and Davis 1996) on the data collected from subjects doing exercises on a treadmill, values of the Green's function were obtained and the value of the energy of the Green's Function, E_G, was determined (based on the sum of squares of the individual G_j values). The relationship between E_G and $\%VO_{2max}$ exhibited a strong correlation. It was analyzed using linear regression techniques to formally characterize this relationship, and resulted in a simple regression model.

This research will utilize the mentioned time series analysis technique, along with factors such as age, body dimensions and heart rate, to develop a multi-regression model capable of predicting relative workloads.

C. Other Prediction Methods and Linear/non linear Regression Models

Many researchers focus on different angles and methods of measuring VO_{2max}. Except for direct measurement, most methods are based on linear or non-linear regression models to predict VO_{2max} values. These methods usually use data collected from treadmill exercises.

Table II.1 lists other researchers' prediction methods, and equations currently used for maximum oxygen uptake measurements. These equations use different variables and different linear/non linear regression models to predict VO_{2max}. The characteristics of each equation, and some of the advantages and limitations, are discussed further below. Jones' equation is especially applied in the next chapters of this thesis for validation purposes.

In 1973, Fox presented a prediction method based on a linear equation relating VO_{2max} to submaximal heart rate during the 5^{th} min of bicycle exercises at 150W. The standard error of estimate (SEE[1]) was ±7.246ml/min (±7.8% of the mean $VO_{2max.}$) and

correlation coefficients (r^2) was (±0.76). Though his method uses the submaximal

heart rate as a basis for the prediction of maximal aerobic power, it differs from the previously mentioned HR-VO_2 linear relationship in that it depends only on the relationship that exists on a single submaximal heart rate determination. Whether or not there is a linear increase in heart rate with oxygen consumption and workload is inconsequential.

Fox	VO_{2max} (mL/min)= 6300- 19.26 x HR (recorded at the 5th min of exercise @150W. b/min))
Jones	VO_{2max} (L/min) = (0.046 x Ht (cm)) - (0.021 x age (yrs)) – (0.62 x Sex) – 4.31 where for sex, men = 0, women = 1
Storer	VO_{2max} (mL/min) = (9.39 x max Watts) + (7.7 x BW (Kg))- (5.88 x age (yrs) +136.7
Astrand-Rhyming bicycle ergometer test	VO_{2max} (L/min) = $VO_{2submax}$ x ((220-age(yrs) – 72/HR_{submax} -72)) where $VO_{2submax}$ (L/min) = (Power (watts) x 0.012)+ 0.3
Dobeln et al.	$VO_{2\max} = 1.29\sqrt{\frac{L}{H-60}}\,e^{-0.00884T}$,where L is load in kilo-pound-meters per minute at submaximal work, H is heart rate after 5-6 mins at load L, and T is age in years.
Womack et al.	VO_{2peak} (mL/kg/min) = (0.00872 * maximal claudication pain time [sec]) + (0.02839 * maximal heart rate [b/min]) - (0.12034 * BMI) + 10.11411

Table II.1 Equations used to predict VO_{2max} (Lynn A and Roberta L 1999)

Jones (1985) presented an equation that was derived from one hundred healthy subjects (50 male and 50 female), selected to provide an even distribution of ages (15

---

[1] SEE: Standard Error of Estimation to measure of the accuracy of predictions.

[2] *r*: called "Pearson's r". It reflects the degree of linear relationship between two variables. It ranges from +1 to -1. A correlation of +1 means that there is a perfect positive linear relationship between variables.

to 71 yr) and heights (165 to 194 cm in males and 152 to 176 cm in females). These subjects underwent a progressively incremental (100 kpm/min each min) exercise test up to a symptom-limited maximum. Measurements were made of O_2 intake and CO_2 output, ventilation and breathing pattern, heart rate and blood pressure, and rating of perceived exertion. See Table II.1 for the equation. (SEE: 0.458; *r*: 0.869). Maximal heart rate (HR) declined as a function of age: HRmax = 202 - 0.72 (Age) beats/min (SEE: 10.3; *r*: 0.72). The researcher found that the VO_2 increased linearly with power throughout the test. The one important aspect of this equation lies in that it showed a possibility that, in an individual subject, the intercept of this relationship was positively influenced by weight and height.

In 1990, Storer developed an equation based on the duration (an analog of maximal work rate, Wmax) of a cycle ergometry[3] (CE), hypothesizing that CE VO_{2max} could be accurately predicted due to its more direct relationship with work rate (W). Thus, healthy, sedentary males (N = 115) and females (N = 116), aged 20-70 yr, were given a 15 $W \cdot min^{-1}$ CE graded exercise test (GXT). His testing method results were developed into a multiple linear regression equation which predicted VO_{2max} ($ml \cdot min^{-1}$) from the independent variables of W_{max} (W), body weight (kg), and age (yr) derived from subjects:

Males: Y = 10.51 (W) + 6.35 (kg) - 10.49 (yr) + 519.3 $ml \cdot min^{-1}$

(SEE: 103 $ml \cdot min^{-1}$; *r*: 0.939)

Females: Y = 9.39 (W) + 7.7 (kg) - 5.88 (yr) + 136.7 $ml \cdot min^{-1}$

(SEE: 147 $ml \cdot min^{-1}$; *r*: 0.932)

[3] Ergometry: Any method of measuring the amount of work done by an organism, usually during exertion. Ergometry also includes measures of power.

Using the 95% confidence limits as examples of the worst-case errors, Storer's equations predict VO_{2max} to within 10% of its true value. Internal (double cross-validation) and external cross-validation analyses yielded r values ranging between 0.920 and 0.950 for the male and female regression equations. These results indicate that use of the equations generated in this study for a 15 $W \cdot min^{-1}$ CE GXT provides accurate estimates of VO_{2max}.

The Astrand-Rhyming submaximal cycle ergometer test is designed to predict VO_{2max} from a 6-minute exercise period. It is one of the most widely used submaximal exercise tests. The testing procedure requires a steady heart rate at an appropriately selected submaximal work rate (kpm/min or watts). This information, together with a predicted maximal heart rate and an age correction factor, is used to predict the subjects' VO_{2max} (Astrand & Rodahl, 2003).

The main assumptions associated with this test are as follows (referred by Adams 1998):

- Subjects resting and maximum heart rates (RHR & MHR) may be estimated according to age.
- MHR decreases by approximately 10 $beats \cdot min^{-1}$ per decade after 30.
- A linear rise in HR up to MHR exists.
- VO_{2max} and work rate have a linear relationship.
- VO_{2max} occurs at the same work rate at which MHR occurs.

A number of researchers have referred to the errors associated with this and similar submaximal tests in attempting to predict VO_{2max}. Some suggested that regression equations derived from direct VO_{2max} data obtained from random samples of specific populations should be used in the application of the Astrand test. It is probably correct that the Astrand test tends to underestimate VO_{2max} in the unfit subjects and to overestimate it in trained subjects.

Von Dobeln et al. (1967) also developed a multiple regression method to predict VO_{2max}. Eighty-four male construction workers aged 30-70 years were tested once at submaximal and maximal loads on a bicycle ergometer. Submaximal and maximal heart rates and maximal oxygen uptake were measured. The prediction of VO_{2max} from the other variables was analyzed by a fitting procedure using a modified least-square criterion. The best equation gave an SEE of 8.4%. In this method, the other variables such as body size (height and weight) were added to the regression equation for the prediction of VO_{2max} on the bicycle ergometer.

Womack et al. (1998) developed a formula to predict peak oxygen consumption using 157 patients with intermittent claudication, to estimate VO_{2peak} in peripheral arterial occlusive disease (PAOD) patients and to determine independent predictors of VO_{2peak} in this population. Medical history, height, weight, body mass index (BMI), age, gender, smoking status, resting and post-exercise ankle/brachial systolic pressure index (ABI), and time to maximal claudication pain and maximal heart rate from an incremental graded exercise test (GXT) were used as potential independent predictors of VO_{2peak}. Time to onset of maximal claudication pain, maximal heart rate, and BMI were all independently associated with VO_{2peak}. These variables were used to estimate VO_{2peak}. The $r = 0.71$, $r^2 = 0.50$ for the developed formula and standard error of estimate = 2.02 mL/kg/min, $p < 0.0001$. The coefficient of variation between estimated and actual VO_{2peak} in this group was 18.3%. Results of this study suggest that a multiple regression equation can be used to estimate VO_{2peak} in patients with intermittent claudication by measuring time to maximal claudication pain and maximal heart rate from a GXT and by measuring BMI.

The Womack et al. (1998) research presents a good example of the multiple linear regression model based on multiple independent variables to predict VO_{2peak}, though the test is done on a certain type of patient. The acceptable standard error level for prediction results provides a promising method for this research; the concept of an MLR model, which is promoted in this thesis for the prediction of physiological demands of construction work.

Except for the above discussed equations or models on the prediction of VO_{2max} based on the data collected from exercises, George et al. (1997) sought to develop a maximal oxygen consumption (VO_{2max}) regression model derived strictly from self-reported non-exercise (N-EX) predictor variables. The VO_{2max} (mean +/- SD; 44.05 +/- 6.6 $ml \cdot kg^{-1} \cdot min^{-1}$) of 100 physically active college students (50 females, 50 males), aged 18 to 29 years, was measured using a treadmill protocol and open circuit calorimetry. Questionnaire-based predictor variables used in the N-EX regression model included (a) the subject's perceived functional ability (PFA) to walk, jog, or run given distances, (b) habitual physical activity (PA-R) data, (c) body mass index (BMI), and (d) gender. BMI ($kg \cdot m^{-2}$) was computed from self-reported body weight in pounds and self-reported body height in feet and inches.

The questionnaire-based N-EX regression model (SEE = 3.44 $ml \cdot kg^{-1} \cdot min^{-1}$, r = 0.85) developed in this study exceeded the accuracy of previously developed N-EX regression models and is comparable to many exercise-based regression models in the literature. Cross-validation using PRESS (predicted residual sum of squares) statistics demonstrated minimal shrinkage (SEE = 3.60 $ml \cdot kg^{-1} \cdot min^{-1}$, r= 0.84,) of the present regression model. The PFA data were useful in explaining observed VO_{2max} variance (squared partial r^2 = 0.155, $p < 0.0001$) and enhanced the ability of the N-EX regression model to accurately predict criterion VO_{2max}.

These results suggest that a questionnaire-based N-EX regression model provides a valid and convenient method for predicting VO_{2max} in physically active college students. And this method provides potentials for using non-exercise physical data such as BMI, and habitual physical activity data, to develop a regression model to predict VO_{2max} and challenges current research methods that rely on data collected from real exercise.

Hermiston and Faulkner (1971) have used a stepwise multiple-regression technique to develop equations for predicting maximal oxygen uptake of physically active and physically inactive men, from data collected during a submaximal treadmill walk. The most accurate prediction for physically active men was obtained from a regression equation which included the subject's age, lean weight, heart rate, factor of carbon dioxide in expired gas, and tidal volume at a submaximum work level, in addition to the rate of change in respiratory exchange ratio. For physically inactive men, the equation included age, lean weight, respiratory exchange ratio, and tidal volume at a submaximum work level. The coefficient of correlation was 0.91 between predicted maximal oxygen upake measure on two different occasions and 0.90 between the observed and predicted maximal oxygen uptake. The multiple regression equations are as follows:

Active:

$$VO_{2max} = 2.966 - 0.031\,(age) + 0.026\,(FFW) - 0.013(HR) + 25.4(FEco_2) + 0.330(V_{T2}) - 8.77(\Delta R)$$

Inactive:

$$VO_{2max} = 3.619 - 0.022(age) - 0.033(FFW) - 2.587\,(R) + 0.253(V_{T9})$$

where VO_{2max} is in liters per minute; age is in years; FFW is fat-free (lean) weight; HR is the heart rate in beats per minute at the end of the 8% grade, $FEco_2$ is the fraction of expired carbon dioxide during the 8-9 min. gas collection; V_{T2} is the tidal volume during the 0% grade gas collection period; ΔR is the rate of change per minute of the respiratory exchange ratio between the gas collection periods of 1-2 min and 8-9 min; R is the respiratory exchange ratio during the 8-9 min gas collection; and V_{T9} is the tidal volume during the 8% grade gas collection period.

The regression equations use a number of independent measures of physiological responses at submaximal workloads. The equations presented above are appropriate for the prediction of VO_{2max} from data collected on adult men during the 1st and 9th min of a treadmill walk. The equations account for age, habitual level of physical activity, and fat-free weight factors, etc. The technique of stepwise multiple-regression allows inclusion of additional independent determinants if a more precise estimate of VO_{2max} is required.

Astorino et al. (2000) did research to better clarify the VO_2 response to exercise at the VO_{2max} level by comparing data derived from different time averaging intervals and exercise protocols. Sixteen active subjects completed three different VO_{2max} tests on a cycle ergometer (a 25 Watt/min ramp protocol (R), a 75 Watt/3 min step protocol (S), and a 25 Watt/min ramp protocol (H) under hypoxic conditions (F_IO_2 = 15 %, P_B = 635 mm Hg) on separate days. All breath-by-breath data were smoothed using an 11-breath moving average. These data were then time-averaged into 15-, 30-, and 60-second sampling intervals.

From their research, data of the change in VO_2 between VO_{2max} and the closest neighboring data point revealed that variability was greatest for the longer time-averaged data. This response was similar for each protocol. They conclude that shorter sampling intervals (breath-by-breath and 15 s) are most suitable for the detection of the VO_2 plateau during progressive exercise to VO_{2max}. In addition, ramp and step protocols produce similar results, and acute normobaric hypoxia does not decrease the incidence of a VO_2 plateau at VO_{2max} using 11 breath or 15 s time averaging procedures. Their research suggested a recommendation on the exercise protocols to detect VO_2 plateau.

II.1.5 Correlation Between Laboratory Test and Actual Output

It is of great interest, both theoretically and practically, whether a correlation exists between an individual's physiological working capacity as measured in the laboratory on a bicycle, ergometer or treadmill, and actual work output in heavy industry. It is also very important to know whether aerobic work capacity as measured in the laboratory conforms to the occupational workload level on heart rate, oxygen uptake and relative workload measurements. Several studies have been done in this area, among which Astrand (1967) presented some explanations more closely related to the construction industry.

In Astrand (1967), a definite relationship was established between aerobic work capacity as measured in the laboratory and the occupational workload level voluntarily chosen by the individual. It stated that such a correlation does exist among lumber jacks, where a worker with a high work production also has a high physical capacity for bicycling; that is, a large oxygen uptake capacity (Hansson 1965). In the construction industry, information is unavailable on an individual's specific production (output) because most tasks are completed by teams of workers. If a correlation exists between the laboratory test results and actual work output, measurements obtained in the laboratory test could be used at least as an estimate of the workload.

II.1.6 Relative Workload

As mentioned in CH I, numerous work physiologists advocate the use of relative workloads to evaluate potentials of physical fatigue (Bonjer 1971, Bink et al. 1961, Michael et al. 1961, Petrofsky and Lind 1978, and Jorgensen 1985). After mean oxygen uptake is determined for a particular task, relative workload is obtained by expressing mean VO_2 as a fraction, or percentage, of the maximal (actual or predicted) oxygen uptake (Kamon 1979).

Practical experience has shown that one cannot tax more than some 30% to 40% of maximal aerobic power during an 8-hour working day without developing subjective or objective symptoms of fatigue (Astrand and Rodahl 2003).

The percentage of relative workload is especially important for occupations with intense physical demands and various demographic groups (old, young, male, and female workers) such as construction and agriculture. If the burden placed on the worker is too high in relation to the person's capacity for sustained physical work, fatigue invariably will develop. Christensen (1962) has concisely summarized the importance of this percentage as follows:

"The determination of oxygen uptake or caloric output and a parallel determination of maximal oxygen uptake of the worker can be valuable tools in our effort to avoid overstrain of the worker at a given job."

To ensure safety and health in the workplace, Brody (1945) first proposed that a suitable safety margin would perhaps be needed in physically demanding jobs. Several research results (e.g. Michael et al. 1961, Bink 1962, Lehmann 1962, Ilmarinen 1992) suggested that 33% of the individual's maximum aerobic capacity (VO_{2max}) should be used as the acceptable standard workload for a general 8-hour physical work shift. Jùrgensen (1985) also proposed that the general upper tolerance limit over an 8-hour workday, consisting of mixed physical work including manual-handling operations, was 30-35%VO_{2max} (based on bicycle legwork and treadmill testing).

II.1.7 Other Measurements of Physiological Demands

Although oxygen uptake and heart rate can be used to assess the physiological demands of muscular work in general, sometimes we need to investigate the load on single muscles as well as groups of muscles. For example, in construction, many tasks require workers to change position, climb, lift, and bear heavy loads at certain times. As Hanson and Jones (1970) pointed out, the recording of heart rate is a quite sensitive index of muscular force and even responds significantly to minor changes in posture. Currently, electromyographic recordings can perform load measurements on single muscles, as well as on groups of muscles. A major advantage of this recording methodology is that it can be used to visualize the effects of practical working procedures on loads imposed on the involved muscles.

Some research has been performed to assess the level of stress imposed on a worker by a given work situation (physical as well as psychological), which is generally reflected by nervous and hormonal reactions, more or less proportional to the degree of stress. Any stressful situation may trigger increases in heart rate and cardiac output, increasing the oxygen uptake and the oxygen delivery to muscles. A lot of research has also been done to observe hormonal and nervous responses and the relationship between heart rate and stress reaction.

II.2 Physical Performance

To achieve top performance, the physiological demands of the event must be perfectly matched to the individual's capabilities. Some common factors can serve as a frame of reference for demands versus individual capabilities. Undoubtedly an individual's genetic factors play an important role in performance capability. Sometimes the environment and geographic location are also important. This is very typical for the construction industry, which is greatly influenced by weather, location, and time. The intensity and duration of work activities also affect oxygen uptake. The recovery time needed before oxygen uptake and rate of aerobic metabolism return to pre-exercise levels differs too. In most of the exercises, oxygen uptake increases roughly linearly with an increase in the rate of exercise.

Physical performance is affected not only by genes, age and sex, but also by biological rhythms, sleep, nutrition, environment, and a number of other factors such as use of alcohol and various drugs. Figure II.1 is a schematic presentation of factors influencing physical performance ability. The effects of the nature of exercise, sex, age and body dimension on oxygen uptake and energy consumption have been explored earlier. In this section, respiration as a limiting factor and the influence of tobacco, alcohol and caffeine use will be discussed. Exploring these factors and their effects on work performance will help us to better understand the physiological performance ability of each worker.

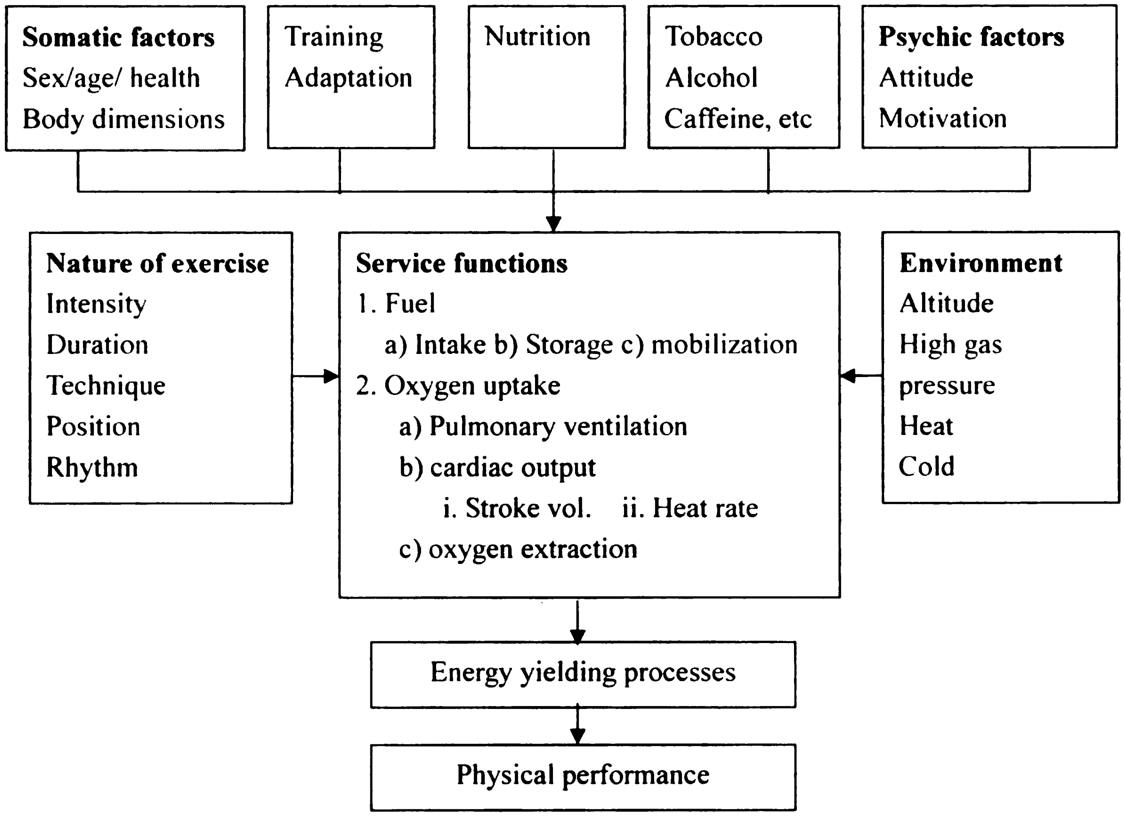


Figure II.1 Factors influencing physical performance ability (Astrand 2003)

II.2.1 Respiration as a Limiting Factor in Exercise

Since oxygen uptake and energy expenditure have a close relationship with the respiratory system of human beings, it is necessary in order to better understand physical fatigue to explore prior research on the human body's mechanical system of respiration, the relationship between physical fatigue and oxygen uptake, and limitations of the respiration process during exercise.

Table II.2 presents data on lung volumes, in liters, obtained from fairly well-trained physical education students about 24 years old (Astrand 1952), who were reinvestigated 21 and 32 years later (I.Astand, P.-O.Astrand et al. 1973;Viljanen 1982).

From the table we can see that the lung volumes are about 10% smaller in women than in men of the same age and size. The ratio of RV/TLC in the young individual is about 20%, but for the 50 to 60 year-old individual, this ratio increases to about 30%, an increase that can be accounted for almost entirely by changes in lung elasticity with age (Viljanen 1982).

	Females			Males		
Function	**1949**	**1970**	**1982**	**1949**	**1970**	**1982**
Vital capacity[4]	4.26	4.25	4.05	5.55	5.39	4.92
Residual volume	1.1	1.71	1.64	1.45	2.04	2.12
Total lung capacity	5.36	5.96	5.69	7.00	7.43	7.04
RV/TLC	20.52%	28.69%	28.82%	20.71%	27.46%	30.11%
Maximal tidal volume	2.24	2.26	2.23	3.38	3.31	3.23

Table II.2 Lung volumes from well-trained physical education students (Astrand 2003)

From the Table II.2, it can be inferred that effects of age and sex on the respiratory system are visible and associated with a reduced vital capacity. Sex and age factors differentiate individuals' capacity for respiration, which may affect the ability of the person to deal with physical fatigue.

According to the research of Astrand and Rodahl (2003) in a group of about 190 individuals 7 to 30 years of age, a significant correlation was found between vital capacity (VC) and maximal oxygen uptake. Individuals with a VC of approximately 4L may have a maximal oxygen uptake of about 2.0 to 3.5 L/min, and vital capacities of 6.0 L/min. are associated with oxygen uptake capacities varying from about 3.5 to

[4] The maximal volume of gas that can be expelled from the lungs following a maximal inspiration is called the vital capacity (VC). When the respiratory muscles are relaxed, there is air still left in the lungs. This air volume is the functional residual capacity (RV). The volume of gas moved during each respiratory cycle is the tidal volume

5.5 L/min. This example shows that one function can appear closely related to another if the data are derived from persons of greatly different size.

Additionally, pulmonary ventilation at rest and during exercise is totally different. Pulmonary ventilation is the mass movement of gas in and out of the lungs. It is regulated mainly to provide the gaseous exchange required for aerobic energy metabolism. According to Astrand and Rodahl (2003), if pulmonary ventilation is expressed in relation to the magnitude of oxygen uptake, it is 20 to 25 ml per liter of oxygen at rest and during moderately heavy exercise, but it increases to 30 to 40 ml per liter of oxygen during maximal exercise. Also in different age groups, the lower ventilation in older individuals is associated with a reduced maximal oxygen uptake. At rest, the respiratory muscles require from 0.5 to 1.0 ml of oxygen per liter of ventilation. During exercise, the oxygen cost per unit ventilation increases markedly.

II.2.2 Smoke, Alcohol, Caffeine and Performance

Smoke contains up to 4% by volume of carbon monoxide, which reduces the oxygen-transporting capacity of the blood. This contributes to the reduced maximal aerobic power and exercise performance following smoking. The term "passive smoking" is used when a person breathes air contaminated by tobacco smoke. Long-term exposure to this environmental tobacco smoke increases the risk of lung cancer and heart diseases.

The effect of cigarette smoking on work capacity is well known. Juurup and Muiro (1946) demonstrated that during submaximal cycle exercise at a fixed oxygen uptake, the heart rate was 10 to 20 beats/min higher when the work test was preceded by smoking one or two cigarettes. Also, the higher the work rate the greater the difference in heart rate between smokers and nonsmokers, as nicotine affects the cardiovascular system.

Since smoking is a really common phenomenon in the construction industry, it is meaningful to look at the metabolic effects of smoking. Wahren et al. (1983) examined the metabolic response to tobacco smoking in 11 healthy, habitual smokers. The consumption of three cigarettes increased oxygen uptake by 11%, which was sustained for more than an hour. In one subject who smoked 20 cigarettes during 11 hours, his energy expenditure was found to be 14% greater than on the following day when he did not smoke. Food intake and physical activity were the same. Wahren et al. (1983) concluded that smoking significantly raises energy expenditure. So tobacco smoking can contribute to earlier fatigue in smokers, compared with nonsmokers who exercise at the same level. Similar effects on exercise tolerance are noted in those who inhale environmental tobacco smoke (McDonough and Moffatt 1999). Women who quit smoking and undergo a vigorous exercise training program demonstrate improved exercise performance over those who continue to smoke.

The American College of Sports Medicine (1982), after conducting a comprehensive analysis of alcohol and exercise, concludes the following:

1. Excessive ingestion of alcohol has a deleterious effect on many psychomotor skills.
2. Alcohol consumption does not substantially influence physiological functions crucial to physical performance.
3. Alcohol ingestion will not improve muscular work capacity and can decrease performance levels.
4. Alcohol consumption can impair temperature regulation during prolonged exercise in a cold environment.

Caffeine is a central nervous system stimulant and is known to have the most apparent effects on cognitive functions of the fatigued subjects, by increasing alertness and repelling drowsiness (Astrand and Rodahl 2003). There are a lot of arguments about the effects of caffeine on perfromance. Moderate doses of caffeine (200-300 mg) may elevate mood and improve psychomotor and intellectual performance, while larger doses can produce symptoms such as headache, irritability, tremors, etc. It may be an effective short-term ergogenic aid, but of the several studies that have been conducted, most have failed to show any ergogenic effects of caffeine on muscle strength and fatigue, work output and speed.

II.3 Physical Fatigue

Measuring the physiological demands of work is only one side of the story, the other important side is evaluation. Astrand and Rodahl outlined the basic tasks in measuring physiological demands as follows:

> "A basic task for the work physiologist must be that of measuring the rate at which the work is being done, i.e. the workload and matching this rate with the worker's ability to perform the work."

Evaluation of measured physiological demand of work and potential for physical fatigue and the limitations it may have on worker productivity has attracted physiologists for many years. The decrease in performance due to fatigue is widely accepted, but no agreement has been reached in trying to quantify this decrease or in setting acceptable limits for it (Christensen 1960; Oglesby, Parker, and Howell 1989).

As Astrand and Rodahl (2003) said, the main object of work physiology is to make it possible for individuals to perform their work tasks without objectively or subjectively developing feelings of physical fatigue.

The discussion in this chapter suggests that physical fatigue is closely associated with oxygen uptake and could be greatly influenced by factors of age, gender and cycles of work and rest. In the past thirty years, numerous evaluation techniques of measuring physiological demands have been proposed such as classification of work severity based on published tables for oxygen uptake and heart rate. Other techniques evaluate physiological demands for potentials of physical fatigue using established physiological limits.

Humans and animals can be viewed as machines that develop and store energy from food, burn it with oxygen to sustain life and, on demand, create movement and power through muscular contractions (Oglesby, Parker, Howell 1989). However, factors such as physical dimensions and condition, weight and age impose limitations on the body's ability to perform certain tasks. Prolonged activity eventually leads to the onset of physical fatigue, a decrease in performance and productivity, as well as the potential for accidents and injuries (Kalsbeek 1971).

Studies of heart rates made over 50 years ago by E.A. Muller (1950) have shown that the heart rate of a worker is a very sensitive and reliable indicator of overexertion and fatigue. Muller reported that in general, an hourly increase of six pulses (heartbeats) per minute is a signal that a person is overexerting on a long-term basis.

Physical fatigue can also be assessed by measuring oxygen uptake and then converting it produced energy (For every liter of oxygen used, 5 kilocalories of energy are produced). Researchers have found that the average young male adult, 5 feet 8 inches tall, weighing 160 pounds and in good physical condition, can develop energy over several hours at an average rate of about 5 kilocalories per minute. The energy required to sustain life processes requires about 1 kilocalorie per minute. It follows that occupations with energy demands less than 5 kilocalories per minute can be carried on continually for an 8-hour shift or more, without being subject to human physical limitation. However, if the energy expenditure is greater than this, intermittent rest is required to recoup the energy taken from storage in the body and prevent the development of physical fatigue (Oglesby et al 1989).

An acceptable workload requires a balance between physical workload and cardio respiratory capacity during 8 hours of work (Aminoff et al. 1998). When this balance is maintained, VO_2 and HR will remain at steady-state with a constant work output. After working a very prolonged time, an accumulation of lactic acid in the blood puts an additional load on the cardiovascular system and causes a sudden increase in HR. Thus, toward the end of a work shift, a markedly higher HR (about 10 beats/min. above steady-state), as compared with the steady-state HR observed during the initial hours of work, is a clear sign of fatigue. This criterion has been applied to determine the acceptable workload for an 8-hour workday (Saha et al. 1979).

With advanced technology, extremely heavy work can be eliminated quite easily. Therefore the more important factor for workers is the manner in which the work is performed, flexibility to govern one's own job, the safety and general atmosphere of the working environment, and the arrangement of work shifts. As summed by Astrand and Rodahl (2003), a workload taxing 30% to 40% of the individual's maximal oxygen uptake is a reasonable average upper limit for physical work performed regularly over an 8-h working day. No more than 40% of maximal muscle strength should be applied in repetitious muscular work.

II.3.1 Classification of Work

Based on the measurement of oxygen uptake and heart rate, different direct measurements or indirect prediction techniques, and all the other assessments on somatic factors of age, sex, body dimension, psychic factors of stress, motivation, tobacco, alcohol, caffeine usage, and environmental factors of heat cold, etc., prolonged physical work can be classified as to severity of workload and to cardiovascular response.

Table II.3a is a general guideline for identifying categories of prolonged physical work. These figures refer to average individuals, 20 to 30 years of age. Table II.3b (adapted from Christensen 1983) provides a guide to classify work severity based on peak oxygen uptake and heart rate values.

Workload	**Oxygen uptake, L/min**	**Heart rate, beats/min**
Light work	up to 0.5	up to 90
Moderate work	0.5-1.0	90-110
Heavy work	1.0-1.5	110-130
Very heavy work	1.5-2.0	130-150
Extremely heavy work	over 2.0	150-170

Table II.3a Prolonged physical work classification

Workload	**Peak Oxygen uptake, L/min**	**Peak Heart rate beats/min**
Very light work	Up to 0.5	Up to 75
Light work	0.5 - 1.0	75 – 100
Moderate work	1.0 - 1.5	100 – 125
Heavy work	1.5 - 2.0	125 – 150
Very heavy work	2.0 - 2.5	150 – 175
Extremely heavy work	Over 2.5	Over 175

Table II.3b Work classification based on peak responses during manual work

II.3.2 Dealing with Physical Fatigue

As shown in Figure II.1, the performance of physical work depends on the ability of the muscle cell to transform chemical energy in the food into mechanical energy for muscular work. This in turn depends on the capacity of the bodily functions that deliver fuel and oxygen to the working muscle. That is, on the nutritional quality of the food ingested; frequency of meals; oxygen uptake, including pulmonary ventilation, cardiac output and oxygen extraction; and the nervous and hormonal mechanisms that regulate these function (Astrand 2003).

Additionally, many of these functions are influenced by age, gender, body dimensions and health situation. At the same time, performance is influenced to a great extent by motivation and attitude toward work. And from the previous section, we know that alcohol also has a negative effect on performance.

Understandably, most studies of measurement of human fatigue are performed in laboratory settings, which may vary greatly from situations encountered in real life. And physical fatigue may include both muscle fatigue and fatigue caused by non-biomechanical muscle activities. The challenge is, therefore, to relate the various factors contributing to experimental fatigue to the fatigue encountered in the workplace.

Literature on physical fatigue suggests several ways of improving these work conditions. With the development of mechanization, automation, and many kinds of labor-saving equipment, modern technology has eliminated much heavy physical work. But the construction industry is still a typically labor-intensive industry, and some heavy physical work is still obligatory. Also, sometimes the greatest problems in the work environment are not the physical loads but rather mental stress and unfavorable working conditions. Therefore, in order to reduce physical fatigue, the supervisor making work assignments should plan to mix heavy and light work, schedule rest periods, and match workloads to the worker's ability to perform the task.

In sum, to deal with physical fatigue occurring during work cycles in different industries, all the above factors have to be included, to find effective ways of improving work conditions and performance. The major objective of the work physiologist is to enable working individuals to accomplish their tasks without undue fatigue, so that at the end of the working day they are left with sufficient vigor to enjoy their leisure time (Astrand and Rodahl 2003).

II.4 Physical Demands of Construction Work

Physiological workload research has been well developed in industries such as automobile manufacturing, where work is labor-intensive and workers often perform their tasks repetitively and in poor working postures due to constrained work places. One study (Min, K, Chung et al. 1999) evaluated physiological workload during screw driving tasks in the automobile assembly line.

The effects of load and work postures on heart rate, oxygen consumption during a screw driving task with varying loads, leg postures (standing an squatting) and trunk postures were studied, using nine male subjects. The effects of load, leg and trunk posture were found to be significant on heart rate and oxygen consumption. Heart rate, oxygen consumption and subjective discomfort rating all showed a significant increase for heavy loads and for bent and twisted trunk postures, and a redesign of work methods for screw driving was highly recommended.

These research studies document the necessity of exploring the physiological demands of different types of work, the need to correctly measure these demands, and to develop ergonomically designed work tools and methods of completing work tasks efficiently. This certainly is true for construction work where it is known that workers consume large amounts of energy in performing their work tasks. The high physical demands of construction work can easily cause physical fatigue among workers. In order for work physiology to achieve the target of eliminating physical fatigue and improving worksite conditions, the physiological demands of work must be measured and evaluated.

The most recent	Average energy expenditure Kcal /
Bricklayer	0.042
Carpenter	0.056
Cement	0.050
Drywall	0.049
Electrician	0.041
Glazier	0.045
Ironworker	0.045
Laborer	0.055
Pipe Fitter	0.043
Sheet Metal	0.048

Table II.4 Average energy expenditure by construction trade (Abdelhamid and Everett 2002)

To illustrate the use of Table II.4, assume that a person weighing 100 kg is considering Bricklaying as a vocation. According to Table II.4, this person should expect to have average energy expenditures at 4.2 kcal/min (0.042 kcal/kg/min×100kg = 4.2 kcal/min). Similarly, if this person is considering working as a Laborer, then he/she should expect to have an energy expenditure of 5.5 kcal/min.

Data such as those in Table II.4 are at a best a guide in assessing human ability to carry out strenuous work tasks with or without intermittent rest. Among those of a given age for the same trade, there are variations in overall body lean and fat weights, lung capacity and blood-circulation rates. With age, heart-stroke volume and rate of beating decrease and the oxygen transport system operates less effectively, reducing the rate of oxygen intake by 20-25 percent between the ages of 25 and 60.

Also, nowadays more and more women work in trades and the construction industry. On the average, women consume less energy in maintaining basic body functions and expend less residual energy in performing heavy tasks. Compared with males, the average female has less muscular strength. Measurements have shown that on the average, women have 20 percent less body mass, 33 percent less lean body (muscle) mass, and 14 percent more body fat. Body surface area for females averages 18 percent less than for males. These factors, coupled with a lower blood circulation rate, explain why women on the average have more difficulty than do men in carrying out heavy tasks and why they are less able to adjust to heat and cold but have more endurance.

Measuring energy expenditure figures, such as the 4.2 and 5.5 kcal/min shown above, only represent one side of the story. The other side is the evaluation of these measurements for the potential of physical fatigue. A widely used rule of thumb is that activities requiring less than 5 kcal per min can be performed continually for a work shift without overly taxing the worker. An activity requiring more than 5 kcal per min can be performed for a limited time before the worker needs rest to recoup energy from stores within the body.

A more accurate assessment of physical fatigue potential is to express the measured energy expenditure as a percentage of the maximum energy expenditure that a person is capable of, which is affected by gender, age, height, weight, conditioning, inheritance, and environmental factors. To illustrate this, let's assume that two different workers may be performing the same activity and expending energy at the same rate of 4 kcal/min. If these two workers respectively have a 10 kcal/min and 15 kcal/min maximum energy expenditure, then the first is working at 40% (4/10) of his/her max while the other is working at 27% (4/15) of his/her max. Clearly, the two workers are taxing their bodies differently. Therefore, expressing the workloads as a percentage, also known as "relative workload," is the only way to take into account individual differences in physiological capacities among workers.

As mentioned previously, determining maximum energy expenditure values requires actual testing procedures, which involve complicated and lengthy laboratory procedures, and could even be dangerous for unfit construction workers. The specific aim of this research is to develop a practical method to predict relative workload from energy expenditure data collected during actual work activities. Another aim of this research is to include factors of individual variability, such as variations in age, gender, weight, etc., in the model for the prediction of relative workloads for the construction industry.

For construction workers, a wide variety of tools and equipment are required in carrying out construction tasks. Failure to have tools of the right kind in sufficient quantity available at the workplace can be a major cause of lower productivity and physical fatigue. To enable efficient use of tools, physical fatigue, awkward positioning of the body, limbs, hands or fingers, and strenuous muscular movements, which may be required to use the tools, have to be factored into the design of those tools, for efficiency and to match them to the tasks and the workers' needs.

II.5 Conclusion

This chapter provided a brief discussion of the literature relevant to this research, regarding what is available and how to deal with and evaluate physical fatigue. Genetic factors such as age, sex, body dimensions, psychic factors of stress and motivation, tobacco and alcohol use, and external environment factors related to physical fatigue and assessment of work performance are discussed as well, along with the classification of work as to severity of workload.

The physical demands of construction work are briefly reviewed, followed by a focus on several methods of measuring maximum oxygen uptake and relative workloads to determine the physiological demands of work. Different equations for VO_{2max} prediction have been discussed. And several factors such as age, gender, weight, height and heart rate have been factored into the prediction techniques developed by different researchers in linear/non linear multiple regression models. All of these previous efforts provided a great resource for this ongoing research to develop a multi-regression model to predict and measure the physical demands of construction work based on the simple regression model developed in Abdelhamid (1999). The next chapter describes the methodology used to achieve the goal of this research.

CHAPTER III

METHODOLOGY

As mentioned previously, this research project is an extension of methods developed in Abdelhamid (1999) to predict relative workload from in-situ collected data. This method has been under validation as part of a grant from the National Institute of Occupational Safety and Health (NIOSH). It is also expected that a multiple linear regression model will increase the overall prediction accuracy of relative workload because, as discussed in Chapter II, factors such as age, gender, hereditary factors, health condition, and exercise history have an established influence on the maximal oxygen uptake (VO_{2max}) value that is central to the prediction method developed in Abdelhamid (1999). The following sections will explain the methodology that was adopted in this research.

III.1 Relation the Between Green's Function and $\%VO_{2max}$

Figure III.1 is a graph showing oxygen uptake data for two different subjects while they were performing one of the treadmill exercise protocols used in Abdelhamid (1999)[5]. The two subjects were performing the same exercise protocol, and they were, respectively, exercising at 36% and 64% of their individual maximum oxygen uptakes. As Figure III.1 shows, there is a clear difference between the two subjects in terms of the recorded oxygen uptake data.

---

[5] Details of the experimental protocol can be found in Abdelhamid (1999) and Appendix C of this thesis. Data series for the whole plots in Figure III.1 and III.2 are listed in Table B.1 in Appendix B.

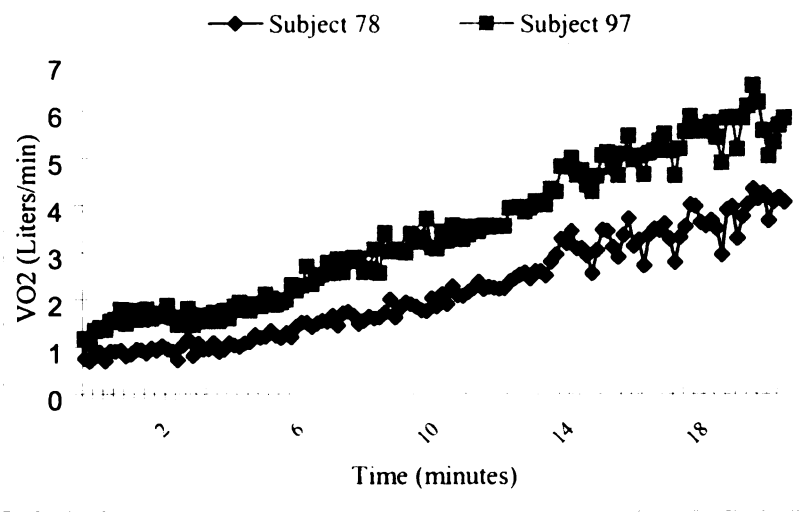


Figure III.1 Oxygen uptake data for subject 78 and 98 (session 3)

The data in Figure III.1 was shown in Abdelhamid (1999) to have auto-dependence or auto-correlation. This property was further exploited using a statistical technique called time series analysis wherein data are auto-regressed to find a linear statistical model that describes one observation in terms of earlier ones. Once an adequate model is found, typically termed an Auto-Regresseive Moving Average model [ARMA(p,q)], numerous statistical, and sometime physical, characteristics can be derived regarding the system that produced the observed data.

Abdelhamid (1999) verified that the time series derived characteristic called the Green's function is positively correlated to $\%VO_{2max}$. Figure III.2 shows a typical plot of the Green's function for the data shown in Figure III.1. It should be noted that the horizontal axis represents a time unit equal to the sampling interval at which observations are measured, and the vertical axis is G_j, which is the value of the Green's function at a particular time unit j. To properly quantify the Green's Function profile and given its asymptotically limited property, the concept of 'mathematical' energy is used, wherein the sum of squares for all individual data points is determined[6].

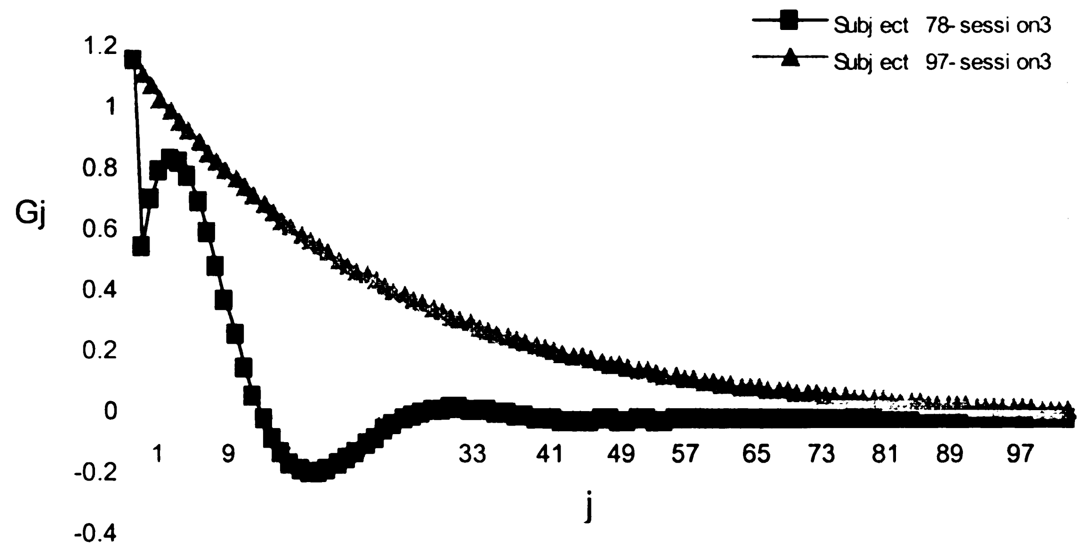


Figure III.2 Green's function for subject 78 and 97 oxygen uptake data (session 3)

Despite being subjected to the same exercise intensity, Figure III.2 shows that the two subjects have drastically different responses to the exercise. Recall that subjects 78 and 97 are, respectively, exercising at 36% and 64% of their individual maximum oxygen uptakes. The value of the energy of the Green's function (E_G) was calculated for the two subjects and found to be 4.79 and 14.16 for subjects 78 and 97, respectively. Clearly, for these two different subjects under the same external effort level, the difference in response is well captured using the Energy of Green's function.

As mentioned in Chapter II, time series analysis was used in Abdelhamid (1999) to develop a simple linear regression model based on the relationship between

---

[6] The Green's function falls under non-periodic signals and is quantified using the concept of "energy" (Abdelhamid 1999).

$\%VO_{2max}$ and E_G on 20 subjects. Therefore in order to achieve the first objective of this thesis, which is to verify the linear regression model on a larger pool of subjects, the same treadmill experimental protocols and analytical procedures that were performed in Abdelhamid (1999) were conducted for a pool of 100 subjects.

III.2 Research Methods

The goal of this research is to develop a multiple linear regression model to predict the physiological demands of construction work. The model will incorporate factors such as age, gender, and heart rate in addition to the factor established in the simple linear regression model developed in Abdelhamid (1999).

To attain this goal the following objectives were established and accomplished:

- Validate the simple linear regression model developed in Abdelhamid (1999) for 100 subjects performing a specified exercise regimen.
- Develop and validate a multiple linear regression model to predict the relative workload from sub-maximal oxygen uptake (VO_2).

III.2.1 Objective I

For the first objective, measurements will be conducted on subjects performing the same treadmill experiment protocol that was performed in Abdelhamid (1999). One hundred 'development' subjects will be tested. For each subject, oxygen uptake and heart rate were measured during three different sessions requiring different levels of effort. In addition, the maximum oxygen uptake was determined for each subject using an exact technique termed the Harbor protocol (McArdle et al 1996). Hence, the exact relative workload for each subject could be determined at each level of effort.

Time series analysis was then performed for each data set collected to arrive at an adequate ARMA(p,q) model from which the energy of the Green's function was obtained and related to the relative workload through regression analysis.

The VO2000 Portable Metabolic System was used to measure oxygen uptake. With this system, the subject wore a face mask and breathed ambient air. The subject also wore a chest vest on which the measuring device was mounted. The Polar Vantage XL was also used to measure heart rate.

A 4-session experiment was designed to investigate the E_G and $\%VO_{2max}$ relation. The experiment was designed such that all subjects were required to perform at the same work intensity. During all sessions, oxygen uptake and heart rate data were collected at 10-second intervals, the lowest possible setting by the VO2000 Portable Metabolic System. The following is a description of the 4-session experiment that was performed on the 100 development subjects:

<u>Session 1; Resting:</u>

The subject was instructed to assume a supine position for 20 minutes prior to which the last food intake had at least been two hours.

<u>Session 2; Treadmill walking (0% grade):</u>

The subject was instructed to walk on the treadmill for twenty minutes at a speed of 3 miles/hr (4.8 km/hr) and level grade. During the first two minutes, the speed was gradually increased from 1.5 mile/hr to 3 miles/hr (2.4 km/hr to 4.8 km/hr). This served both as a warm up period and a familiarization period. After finishing the exercise, the subject was allowed to rest until oxygen uptake and heart rate values returned to pre-exercise values (resting values). Data measurement was stopped after this recovery period.

Session 3; Treadmill walking (12% grade):

The subject was instructed to walk on the treadmill for twelve minutes at a speed of 3 miles/hr (4.8 km/hr) and 12% grade. The exercise started at 1.5 miles/hr (2.4 km/hr) and 0% grade, and during the first minute speed and grade were gradually increased to 3 miles/hr (4.8 km/hr) and to 12% grade, respectively. After finishing the exercise, the subject was allowed to rest until oxygen uptake and heart rate values returned to pre-exercise values (resting values). Data measurement was stopped after this recovery period.

Session 4; Harbor protocol for VO_{2max} measurement:

This session was performed to determine the exact value of maximum oxygen uptake using the Harbor protocol. The subject was instructed to walk on the treadmill for three minutes at a speed of 3.3 miles/hr (5.3 km/hr) and level grade. Then, the grade was increased 2% every following minute. If the subject reached the 15% grade, and was still able to continue, the speed was increased 0.5 miles/hr every following minute. The exercise continued until the subject was unable to continue walking/running. After finishing the exercise, the subject was allowed to rest until oxygen uptake and heart rate values returned to pre-exercise values (resting values). Data measurement was stopped after this recovery period. In order to determine if a true VO_{2max} was achieved, a "peaking-over" in oxygen uptake was used as criteria (McArdle et al 1996).

The collected data from the 100 development subjects was used to examine the validity of the single linear regression model developed in Abdelhamid (1999).

III.2.2 Objective II

The second objective will be achieved by these following steps:

- Conduct a literature review to understand contemporary methods of predicting physiological demands of work.
- Develop a multiple linear regression model to reflect the variables that may affect the prediction of relative workload, such as body dimensions (height and weight), age, gender and heart rate.
- Assess the performance of the multiple linear regression model on a pool of validation subjects performing random exercises, or working at intensities ranging from light to heavy, as well as performing a maximum oxygen uptake test to determine the actual $\%VO_{2max}$ at which each subject was exercising/working.
- Evaluate the predictive capability of the regression model by predicting the $\%VO_{2max}$ from the validation subjects and comparing results with the actual values.

III.3 Hypothetical Multiple Linear Regression Model

Building on the relation between Green's function and $\%VO_{2max}$ discussed in section III.1, this research will develop a multiple linear regression model to predict and measure the physiological demands of physical work, such as construction work.

This research will focus on heart rate, age, body dimensions, and gender as the factors that may affect the simple linear regression method and develop a multiple linear regression model accordingly. Inclusion of these factors accounts for the inherent inter-subject variability in terms of physical capacity and the type and length of the activity performed.

The reason other factors, such as age and heart rate, need to be taken into account is that inter-individual variability in terms of physical capacity exists in the real world, especially in construction work. In addition, every worker is unique, and performs different and sometimes unique work, due to variability of location, time and amount of work. Also, as Christensen (1962) suggested, "we have to decide if the load of a given job is reasonable or unreasonable for a given worker." Therefore, as many relevant factors as possible should be incorporated in regression models used for prediction of physiological demands.

To fit measured data to a certain model, one has to decide upon the form of the model. For the prediction of relative workload, i.e. $\%VO_{2max}$, it is possible to make an educated guess regarding the form of the model, rather than conducting a laborious search process for the correct one. It has been well established that $\%VO_{2max}$ can be expressed linearly as a function of E_G as developed earlier by Abdelhamid (1999). It has also been established by other researches that $\%VO_{2max}$ has a linear relationship with heart rate, weight, height, age, gender, and working power. So the basic multiple linear regression model that will be investigated in this research will be generically expressed in the following form:

$$\%VO_{2max} = f\,(E_G, \text{HR}, \text{age}, \text{gender}, \text{height}, \text{weight}) \qquad \text{(Eq 3.1)}$$

A hypothetical multi-regression model may take the following form:

$$\%VO_{2max} = a_1 E_G + a_2 HR + a_3 Age + a_4 Height + a_5 Weight + C \qquad \text{(Eq 3.2)}$$

where a_1, a_2, a_3, a_4 and a_5 are the parameters of the model and C is a constant.

It is possible to combine the height and weight of a person using the Body Mass Index (BMI) or the Body Surface Area(BSA). BMI is expressed as follows: BMI = [Weight (kg) / Height^2 (m)] while BSA is most commonly expressed as (Mosteller 1987): BSA = ([Height (in) x Weight (lbs)]/ 3131)^{½}. As shown, either expression combines both height and weight, which is an advantage when constructing the mathematical model. So the Eq.3.2 may change to the following:

$$\%VO_{2max} = a_1 E_G + a_2 HR + a_3 Age + a_4 BMI(orBSA) + C \qquad \text{(Eq 3.3)}$$

This equation of the model can be analyzed by the methods of multiple linear regression (MLR) to estimate the parameters a_1, a_2,..., a_n by minimizing the sum of squared errors: $\min \sum_i \varepsilon^2$, where $\varepsilon_i = \hat{y}_i - y_i$ and $\hat{y}_i$ is the i-th predicted value and y_i is the i-th observed value. This is method is called the least squared errors and is the method used in this research. It should be noted that using linear programming may provide a better model because the actual deviations are minimized rather than the square of the deviations.

The statistical properties of the model such as the standard error of estimation (SEE), coefficient of determination (r^2), and inferences about prediction of VO_{2max} will be determined and analyzed. The effects of multi-collinearity will also be investigated.

The developed multiple regression model will be verified on data collected for 100 subjects exercising/working during the validation sessions. The subjects were instructed to perform random exercise or work at intensities ranging from light to heavy. Subjects were allowed to choose the exercise equipment or the type of work at their own discretion. These conditions were intended to match the random nature of work that dominates real-world work situations. Maximum oxygen uptake was determined for each subject using the Harbor protocol, as was done for the 100 development subjects. The same time series analysis technique was applied to the validation subjects' oxygen uptake data sets to obtain the Green's function and its energy. The predictive capability of the multiple linear regression model will be evaluated by calculating the mean squared prediction error.

III.4 Summary

The construction industry differs from other industries in many unique ways. An ever-changing job site under varying weather conditions and job demands are all factors that make it critical to find a reliable technique for the accurate evaluation of physical demands, and identify and eliminate potential causes of physical fatigue.

It is expected that the proposed multi-regression model will improve the accuracy of relative workload predictions from sub-maximal oxygen uptake data collected in-situ. The multi-regression model will include both the promising time series analysis technique developed by Abdelhamid (1999) and other factors that affect oxygen uptake such as age, body dimensions, heart rate, gender, etc.

If successful, the multiple linear regression model developed in this research will be of great importance in better understanding physical demands on today's workers.

This prediction method will be safer for unfit subjects and easier to use in general, compared to maximal testing protocols and restrictive lab requirements. This methodology will have widespread application in identifying excessively demanding tasks so they can be better matched to the abilities of subjects. Women, older workers, and workers who are partially disabled now can be placed in jobs according to their capabilities.

CHAPTER IV

RESULTS

IV.1 Introduction

The literature review in Chapter II reveals that typical influential factors in the prediction of relative workload (%VO_{2max}) are heart rate, age, weight, height, and gender. Combining these factors with the Energy of the Green's function, as found in Abdelhamid (1999), is expected to yield more accurate predictions of relative workload from sub-maximal oxygen uptake and heart rate data collected in-situ. The current research is limited to incorporating the factors of weight, height, age, and heart rate in the development of a multiple linear regression model of %VO_{2max}.

In this research, the same experimental protocol performed in Abdelhamid (1999) was used on 100 subjects. The resulting data were analyzed to develop and validate a simple linear regression model between %VO_{2max} and the Energy of the Green's function. In addition, multiple linear regression models were developed to include the other influential variables discussed earlier. Validation of the multiple regression models was undertaken on an additional 100 validation subjects. Comparison of the multiple regression models with the simple linear regression model was performed and the result revealed a significant improvement in the accuracy of prediction in %VO_{2max} and the VO_{2max}, respectively.

This chapter presents the results of redeveloping the simple regression model on the larger pool of subjects and the development of the multiple linear regression (MLR) models, with age, height, weight, and heart rate factors. The statistical properties of the developed regression models are derived and analyzed against the basic assumptions upon which the models were constructed. The chapter concludes with a presentation of the validation results for all the developed regression models.

IV.2 Participants

The study details were announced to students, staff and faculty from Michigan State University. The target number of participants was 200, respectively divided into 100 development and 100 validation subjects. As the title implies, the data collected for the development subjects were used to build the regression models, both simple and multiple. Data collected for the validation subjects were used to verify the simple and multiple linear regression models' predictive accuracy. The validation compares actual values observed for the validation subjects to predicted values for the same subjects, using the developed regression equations.

Descriptive physical data and exercise data for the 200 experimental and validation subjects are presented in Table IV.1[7]. The age variable, with a range of 19 years for experimental subjects and 24 years for the validation subjects, seems to show the least degree of variation among the other variables. Around 80% of the subjects are 24-32 years old. The values for VO_{2avg}, VO_{2max}, $\%VO_{2max}$, HR_{avg}, HR_{max} and RHR are also very close for these two groups of subjects. HR_{max} is calculated by the formula HR_{max} = 220-age.

[7] The whole data series are listed in Appendix B Table B.2 and B.3.

Development Subjects						
Variable	Mean	SE Mean	StDev	Min	Max	Range
Height(inch)	68.198	0.342	3.506	57.5	76.75	19.25
Weight(lb)	156.59	2.35	24.04	105.6	231	125.4
BSA(m^2)	1.8434	0.017	0.1744	1.45	2.36	0.91
Age(yr)	24.438	0.45	4.614	18	37	19
VO_{2avg}(liter/min)	1.0355	0.043	0.441	0.2758	2.0803	1.8045
VO_{2max}(liter/min)	3.3991	0.0754	0.7728	1.98	5.06	3.08
$\%VO_{2max}$	0.3095	0.0124	0.1272	0.1249	0.6578	0.5329
HR_{avg}(Beat/min)	109.49	2.28	23.41	69.27	173.67	104.4
HR_{max}(Beat/min)	195.56	0.45	4.61	183	202	19
RHR	0.5599	0.0116	0.119	0.36	0.9	0.54

Validation Subjects						
Variable	Mean	SE Mean	StDev	Min	Max	Range
Height(inch)	68.867	0.338	3.888	60.5	80.5	20
Weight(lb)	165.06	2.4	27.52	111	239	128
BSA(m^2)	1.8928	0.0181	0.2085	1.47	2.39	0.92
Age(yr)	25.773	0.449	5.155	19	43	24
VO_{2avg}(liter/min)	1.7137	0.0436	0.5014	0.84	2.87	2.03
VO_{2max}(liter/min)	3.5471	0.0761	0.8747	1,52	5.93	4.41
$\%VO_{2max}$	0.49098	0.00919	0.10563	0.26	0.67	0.41
HR_{avg}(Beat/min)	136.84	1.48	16.98	100.71	172.35	71.64
HR_{max}(Beat/min)	194.23	0.449	5.15	177	201	24
RHR	0.705	0.00768	0.0882	0.52	0.89	0.37

Note: VO_{2max}=maximal oxygen uptake, obtained from Harbor protocol for VO_{2max} measurement; HR_{max} =maximal heart rate=220-age; $\%VO_{2max}$ = VO_{2avg}/VO_{2max}; RHR=HR_{avg}/HR_{max}; BSA(m^2)=([Height(in) x Weight(lbs)]/ 3131 $)^{1/2}$ (The Mosteller formula)

Table IV.1 Descriptive Statistics and maximal exercise data for experimental/validation subjects

IV.3 Models Analysis

The models analysis is divided into three parts. In Part A, the development of the single linear regression model is performed using the data from the 100 development subjects. This simple regression model is based on the relation between the Energy of the Green's function and relative workload ($\%VO_{2max}$), which is the method advocated by Abdelhamid (1999). Statistical properties of the simple linear regression model are derived and illustrated. Part B discusses the motivation for developing the multiple linear regression models and how the MLR models are set up, with the accompanying statistical analysis to verify the suitability of the multiple regression models. A comparison of a number of multiple linear regression models is conducted to determine the best fit multiple linear regression model. Part C verifies the simple linear and multiple linear regression models on the 100 validation subjects for the appropriate applications.

IV.3.1 Part A: Simple Linear Regression Model Development

IV.3.1.1 SLR Model Setup

The simple linear regression model using the relationship between the Energy of the Green's function and $\%VO_{2max}$ is developed by Abdelhamid (1999). However, in that research, the relation was developed based on data for 20 subjects and validated on 5 (Abdelhamid 1999). Therefore, this research begins with redeveloping this simple linear regression relationship on 100 experimental subjects. This is also the part of the research that involves the NIOSH project.

As explained in Ch III, this research uses the same time series method to obtain the Green's function for each experimental subject on the treadmill exercises. Because Session 1 exercise is a resting cycle, subjects are under less demanding exertions. As a result, the Energy of the Green's function doesn't change significantly for each subject. The trend is entirely different for Sessions 2 and 3, wherein significant differences are observed in the values of the Energy of the Green's function.

Values of the Energy of the Green's function and $\%VO_{2max}$ for each experimental subject are plotted in Fig.IV.1. As shown, the relation between the Energy of the Green's function and relative workload are strongly correlated. The solid line in Figure IV.1 represents the best-fit curve (logarithmic) between the Energy of the Green's function and VO_{2avg}/VO_{2max}. This verifies that a non-linear relation exists between the two variables for a larger pool of subjects.

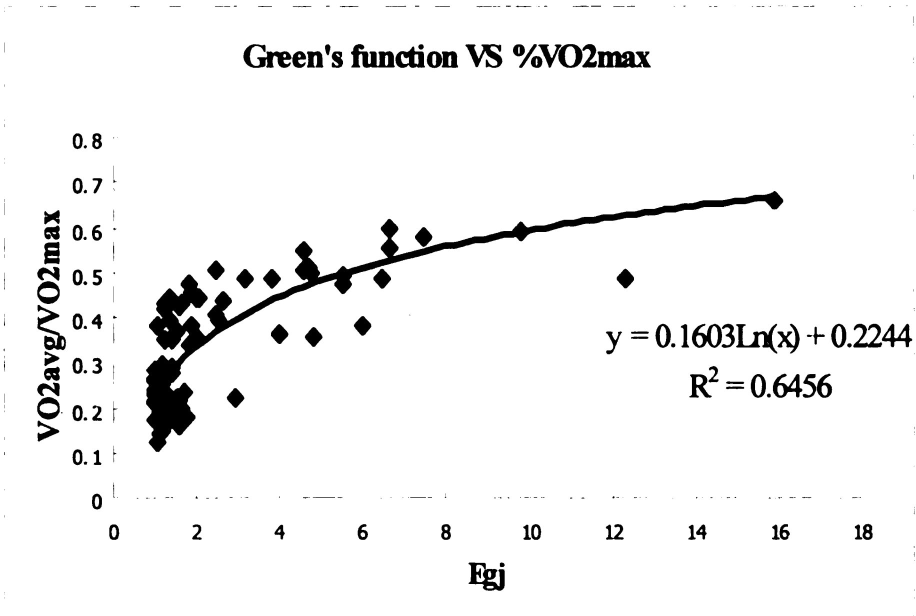


Figure IV.1 Energy of the Green's function and VO2avg/VO2max

To allow using linear regression, the Energy of the Green's function is transformed using the natural logarithm (Ln). The result is shown in Figure IV.2[8].

Table IV.2 presents the running output from the Minitab software[9] for the regression of $\%VO_{2max}$ based on the Energy of the Green's function. From the results,

---

[8] All data plotted in Figure IV.1 are listed in Appendix B Table B.4.

[9] In order to avoid exhausting calculations on the data, this thesis uses the software of Minitab, Excel and SPSS for linear regression model running outputs.

we can also see the same linear regression equation between these two variables derived from Figure IV.2.

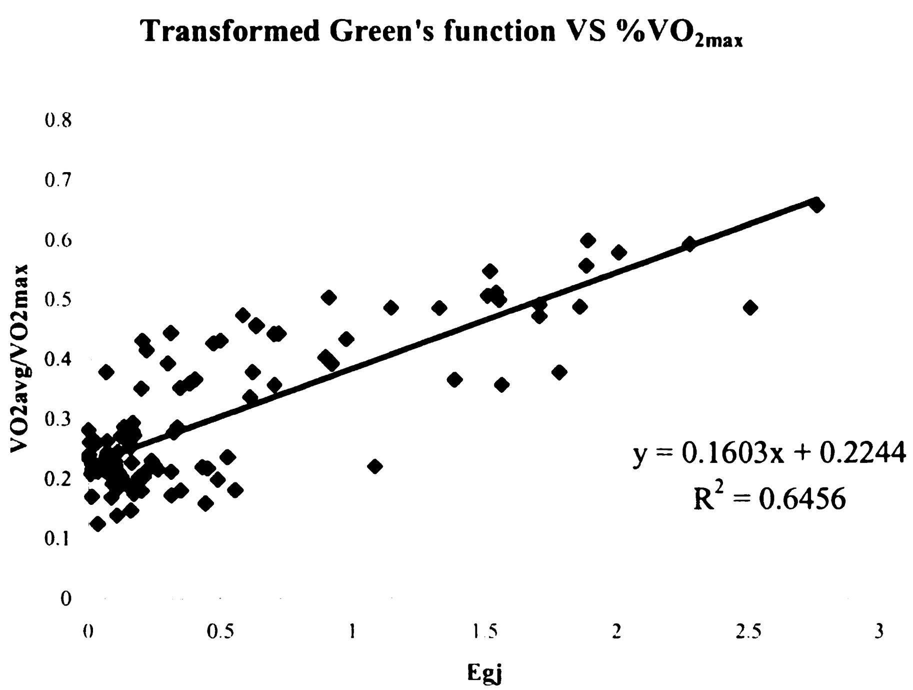


Figure IV.2 Transformed Energy of the Green's function and VO_{2avg}/VO_{2max}

Regression Analysis: $\%VO_{2max}$ versus $Ln(E_G)$					
$\%VO_{2max} = 0.224 + 0.160\,Ln(E_G)$					
S = 0.0760997 R-Sq = 64.6%					
Predictor	**Coef**	**SE Coef**	**T**	**P**	
Constant	0.224405	0.00968	23.18	0	
$Ln(E_G)$	0.1603	0.0117	13.7	0	
Analysis of Variance					
Source	DF	SS	MS	F	P
Regression	1	1.0868	1.0868	187.66	0
Residual Error	103	0.5965	0.0058		
Total	104	1.6833			

Table IV.2 Regression output for the $\%VO_{2max}$ by Minitab

Therefore, the following single linear regression model results:

$$\%VO_{2max} = 0.224 + 0.160\,Ln(E_G) + \varepsilon \qquad \text{(Eq IV.1)}$$

The intercept and slope for the linear regression model are estimated as 0.224 and 0.160 respectively, with a standard deviationσ, or standard error of estimation (SEE), of ±0.076.

IV.3.1.2 Normality and Independence of Error Terms of SLR Model

Several inferences from the SLR model in Eq IV.1 such as the standard deviation, and normality and independence of the error terms have to be validated to ensure the developed model can be considered appropriate for its application.[10]

A. Standard Deviation

In statistical theory, the deviations ε in a simple linear regression model are assumed to be independent and normally distributed random variables with mean 0 and standard deviation σ or $\sqrt{MSE}$ (MSE stands for mean squared error). For a simple linear regression model, the σ, which measures the variation of the dependent variable, in this case the $\%VO_{2max}$, about the regression line can be determined from:

$$s = \sqrt{\frac{\sum e_i^2}{n-2}} = \sqrt{\frac{(Y_i - \hat{Y}_i)^2}{n-2}} \qquad \text{(Eq IV.2)}$$

The sum is averaged by dividing over n-2 to make s an unbiased estimate of σ. The quantity n-2 is known as the degree of freedom for s. From the Minitab running output (see Table IV.2), the estimated standard deviation 's' for the regression model to analyze the relationship between $\%VO_{2max}$ and $Ln(E_G)$ is calculated as ±0.076 or

[10] In order to make the illustration clear and easy to understand, some statistical background terminologies are included in the analysis. For more detailed information regarding single and multiple linear regression models, please refer to the referenced statistical textbooks.

±7.60% for all the experimental subjects. This demonstrates that the standard error of prediction for relative workload, i.e., $\%VO_{2max}$, using the Eq IV.1 is ±7.60%.

B. Normality and Independence of Error Terms

The SLR model consists of the predicted mean of $\%VO_{2max}$ and deviations of the data from the line of means, ε. As mentioned earlier, normality and independence of the error terms have to be verified such that the developed model Equation IV.1 using linear regression is considered appropriate for its intended application.

The normality is verified using a normal probability plot of the residuals. A normal probability plot is a plot of ordered residuals against their respective expected values, which are assumed to follow a normal distribution. Figure IV.3 shows a plot of the ordered residuals versus their expected value under normality by using the Minitab software. The nearly linear plot indicates agreement with normality, i.e., the distribution of the error terms can reasonably be assumed to be normal.

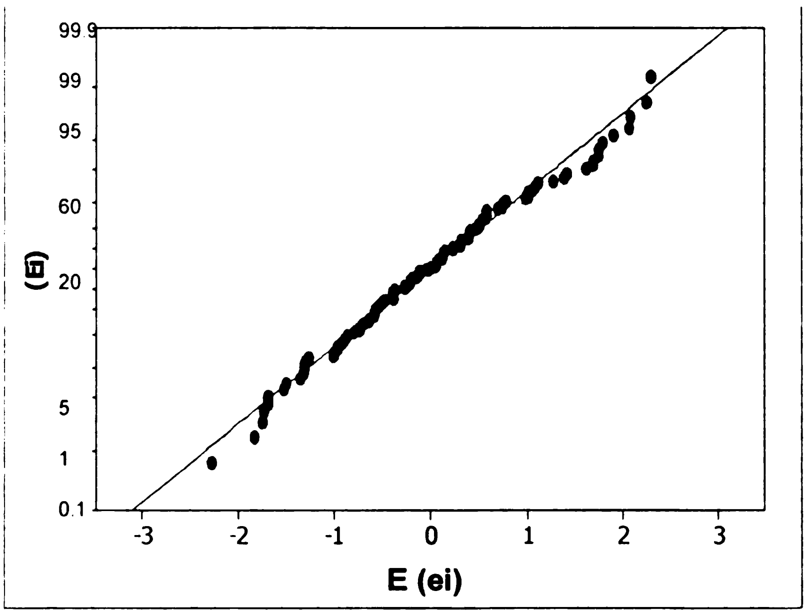


Fig IV.3 Normal probability plot for residuals

In linear regression, it is assumed that the residuals are independent of (not correlated with) one another. If the independence assumption is violated, some model fitting results may be questionable. The independence for the residuals e_i was tested using Minitab. The method used in Minitab involves graphing residuals versus the ordered data. Once constructed, the graph provides a visual depiction of the residuals' independence. A positive correlation is indicated by a clustering of residuals with the same sign. A negative correlation is indicated by rapid changes in the signs of consecutive residuals.

Figure IV.4 shows the plots of residuals versus ordered data for the single linear regression Equation IV.1. From the plot, it is indicated that there are rapid changes in the signs of consecutive residuals and there is no visible clustering of residuals with the same sign. Therefore, there is no evidence of serial dependence in the observed residual data, indicating independence of the residuals e_i.

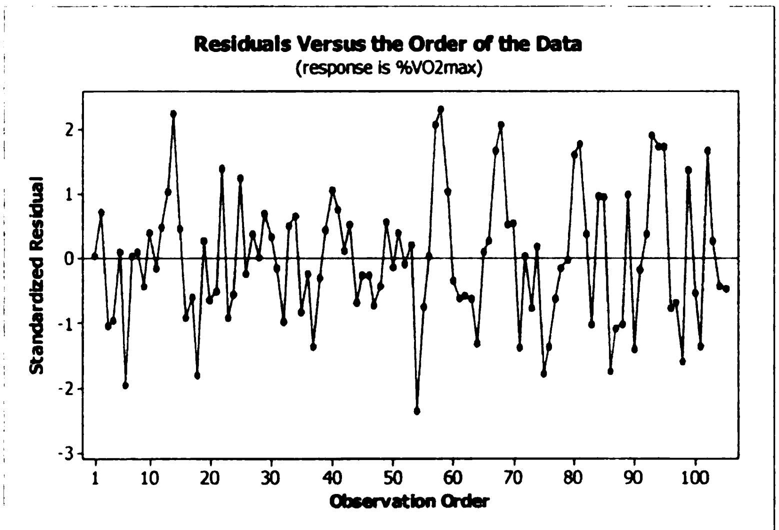


Figure IV.4 Minitab residuals versus order chart

Residual analysis is not complete without considering whether there is a possibility of residual outliers. Fig. IV.5 is a standardized residual plot generated by the Minitab program. It reflects the relation of standardized residuals (ε_i / σ) and the independent variable X, in this case the Energy of the Green's function.

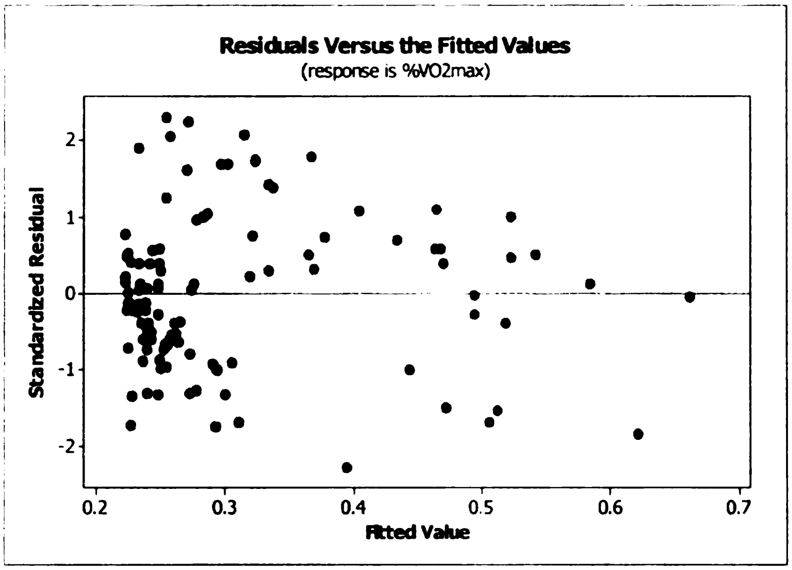


Figure IV.5 Minitab standardized residual plot

For a standardized residuals plot, outliers are considered as points, which are four or more standard deviations from zero. Fig IV.5 shows that most of the residuals are scattered within a band of ±2 standard deviations from zero. Therefore, there is not sufficient evidence that outliers exist.

In sum, both the normality and independence of error terms have been checked and they verify that the single linear regression model using the Energy of the Green's function to predict relative workload (%VO_{2max}) is valid, and the linear relation between the Energy of the Green's function and %VO_{2max} exists, even with a larger pool of subjects. The developed equation using linear regression is considered appropriate for the application.

The next step for the validation of the single linear regression model is to check the statistical properties of the model equation to see how this model reflects the capability of predicting $\%VO_{2max}$ and how accurate is the model's prediction of relative workload.

IV.3.1.3 Statistical Properties of the SLR Model

A. Correlation coefficient, T value and P value

Table IV.2 indicates that the coefficient of determination for the regression Equation IV.1 is r^2=0.646 and the coefficient of correlation is r=0.80. In general, values of r can range from -1 to +1, and fall between 0 (no correlation) and 1 (perfect correlation). On the one hand, a positive value indicates that two variables tend to increase together. On the other hand, a negative value indicates that one variable tends to increase as the other decreases. In this model, an r-value of 0.8 indicates that E_G and $\%VO_{2max}$ are highly correlated. In addition, an r^2 value of 0.646 means that around 64.6% variation in relative workload ($\%VO_{2max}$) can be explained by Ln(E_G).

However, the interpretation of r^2 as the proportion of the total variation of $\%VO_{2max}$ explained by E_G is frequently taken literally. A value of r^2 close to 1 is not an indication of perfect inference of $\%VO_{2max}$ from E_G using the estimated regression model. The usefulness of a regression model in predicting $\%VO_{2max}$ from E_G depends upon the width of the confidence or prediction intervals, which will be investigated next.

In order to check the significance of the predictors in the model, two other reference values can be checked: t-value (T) and p-value (P). The t-value for testing the regression coefficients is obtained by dividing the estimates by their standard errors. The bigger the absolute value of the t-value, the more likely the predictor is significant.

The p-value is used in hypothesis testing to help decide whether to reject a null hypothesis. The p-value is the probability of obtaining a test statistic that is at least as extreme as the actual calculated value, if the null hypothesis is true. That is, the p-value represents the probability of rejecting the null hypothesis when it is actually true. The smaller the p-value, the smaller the probability that rejecting the null hypothesis would be a mistake. A commonly used cut-off value for the p-value is 0.05. The null hypothesis in this case would be that H_0: $\beta_1 = 0$, i.e., that there is no straight-line relationship between E_G and $\%VO_{2max}$ and that linear regression of $\%VO_{2max}$ on E_G is of no value in prediction.

For the relation depicted here, between E_G and $\%VO_{2max}$, the t-value for the β_1 is 13.70 (see Table IV.3), indicating that the significance of the predictor $Ln(E_G)$. In addition, Table IV.3 also shows that the p-value is equal to zero for H_0: $\beta_1 = 0$, which indicates that H_0 is rejected. This verifies that the correlation between the Energy of the Green's function and relative workload exists and is valuable.

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
β_0	0.224405	0.009679691	23.18305	1.14E-42	0.205207	0.243602
β_1	0.1603	0.011701705	13.69886	6.08E-25	0.137092	0.183508

Table IV.3 Regression output from Excel for regression slope and Intercept

B. Inferences about β_1 and prediction of $\%VO_{2max}$

In statistical analysis, a *confidence interval* refers to the range in which the estimated mean response for a given set of predictor values is expected to fall. The interval is defined by lower and upper limits, which Minitab calculates from the confidence level selected and the standard error of the fitted values. A *prediction* *interval* refers to the range in which the predicted response for a new observation is expected to fall. The interval is defined by lower and upper limits, which Minitab calculates from the confidence level selected and a calculated standard error of prediction. The prediction interval is always wider than the confidence interval because of the added uncertainty involved in predicting a single response versus the mean response. In this research, 95% intervals are considered appropriate.

From Table IV.3, the 95% confidence interval for β_1 is (0.137,0.184). It means we estimate with 95% confidence that an increase of 1 in the logarithm of the Eg is associated with an increase of between 0.137 and 0.184 times of $\%VO_{2max}$.

The fitted line plot for the predicted relative workload with 95% prediction interval is illustrated in Figure IV.6 by Minitab software. Using the regression model to predict $\%VO_{2max}$, it is indicated from the chart that nearly all of the plots are falling within the prediction intervals. In other words, using the simple linear regression model is expected to have a reasonable prediction accuracy of $\%VO_{2max}$.

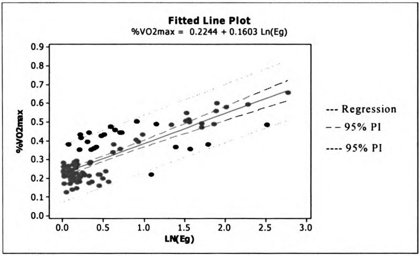


Figure IV.6. confidence interval & prediction intervals plot (Minitab)

Table IV.4 displays a sample Minitab confidence and prediction interval analysis for specific values of $Ln(E_G)$. For example, for a subject with $Ln(E_G)=0.06$, the predicted mean $\%VO_{2max}$ is 0.23442 (practically 23%) with a standard error of 0.00923 (approximately 1%). The 95% confidence interval is (0.21612, 0.25272). In other words, for this subject, we are 95% confident that the $\%VO_{2max}$ falls between 21.6% and 25.3%. And if $Ln(E_G)$ is 0.06, it is predicted with 95% confidence that the $\%VO_{2max}$ would fall between 8.24% and 38.65% for a new observation. Clearly, the prediction interval is quite wide, underscoring the need to consider a multiple regression approach.

New Obs	$Ln(E_G)$	Fit	SE Fit	95% CI	95% PI
1	0.06	0.23442	0.00923	(0.21612, 0.25272)	(0.08239, 0.38645)
2	0.09	0.23852	0.00905	(0.22056, 0.25647)	(0.08653, 0.39051)
3	0.11	0.24218	0.0089	(0.22452, 0.25984)	(0.09022, 0.39413)
4	0.21	0.25821	0.00832	(0.24172, 0.27470)	(0.10639, 0.41004)

Table IV.4 Sample of Minitab Output on CI &PI for four value of $Ln(E_G)$

As mentioned earlier, $\%VO_{2max} = \dfrac{VO_{2avg}}{VO_{2max}}$; hence VO_{2max} can be calculated easily.

Table IV.5 lists sample results for the actual $\%VO_{2max}$, VO_{2max} and predicted $\%VO_{2max}$ and VO_{2max} and their e_is [11] respectively. Either using the equation of $s = \sqrt{\dfrac{\sum e_i^2}{n-2}} = \sqrt{\dfrac{(Y_i - \hat{Y}_i)^2}{n-2}}$, or using Minitab, we can easily get the estimated standard error of prediction, or $\sqrt{MSE}$ for maximum oxygen uptake (VO_{2max}) for all experimental subjects, which is estimated at ± 0.6523 liter $\cdot$ min^{-1} (Recall that the standard error of prediction, for $\%VO_{2max}$ was $\pm$ 7.60%).

[11] See Appendix B- Table B.6 for all data of Table IV.5.

%VO_{2max} exact	%VO_{2max} predicted	VO_{2max} exact	VO_{2max} predicted	E_i^2 [1-2]	E_i^2 [3-4]
0.214608	0.2339952	2.56	2.34791141	0.0003759	0.0449816
0.245296	0.2417408	2.35	2.38453749	1.264E-05	0.0011928
0.240882	0.2244656	2.8	3.00478113	0.0002695	0.0419353
0.229237	0.240296	2.84	2.70928355	0.0001223	0.0170868
0.169172	0.2380848	4.24	3.01275008	0.004749	1.5061424
0.204126	0.257744	3.19	2.52638277	0.0028749	0.4403878
0.197736	0.243864	3.61	2.92716432	0.0021278	0.4662646
0.211912	0.27412	3.31	2.55884284	0.0038698	0.5642371
0.263785	0.2352752	3.21	3.59897686	0.0008128	0.151303

Table IV.5 Sample data for regression analysis results

IV.3.1.4 Summary

In this section, time series analysis techniques are used to determine the Green's function values, from which the Energy of the Green's function is calculated as the sum of squared values of individual Green's function values. A linear regression equation is constructed between the Energy of the Green's function and relative workload (%VO_{2max}). The standard error of prediction for %VO_{2max} and VO_{2max} are ±7.6% and ±0.6523 $\text{liter} \cdot \text{min}^{-1}$, respectively. In Abdelhamid (1999), this equation was termed Relative Workload Prediction equation - RWP equation. In this thesis, this term RWP will still be used hereafter to refer to Equation IV.1. The statistical properties of the equation have been analyzed and the results indicate that the regression model has merit in predicting relative workload from sub-maximal oxygen uptake data.

Further steps taken to develop a multiple regression model that improves the accuracy of the prediction as well as validating all models are discussed in the following sections, Parts B and C.

IV.3.2 Part B: Multiple Regression Models

This section focuses on the development of a multiple regression model (MLR) to predict relative workload from sub-maximal oxygen uptake (VO_2), which is the second objective of this thesis. The section begins with a discussion of the motivation behind developing the MLR and the factors to include in the MLR model. Then the section focuses on the model setup and statistical properties analysis, and concludes with a comparison of the MLR model to the SLR model developed in Part A.

IV.3.2.1 Factors for MLR Models

The analysis performed in Part A indicates that using the RWP equation has a standard error of prediction for relative workload ($\%VO_{2max}$) equal to ±7.60%. This is higher than the ±5.0% of value reported in Abdelhamid (1999), which was based on 20 development subjects. This difference indicates the need to consider other factors in addition to the Energy of the Green's function, which could potentially improve predictive accuracy.

In the RWP equation, there is only one predictor—the Energy of the Green's function. As discussed in Chapter II, several researchers have investigated the development of multiple regression models to include predictors of VO_{2max} such as heart rate, age, gender, physical dimension, and work duration. The inclusion of such factors along with the Energy of the Green's function in a multiple regression model was investigated in this research. This was expected to increase predictive accuracy for relative workload derived from sub-maximal oxygen uptake data.

A. Heart Rate

In many types of exercise, heart rate increases linearly with exercise intensity. In most test procedures, the evaluation, from submaximal rates of exercise, of an individual's maximal oxygen uptake or capacity to perform work involves measuring the heart rate during steady state and then extrapolating to a fixed heart rate or to an assumed maximal heart rate. As mentioned in Chapter II, there are many pitfalls with this method of predicting VO_{2max} from HR.

Despite criticism concerning the linear oxygen uptake/heart rate relationship, heart rate still remains a very important factor in reflecting the feeling of strain during an exercise. While the use of submaximal heart rate as a basis for the prediction of maximal oxygen uptake is not new, this factor will be used in developing the multiple linear regression (MLR) model. This is possible to investigate because the treadmill tests have recorded the heart rate for both the experimental and validation subjects in beats $\cdot$ min^{-1}.

B. Age

Jones (1985) and Von Dobeln et al. (1967) all considered the age factor in their VO_{2max} prediction equations. This is primarily because of the typical effect of the aging process on various body functions, such as circulatory and pulmonary capacity in older individuals (Astrand and Rodahl 2003). Thus, age will be included in the MLR models to verify its influence on the prediction accuracy of the models.

C. Body Surface Area (BSA)

As mentioned earlier in chapter III, Body Surface Area (BSA) is the total surface area of the human body. Jones (1985) developed a prediction equation for VO_{2max}

that accounts for this factor. Differences in body size are as important as age in VO_{2max} prediction because of the effects on the circulatory capacity, heart rate, stroke volume, and cardiac output. It is especially important to consider the influence of the body size factor in construction fieldwork where many tasks require workers to lift, rotate, climb up and down, and walk, etc. In this research, the BSA factor is considered as a candidate for the MLR model.

In sum, based on the simple linear regression model developed in the previous section, this part of the thesis will focus on developing a multi-regression model that incorporates the Energy of the Green's function, heart rate, age, and BSA for the prediction of $\%VO_{2max}$. The independent and combined effects of heart rate, age, and BSA will be investigated in terms of their contribution to the accuracy of predicting $\%VO_{2max}$. Statistical properties of the developed models, such as the coefficient of determination and prediction accuracy, will be presented.

IV.3.2.2 MLR Model Development

For single regression models, it is assumed that there is a linear relationship between a response variable Y and a single explanatory variable X. With multiple linear regression, more than one explanatory variable explains or predicts a single response variable. The introduction of more explanatory variables may lead to a more complicated situation, with many additional factors. As with single linear regression, multiple-regression can be utilized for forecasting purposes.

In multiple regression, the response Y depends on X_1, X_2,..., X_k explanatory variables, which will be denoted by X_k. The statistical model for multiple linear regression is

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + ...\beta_k X_{ik} \qquad \text{(Eq IV.5)}$$

for i=1, 2, ...,n. The mean response Y is a linear function of the explanatory variables:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ...\beta_k X_k \qquad \text{(Eq IV.6)}$$

The deviation ε_i is assumed to be an independent and normally distributed random variable with mean 0 and standard deviation σ. The coefficients of the model are β_0, β_1, β_2,..., β_k, and σ. It implies that the mean response Y can be predicted from estimates of the coefficients β. To the extent that this model is accurate, it is a useful tool for describing how Y varies with the X_k's.

For the simple linear regression, the least square method is used to obtain estimates of the intercept and slope of the regression model. The multiple linear regression model uses a similar method but details are more complicated. Assume b_0, b_1, b_2, ..., b_k denote the estimators of the coefficients β_0, β_1, β_2, ..., β_k. The predicted response for the ith observation is:

$$\hat{Y}_i = b_0 + b_1 X_1 + b_2 X_2 + ...b_k X_k \qquad \text{(Eq IV.7)}$$

The ith residual or the difference between the observed and predicted response is calculated by:

$$\varepsilon_i = Y_i - \hat{Y}_i = Y_i - b_0 - b_1 X_{i1} - b_2 X_{i2} - ... - b_p X_{ip} \qquad \text{(Eq IV.8)}$$

For the least square method, the values of b's are obtained by minimizing the sum of the squares of the residuals, i.e., the coefficients b_0, b_1, b_2, ..., b_k by minimizing the quantity: $\sum (Y_i - b_0 - b_1 X_{i1} - b_2 X_{i2} - ... - b_k X_{ik})^2$

The Minitab program performs these calculations based on the least square method. In a similar fashion to simple linear regression, the parameter σ^2, which measures the variation of the responses about the regression model, is estimated by an average of the squared residuals as,

$$s^2 = \frac{\sum e_i^2}{n-k-1} = \frac{\sum (Y_i - \hat{Y}_i)^2}{n-k-1} \qquad \text{(Eq IV.9)}$$

where $n-k-1$ is the degrees of freedom related with s^2. The degrees of freedom are equal to the sample size n minus the number of β's used to fit the model. When k=1, the multiple regression model is reduced to the single regression one.

For simple linear regression, the coefficient of determination r^2 is equal to the ratio of *SSM* (model sum of squared errors) to *SST* (SST = SSE +SSM – where SSE is the sum of squared errors) and is interpreted as the proportion of variation in Y explained by X. A similar calculation is applicable for multiple regression models and is calculated as follows:

$$r^2 = \frac{SSM}{SST} = \frac{\sum (\hat{Y}_i - \bar{Y})^2}{\sum (Y_i - \bar{Y})^2} \qquad \text{(Eq IV.10)}$$

In the case of multiple regression, r^2 is interpreted as the proportion of the variation observed in the response Y that is explained by the dependent variables X_1, X_2, ..., X_p. Usually, r^2 is multiplied by 100 and expressed as a percent. It is also called multiple correlation coefficient and is the correlation between the observation Y_i and the predicted $\hat{Y}_i$.

In this research, a series of physiological data and subject characteristics were collected for 100 experimental and 100 validation subjects during specified as well as random exercise protocols. This data and the four factors discussed earlier (Energy of the Green's function, HR, Age, and BMI) were analyzed using multiple regression to develop a number of multiple-regression models. The three best models are presented next.

To enable easy comparisons between all of these models, the RWP model and the three best MLR models are listed together. With the help of Minitab, the standard deviation or $\sqrt{MSE}$ and coefficient of correlation r^2 for each equation has been calculated and presented as well.

$$\%VO_{2max} = 0.224 + 0.160\ Ln(E_G)$$

(S = 0.076 r^2 = 64.46%) (RWP)

$$\%VO_{2max} = -\ 0.0891 + 0.0832\ Ln(E_G) + 0.633\ RHR$$

(S = 0.0503065 r^2 = 84.7%) (Model A)

$$\%VO_{2max} = -\ 0.0879 + 0.0831\ Ln(E_G) + 0.633\ RHR - 0.00005\ Age$$

(S = 0.0505543 r^2= 84.7%) (Model B)

$$\%VO_{2max} = -\ 0.232 + 0.0792\ Ln(E_G) + 0.662\ RHR + 0.0699\ BSA$$

(S = 0.049086 r^2= 85.5%) (Model C)

A detailed description of each model is explained separately in the following sections. Independent variables (IVs) considered for possible inclusion in the multiple regression models A, B, and C include the combination of factors of the Energy of the Green's function, age, body surface area (BSA), and heart rate.

The Pearson Product Moment correlation values (r) are computed between observed and predicted $\%VO_{2max}$. In addition, paired t-test, MSE, and analysis of variance are considered in the analysis. A comparison between the four models is performed to evaluate the predictive ability of each model and the contribution of each predictor. Based on the results, the final best fit MLR model that provides the most accurate predictions of the relative workload is selected and verified on the 100 validation subjects.

Model A: Ln(E_G) and Heart Rate (RHR)

Model A uses the E_G and heart rate to predict $\%VO_{2\,max}$. Because heart rate responses to the same exercise or work vary individually, using it as a predictor requires expressing it as a percentage of maximum heart rate, or as termed here, RHR, Relative Heart Rate. *RHR* is calculated as RHR = HR_{avg}/HR_{max}, where HR_{avg} is the average heart rate and HR_{max} is maximum heart rate which is calculated by using the formula HR_{max} = (220-age). Minitab is used to construct the MLR equation, determine its properties, and conduct the necessary statistical analysis. The model takes the following form:

$$\%VO_{2max} = -\ 0.0891 + 0.0832\ \mathrm{Ln}(E_G) + 0.633\ \mathrm{RHR}\ (HR_{avg}/HR_{max});$$

$$r^2 = 84.7\%;\ SD = \pm 0.050; \qquad \text{(Eq IV.11)}$$

Other results are tabulated in Table IV.6.

Regression Analysis: %VO_{2max} versus Ln(E_G), RHR					
%VO_{2max} = - 0.0891 + 0.0832 Ln(E_G) + 0.633 RHR					
S= 0.0503065 R-Sq = 84.7%					
Predictor	**Coef**	**SE Coef**	**T**	**P**	**VIF**
Constant	-0.08914	0.02786	-3.2	0.002	
Ln(E_G)	0.08316	0.01022	8.14	0	1.7
RHR	0.6331	0.05475	11.56	0	1.7
Analysis of Variance					
Source	DF	SS	MS	F	P
Regression	2	1.42512	0.71256	281.56	0
Residual Error	102	0.25814	0.00253		
Total	104	1.68325			

Table IV.6 Minitab regression output for model A

In model A, the response variable is the %VO_{2max}. The explanatory variables are the Ln(E_G) and RHR. The first step in analyzing this model is to carefully examine each of the variables. Means, standard deviation and minimum and maximum values appear in Table IV.7.

Variable	Mean	SE Mean	StDev	Minimum	Maximum	Range
HR_{avg}	109.49	2.28	23.41	69.27	173.67	104.4
HR_{max}	195.56	0.45	4.61	183	202	19
RHR	0.5599	0.0116	0.119	0.36	0.9	0.54
LN(E_G)	0.5305	0.0622	0.6377	0.00018	2.7654	2.7652

Table IV.7 Descriptive statistics for the experimental subjects HR and Ln(E_G) by Minitab

The heart rate data shows that the average and standard deviation for the three variables HR_{avg}, HR_{max}, and RHR are 109.49 ±23.41 (beat · min^{-1}), 195.56 ± 4.61 (beat · min^{-1}), and 0.5599 ± 0.119, respectively. The minimum value for the Ln(E_G) variable appears to be rather extreme with a minimum value of 0.00018 and maximum value of 2.7654, range =2.7652. The mean of Ln(E_G)=0.5305±0.6377. The big standard deviation value may be caused by the wide range of the Ln(E_G) data. As mentioned earlier, the Green's function reflects the system's response to a change until it returns to equilibrium. It is inferred here that each subject's response to the treadmill exercise varied greatly.

The second step in the analysis is to assess the correlation between the dependent and individual independent variables. This can be accomplished by applying the Pearson Correlation Coefficient (r) to each independent variable, which would indicate how much of the change in dependent variable can be explained by the change in the independent one. Those independent variables with a high r^2 should then be used for multiple regression. The same correlation coefficient can be applied to multiple independent variables to ascertain how much of the change in dependent variables can be explained by changes in all the independent variables.

The correlations matrix using Minitab software appears in Table IV.8. The output includes the p-value resulting from testing the null hypothesis that the population correlation is 0 versus the two-sided alternative for each pair. Thus, the correlation between $\%VO_{2max}$ and RHR is 0.8643 with a p-value of 0, whereas the correlation between $\%VO_{2max}$ and $Ln(E_G)$ is 0.80351 with a p-value of 0 too. From the output we can infer that both are statistically significant and the RHR and $Ln(E_G)$ are useful predictors for the MLR model A.

Correlations: %VO2max, RHR, Ln(E_G)			
P Value	%VO2max	RHR	Ln(Gj)
%VO2max	1 0	0.8643 0	0.80351 0
HRavg/HRmax	0.8643 0	1 0	0.65311 0
Ln(Gj)	0.80351 0	0.65311 0	1 0

Table IV.8 Minitab matrix of correlation between variables for model A

The relationship between the independent variables $Ln(E_G)$ and RHR and the dependent variable $\%VO_{2max}$ is explored in the next sections.

A. Standard Deviation

Table IV.6 indicates that the standard error of prediction for relative workload using the model A is ± 5%. Compared with the standard error of prediction of the RWP equation, with a value of ± 7.60%, the new MLR model A provides a significant improvement in the prediction of $\%VO_{2max}$. In addition, the estimated standard error of prediction, or $\sqrt{MSE}$, for maximum oxygen uptake (VO_{2max}) for model A is ±0.50 $liter \cdot min^{-1}$. Again, compared with the RWP model, this standard error of prediction value is smaller, which indicates an improvement in accuracy of the prediction method of model A.

B. Correlation Coefficient, t-value and p-value

From Table IV.6, the coefficient of determination r^2 is 0.847 (r=0.92). That is, 84.7% of the observed variation in the $\%VO_{2max}$ is explained by the linear regression with $Ln(E_G)$ and RHR. In other words, model A is better than the RWP equation, which had a coefficient of correlation r= 0.80, in showing how closely $\%VO_{2max}$ is related to the variables. Hence, by adding the RHR as a predictor, the MLR model A has improved the prediction ability of $\%VO_{2max}$ from submaximal data.

For model A, the t-value for $Ln(E_G)$ and RHR are 8.14 and 11.56, respectively. The p-value for both was equal to zero. Therefore, the null hypothesis: H_0: $\beta_1 = \beta_2 = 0$ can be rejected, indicating that the regression coefficients for $Ln(E_G)$ and RHR achieves statistical significance. This result gives confidence that $\%VO_{2max}$, $Ln(E_G)$, and RHR are indeed correlated.

C. Normality and independence of error terms

Similar to simple linear regression, the residuals should always be examined as aids to determining whether the multiple regression model is appropriate. Because there are several explanatory variables, several residual plots must be examined. It is typical to plot the residuals versus the predicted value and also versus each of the independent variables, and to look for outliers, influential observations, evidence of a curved (rather than linear) relation and anything else unusual. Again, Minitab is used to generate these plots.

Using the same analysis methods used with the RWP equation, Figure IV.7 illustrates the residual plot for MLR Model A. The plot indicates that most of the residuals are scattered within a band of ±2 standard deviations from zero. Hence, there is not sufficient evidence of outliers or serial dependence in the observed residual data, which means that the residuals e_i can be considered normally distributed.

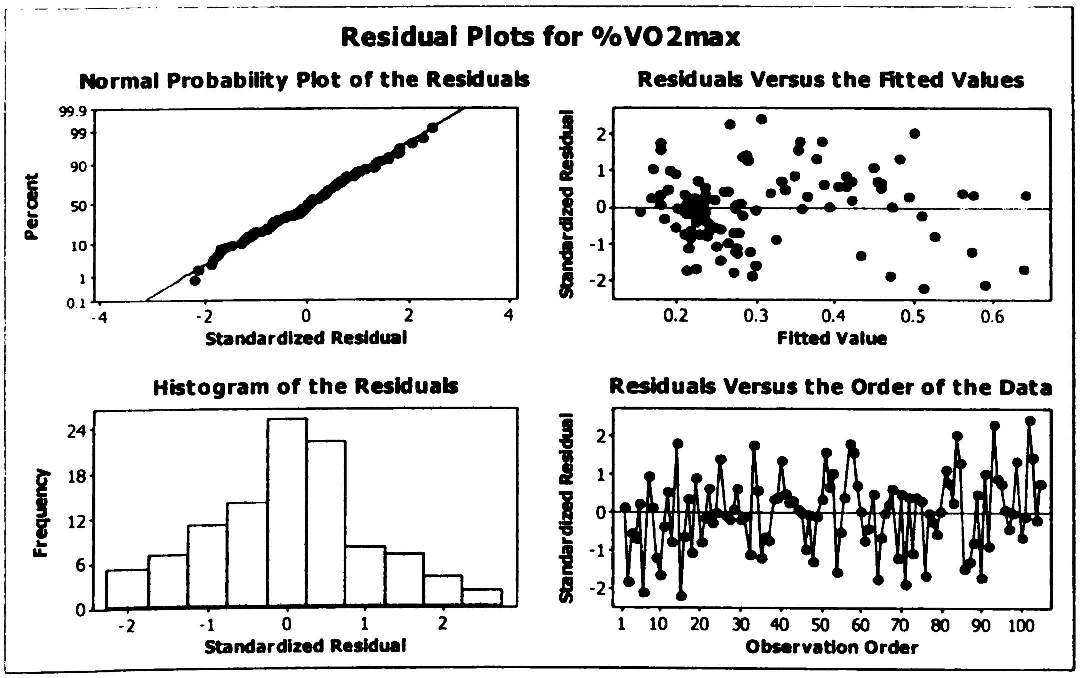


Figure IV.7 Minitab outputs for residual plots for %VO_{2max}

From the preceding normality and residual analysis, it is inferred that the multiple linear regression model using the Energy of the Green's function and relative heart rate (RHR) to predict the relative workload ($\%VO_{2max}$) is valid and the linear relation between the predictors and the dependence variable exists. In other words, the developed equation using linear regression is considered appropriate for the prediction.

D. Inferences about β_i and prediction of $\%VO_{2max}$

The confidence intervals and significance tests for each of the regression coefficients β_i's are performed similar to how it is performed in simple linear regression. The standard errors of the β_i's have more complicated formulas, but all are multiples of the overall model standard deviation. Again, the calculations are performed using Minitab, which in this case allows performing these rather complex calculations without an intimate knowledge of all of the computational details. Basically, the same commands to construct confidence and prediction intervals for simple linear regression are also used for multiple linear regression models. The only difference is that a list of explanatory variables is specified rather than just a single variable.

Table IV.9 shows a sample output from Minitab running output for model A for three subjects. For example, for subject 2 the predicted mean $\%VO_{2max}$ is 0.37049 with a standard error of ±0.00555. The 95% confidence interval for this predicted mean is (0.35947,0.38150), i.e., it is estimated with 95% confidence that $\%VO_{2max}$ lies between 35.95% and 38.15%. The 95% prediction interval of (0.27010, 0.47088) is interpreted in a very similar manner to the confidence interval. The fitted line plot for the predicted relative workload using model A with the 95% prediction interval is shown in Figure IV.8.

New	$Ln(E_G)$	RHR	Fit	SE Fit	95% CI		95% PI	
2	0.8	0.62	0.37049	0.00555	(0.35947	0.38150)	(0.27010	0.47088)
3	0.47	0.45	0.23489	0.00747	(0.22007	0.24970)	(0.13401	0.33576)
4	0.5	0.53	0.28512	0.00519	(0.27481	0.29542)	(0.18480	0.38543)

Table IV.9 Sample of Minitab running output for 95%CI and 95%PI

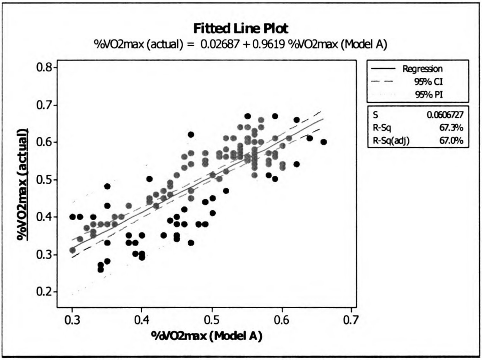
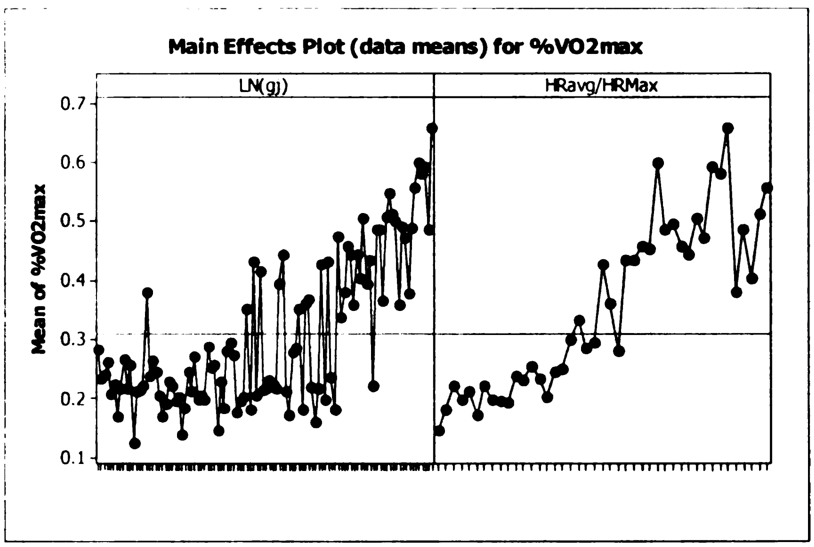


Figure IV.8. Minitab confidence Interval & prediction intervals plot for model A

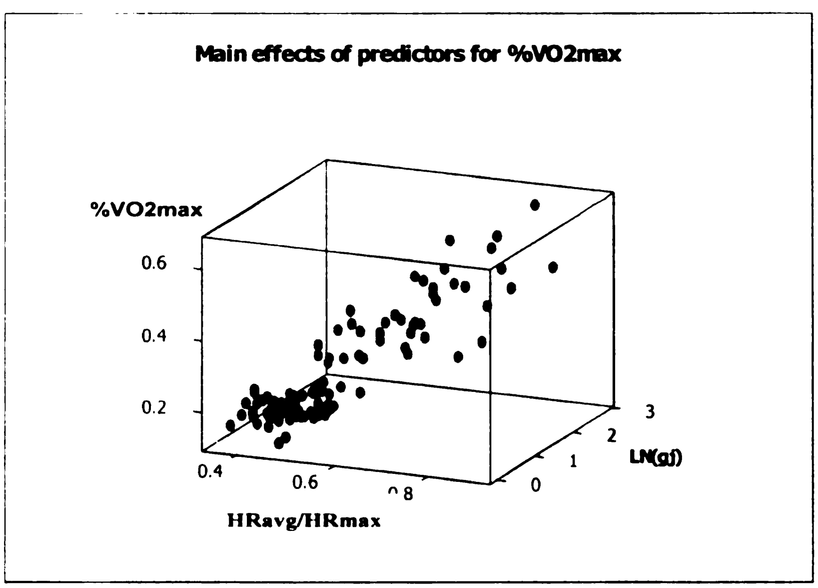
E. Main Effects Plots for $\%VO_{2max}$

The main effects plot chart of $Ln(E_G)$ and RHR have been displayed in the 2-D and 3-D surface in Figure IV.9. The plots provide visual evidence that using both variables in Model A as predictors of $\%VO_{2max}$ is better compared to the RWP model. For example, the 2-D chart shown in Figure IV.9(a), indicates that both RHR and $Ln(E_G)$ have a positive relation with $\%VO_{2max}$, i.e., an increase in $Ln(E_G)$ and RHR is associated with an increase in $\%VO_{2max}$. This trend is expected because of the nature of the two variables. On the one hand, E_G reflects the system's response from excitation back to the state of equilibrium, hence, a high value of E_G is expected to reflect a high value of VO_{2max}. On the other hand, high values of RHR will be associated with high values of VO_{2max}, and vice versa, because of the increased/decreased demands that are placed on the cardio-vascular system. Figure IV.9(b) is a 3-D plot showing again the positive relationship between the predictors and response variable.



(a)

Figure IV.9 Main effects plot of predictors for %VO2max



(b)

Figure IV.9 Main effects plot of predictors for %VO2max

To sum it all, the regression model A has a standard error of prediction of ± 5% and ±0.5 liter · min^{-1} for $\%VO_{2max}$ and VO_{2max}, respectively. Compared to the RWP equation, model A generates better results for the prediction of $\%VO_{2max}$ and VO_{2max} from the two predictors $Ln(E_G)$ and RHR as derived and measured from sub-maximal VO_2 and HR data.

Model B: Ln(E_G), RHR and Age

As previously discussed, the age of an individual typically has an effect on maximum oxygen uptake. The effect of this factor on the prediction of $\%VO2_{max}$, and subsequently VO_{2max}, is investigated using multiple regression in a manner similar to how model A was developed and analyzed. The following model results:

$$\%\mathbf{VO_{2max}} = \mathbf{- 0.0879 + 0.0831\ LN(gj) + 0.633\ RHR - 0.00005\ Age} \qquad \text{(Eq 4.12)}$$

Table IV.10 shows the Minitab outputs for model B. As shown, r^2 for this model is 84.7% and the standard deviation, σ, is estimated at ± 0.05%. Compared with the previous running outputs of model A, the value of r^2 has not considerably changed. In other words, adding the age factor to the model resulted in almost no change to the explanatory/prediction power of the model. The measurements of variation about the fitted equation are also nearly identical between model B and model A. The p-value for the individual regression coefficients indicate that $Ln(E_G)$ and RHR are still significant with p=0. However, the regression coefficient for age is 0.00005, which is a very small figure, with no statistical significance for the prediction of $\%VO_{2max}$ (p-value =0.961).

Regression Analysis: %VO_{2max} versus Ln(E_G), RHR and Age					
%VO_{2max} = - 0.0879 + 0.0831 Ln(E_G) + 0.633 RHR - 0.00005 Age					
S=0.050554 R-Sq = 84.7%					
Predictor	**Coef**	**SE Coef**	**T**	**P**	**VIF**
Constant	-0.08788	0.03805	-2.31	0.023	
Ln(E_G)	0.08312	0.01029	8.08	0	1.8
RHR	0.63318	0.05505	11.5	0	1.7
Age	-5.30E-05	0.001077	-0.05	0.961	1
Analysis of Variance					
Source	DF	SS	MS	F	P
Regression	3	1.42512	0.47504	185.87	0
Residual Error	101	0.25813	0.00256		
Total	104	1.68325			

Table IV.10 Minitab Regression output of %VO2max for Model B

The results of model B indicate that age does not contribute in any significant way in the prediction of %VO_{2max}. However, VO_{2max} and heart rate will decrease with age and some researchers have developed MLR models that incorporate age as a variable. The insignificant effect of age on the prediction of %VO_{2max} is primarily an artifact of the subject population used in this research. Recall that the subjects in this research are recruited from the student and staff population at Michigan State University. While the range of subjects participating in the study is between the ages of 19 and 43, approximately 80% of the subjects were in the age group 28-32. Clearly, inclusion of this important factor requires the involvement of more subjects over a wider age group. Such an effort is outside both the research scope and available funds. In sum, for the subject population included in this research, age doesn't show a significant effect on the prediction of %VO_{2max}.

Model C: Ln(E_G), RHR and BSA

Body Surface Area (BSA) is combined with Ln(E_G) and RHR to form the multiple regression model C. The following model is created:

%VO2max = - 0.232 + 0.0792 Ln(E_G) + 0.662 RHR + 0.0699 BSA (Eq 4.13)

Table IV.11 shows the Minitab outputs for model C. r^2 for this model is 85.5% and the standard deviation, σ, is estimated at ± 0.049%. The estimated standard error of prediction of model C is ±4.9% and ±0.5 liter·min^{-1} for %VO_{2max} and VO_{2max}, respectively. By adding BSA to Model A, a change is observed in the regression coefficients of the variables and the intercept. This phenomenon occurs generally in multiple regression. Individual regression coefficients, their standard errors, and significance tests are meaningful only when interpreted in the context of the other explanatory variables in the model. By adding the BSA as a predictor, the MLR model achieves a slight improvement over model A.

Regression Analysis: %VO_{2max} versus Ln(E_G), RHR and BSA
%VO_{2max} = - 0.232 + 0.0792 Ln(E_G) + 0.662 RHR + 0.0699 BSA
S= 0.049087 R-Sq = 85.5%

Predictor	**Coef**	**SE Coef**	**T**	**P**	**VIF**
Constant	-0.232	0.0638	-3.64	0	
LN(gj)	0.0792	0.0101	7.84	0	1.8
HRavg/HRMax	0.6617	0.0547	12.11	0	1.8
BSA	0.07	0.0282	2.48	0.015	1

Analysis of variance

Source	DF	SS	MS	F	P
Regression	3	1.4399	0.48	199.2	0
Residual Error	101	0.2434	0.0024		
Total	104	1.6833			

Table IV.11 Regression output for Model C

The correlations matrix, as calculated in Minitab, is shown in Table IV.12. The matrix indicates that the individual regression coefficients for $Ln(E_G)$ and RHR are still significant with p=0. The individual regression coefficient of BSA with its response variable $\%VO_{2max}$ (p-value=0.144>0.05) does not achieve statistical significance, similar to what is found with the age factor.

Correlations: %VO2max, RHR, Ln(E$_G$) and BSA				
P Value	%VO2max	RHR	Ln(Gj)	BSA
%VO2max	1 0	0.864 0	0.8041 0	0.017 0.862
HRavg/HRmax	0.8643 0	1 0	0.65311 0	-0.143 0.144
Ln(Gj)	0.80351 0	0.65311 0	1 0	0.025 0.798
BSA	0.017 0.862	-0.143 0.144	0.025 0.798	1 0

Table IV.12 Minitab output of correlation between variables for model C

As discussed above, adding BSA as a predictor for $\%VO_{2max}$ was only expected to have a slight increase in the accuracy of the model. This finding is in agreement with that of Von Dobeln et al. (1967). The most likely explanation for this is that the relationship between body surface area and $\%VO_{2max}$ is accounted for in both the VO_2 and HR data. It is worth noting that the Body Mass Index (BMI), which is a more common body dimension measurement, was considered but yielded an r^2= 84.8%. Hence, the BSA measurement was used instead.

IV.3.2.3 MLR Models Comparison

The main effects of $Ln(E_G)$ and RHR, Age, BSA on the prediction of $\%VO_{2max}$ are plotted as shown in Figure IV.10. Careful examination of the plots indicates that BSA has a slight influence on the prediction of $\%VO_{2max}$, with age having hardly any impact.

Table IV.13 lists all the attempted regression models, with the resulting r^2 and s, based on the variables Ln(E_G), RHR, Age, and BSA. The results show a significant improvement of r^2 and s when Ln(E_G) and RHR are incorporated in any of the models. The precision is reduced when BSA is omitted. Age had no significant association with $\%VO_{2max}$. The results from Figure IV.9 and Table IV.13 indicate that the most accurate prediction of $\%VO_{2max}$ is achieved when Ln(E_G), RHR, and BSA are used.

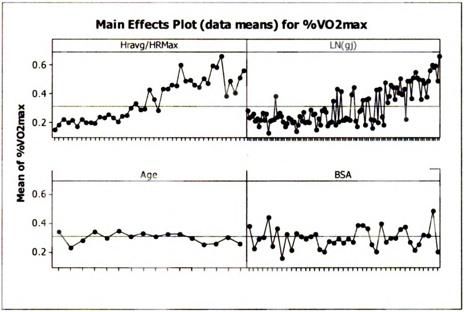


Figure IV.10 Main effects plot of predictors for $\%VO_{2max}$

Variables	Regression Model for %VO2max	r^2	R	S
Ln(E_G)	$\%VO_{2max} = 0.224 + 0.160$ Ln(E_G)	64.60%	0.8037	0.0761
Ln(E_G), Age	$\%VO_{2max} = 0.217 + 0.160$ Ln(E_G)+ 0.00032 Age	64.60%	0.8037	0.0766
Ln(E_G), BSA	$\%VO_{2max} = 0.229 + 0.160$ Ln(E_G)-0.0023BSA	64.60%	0.8037	0.0765
RHR	$\%VO_{2max} = -0.208 + 0.924$ RHR	74.70%	0.8643	0.0643
RHR, Age	$\%VO_{2max} = -0.192 + 0.924$ RHR - 0.00065 Age	74.80%	0.8649	0.0645
RHR, BSA	$\%VO_{2max} = -0.414 + 0.946$ RHR + 0.105 BSA	76.70%	0.8758	0.062
Ln(E_G), RHR	$\%VO_{2max} = -0.0891 + 0.633$ RHR + 0.0832 Ln(EG)	84.70%	0.9203	0.0503
Ln(E_G),RHR, Age	$\%VO_{2max} = -0.0879 + 0.633$ RHR + 0.0831 Ln(EG) - 0.00005 Age	84.70%	0.9203	0.0506
Ln(E_G),RHR, BSA	$\%VO_{2max} = -0.232 + 0.662$ RHR + 0.0792 Ln(EG) + 0.0699 BSA	85.50%	0.9247	0.0491

Table IV.13 Minitab MLR Model running output for different variables to prediction of $\%VO_{2max}$

While model C appears to be the clear favorite in terms of prediction accuracy, the model development assumes the independence of the model variables, namely, $Ln(E_G)$, RHR, and BSA. If this assumption does not hold, i.e., the independent variables are highly correlated themselves, then this will lead to high variance in the estimation of the model β_i's. This problem is known as "Multi-colinearity" of the multiple regression model, which significantly compromises the forecasting power of the developed model. In addition, extremely high correlations can terminate the model development procedure altogether. For this reason, the independence of the variables $Ln(E_G)$,RHR and BSA was investigated.

Multi-colinearity can be checked by finding the r^2 between the independent variables. As a rule-of-thumb, r-values higher than 0.5 between the two variables being tested indicate that some level of dependence exists. Another measure of multi-colinearity is known as the Variance Inflation Factor (VIF), which measures how much the variance of an estimated regression coefficient increases if the predictors are correlated. A VIF = 1 indicates no relation among predictors, a VIF > 1 indicates that the predictors are correlated, and a VIF> 5 indicates that the regression coefficients are poorly estimated.

The values of VIF for model C are listed in Table IV.11. As shown, the VIFs for $Ln(E_G)$, RHR and BSA are 1.8, 1.7 and 1, respectively. The results indicate that there is no correlation between BSA and the other two independent variables. However, the VIF values indicate that a correlation exists between $Ln(E_G)$ and RHR. This means that using both of these predictors in a multiple regression equation may undermine the prediction accuracy of the resulting model. Therefore, the effect of this correlation on the prediction accuracy of the model must be further investigated.

The basic idea is to enter $Ln(E_G)$ and also the component of RHR that is unrelated to $Ln(E_G)$ into the MLR regression model as predictors. The component of RHR that is unrelated to $Ln(E_G)$ is derived by creating a multiple regression model, where RHR is the dependent variable and $Ln(E_G)$ is the independent variable. From the running output, the "unstandardized residuals" can be obtained. These residuals form the component of RHR that is unrelated to $Ln(E_G)$. Consequently, these residuals are used with $Ln(E_G)$ to form the multiple regression model with RHR as the dependent variable. The analysis results are listed in Table IV.14.

Regression Analysis: %VO_{2max} versus $Ln(E_G)$,Unstandardresidue %VO_{2max} = - 0.224405 + 0.1603 $Ln(E_G)$ + 0.6331unstandardresidue S= 0.0503063 R-Sq = 84.7%					
Predictor	**Coef**	**SE Coef**	**T**	**P**	**VIF**
Constant	0.224405	0.006399	35.07	0	
LN(gj)	0.1603	0.007736	20.72	0	1
Unstandardresidue	0.6331	0.05475	11.56	0	1
Analysis of Variance					
Source	DF	SS	MS	F	P
Regression	2	1.42512	0.71256	281.56	0
Residual Error	102	0.25813	0.00253		
Total	104	1.68325			

Table IV.14 Minitab outputs for MLR using unstandardized residual and $Ln(E_G)$

The VIF values shown in Table IV.14 indicate that all the independent variables for the multiple regression model using $Ln(E_G)$ and the "unstandardized residuals" are not correlated. Comparing Table IV.16 results with those in Table IV.5 for model A, it becomes evident that the r^2 and s for the prediction of %VO_{2max} are almost the same.

Therefore, it can be concluded that the degree of correlation between $Ln(E_G)$ and RHR does not undermine the prediction ability of model C. In other words, the multicolinearity between $Ln(E_G)$ and RHR can be ignored.

In sum, the MLR prediction model C generated based on the variables of $Ln(E_G)$, RHR and BSA is valid for the prediction of relative workload and maximum oxygen uptake. The estimated standard error of prediction of model C is ±4.9% and ±0.5 $liter \cdot min^{-1}$ for $\%VO_{2max}$ and VO_{2max}, respectively. The next step is to validate this model against the results of 100 validation subjects who performed random exercise protocols as described before in Chapter III.

IV.3.3 Part C: Regression Models Validation

Validation of the regression modelswas performed through the collection of new oxygen uptake data for 100 validation subjects, including a limited number of construction workers. The subjects were instructed to perform random exercise or work at intensities ranging from light to heavy. Maximum oxygen uptake was determined for each subject using the same Harbor protocol used for the development subjects. The time series analysis techniques discussed in Chapter III and IV are used to calculate the Energy of the Green's function (E_G). The RHR and BSA for each validation subject were also determined. The final step is to use this data, i.e., E_G, RHR, age and BSA to predict the $\%VO_{2max}$ and VO_{2max} for each subject using the regression model C[12].

---

[12] See Appendix B-Table B.5 for all the data.

For comparison purposes, the validation of RWP equation and multiple linear regression models A and C is combined. For a limited number of subjects[13], actual and predicted values for $\%VO_{2max}$ and VO_{2max} have been tabulated in Table IV.15,. Jones's equation (referred to as J in the table) is also applied on the validation subjects for reference to predict $\%VO_{2max}$ and VO_{2max}.

#	$\%VO_{2max}$ (actual)	RWP	A	C	J	VO_{2max} (actual)	RWP	A	C	J
1	0.38	0.33	0.36	0.35	0.44	3.22	3.73	3.42	3.53	2.8
2	0.3	0.41	0.4	0.38	0.29	3.06	2.2	2.29	2.37	3.14
3	0.43	0.4	0.35	0.34	0.38	2.52	2.75	3.1	3.2	2.9
4	0.35	0.4	0.38	0.4	0.38	4.52	3.92	4.15	3.91	4.07
8	0.5	0.35	0.41	0.39	0.36	2.09	2.99	2.56	2.66	2.86
10	0.4	0.39	0.36	0.39	0.53	4.96	5.11	5.54	5.14	3.79
11	0.56	0.49	0.53	0.55	0.58	3.35	3.89	3.54	3.42	3.23
12	0.57	0.42	0.49	0.48	0.45	2.27	3.14	2.67	2.7	2.9
13	0.38	0.51	0.48	0.47	0.36	2.75	2.07	2.19	2.23	2.92
14	0.42	0.53	0.46	0.45	0.39	2.86	2.26	2.63	2.67	3.09
15	0.26	0.35	0.34	0.35	0.37	5.04	3.77	3.81	3.75	3.58

Table IV.15 Sample for MSPR check and Jones' equation comparison on validation subjects

A. MSPR Check

For the validation process, the prediction capability of a regression model is measured by calculating the mean squared prediction error, denoted as MSPR, and calculated as follows (Neter et al. 1990):

$$\text{MSPR} = \frac{\sum_{i=1}^{n^*}(Y - \hat{Y}_{i\,i})^2}{n^*} \qquad \text{(Eq 4.14)}$$

where Y_i is the value of the response variable in the ith validation case, $\hat{Y}_i$ is the predicted value for the ith validation case based on the original model, and n* is the

[13] See Appendix B-Table B.6 for all the data.

number of cases in the validation data set. After MSPR is calculated, it is then compared to the MSE value from the original regression model. If the two are close, then MSE is not seriously biased and gives an appropriate indication of the predictive capability of the selected regression model. If MSPR is much larger than MSE, the MSPR should be used as an indicator of the prediction capability of the original model and not its MSE (Neter et al.1990).

Using the data available for the validation subjects, the MSPR for $\%VO_{2max}$ and VO_{2max} can be readily derived from Eq IV.14 for each regression model, i.e., the RWP equation, and Model A and C. The MSE values for these models were given earlier in this Chapter. Table IV.16 lists the MSE and MSRP values for relative workload $\%VO_{2max}$ and VO_{2max} for available validation subjects' data.

Model Type	**Equation**	**$\%VO_{2max}$**		**VO_{2max}**	
		MSE	**MSRP**	**MSE**	**MSRP**
RWP	$\%VO_{2max} = 0.224 + 0.160\ Ln(E_G)$	0.58	0.69	0.43	0.44
A	$\%VO_{2max} = -\ 0.0891 + 0.0832\ Ln(E_G) + 0.633\ RHR$	0.25	0.37	0.25	0.25
C	$\%VO_{2max} = -\ 0.232 + 0.0792\ Ln(E_G) + 0.662\ RHR + 0.0699\ BSA$	0.24%	0.35%	0.28	0.22
Jone's	VO_{2max} (L/min) = (0.046 x Ht (cm)) - (0.021 x age (yrs)) – (0.62 x Sex) – 4.31 where for sex, men =0, women = 1	N/A	1.3%	N/A	0.56

Table IV.16 MSE and MSRP for $\%VO_{2max}$ and VO_{2max} for validation subjects

The MSE and MSRP values listed in Table IV.16 indicate that both of these errors are close. For the $\%VO_{2max}$ figures, the difference is within the range of 0.1 and for the absolute VO_{2max} value, the gap is around 0.01. It would, therefore, appear that the MSE for each respective model is providing an appropriate indication of how well the model can predict $\%VO_{2max}$ and VO_{2max}. It is also clear that Model C provides the least MSE and MSRP values compared to the other models, which confirms the expectation that Model C would outperform the other models in the prediction of $\%VO_{2max}$ and VO_{2max}. While the the MSE value for Jones's model for the original model is not available, the MSRP for the validation subjects was calculated as 1.3% for $\%VO_{2max}$ and 0.56 for VO_{2max} value, respectively. Compared to the values from the RWP and MLR models, it is clear that the MLR model provides better prediction.

Figure IV.11 shows the individual value plot of $\%VO_{2max}$ for both the actual values and predictions from Model C. From the displayed plots, it is visibly clear that no significant difference exists between the predicted values and the actual measurements.

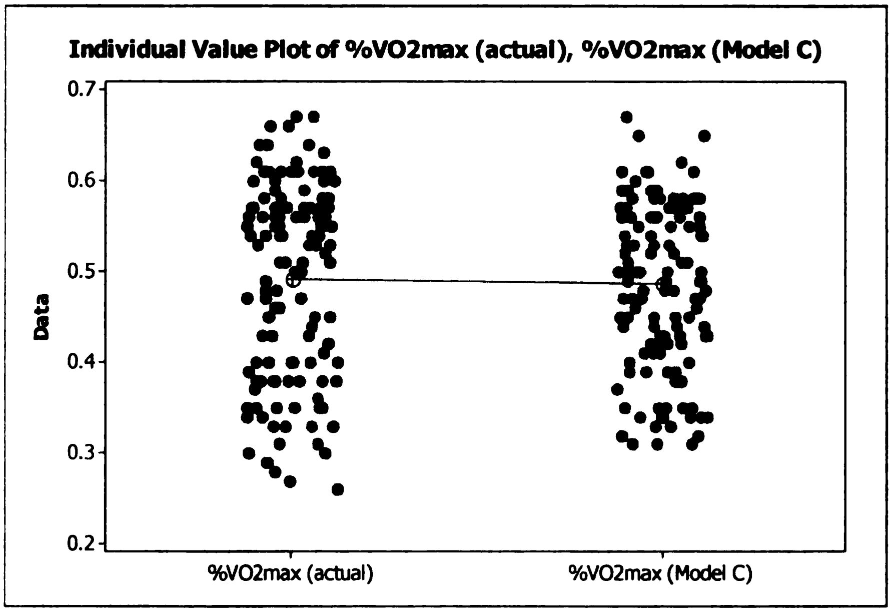


Figure IV.11 Individual value plot of $\%VO_{2max}$ for Model C (actual VS prediction)

B. p-value Validation

To complete the analysis, it is imperative to determine the statistical significance of the prediction produced by model C, i.e., whether the difference between the MSE and the MSRP of Model C is statistically significant. The p-value for the application at hand involves the use of the 2-sample t-test, with the null and alternative hypotheses being the following:

- H_o: $\%VO_{2max}$ (MLR) - $\%VO_{2max}$ (Actual) = 0
- H_a: $\%VO_{2max}$ (MLR) - $\%VO_{2max}$ (Actual) $\neq$ 0

Here, the $\%VO_{2max}$ (MLR) means the predicted $\%VO_{2max}$ value obtained from Model C and $\%VO_{2max}$. (Actual) means the actual value measured for the validation subjects. The null hypothesis means that there is no significant difference between the predicted value and the actual value (note that H_o is *rejected* when *P-value* $\leq \alpha$). Table IV.17 shows the paired t-test results from Minitab.

Two-sample T for %VO2max (actual) vs %VO2max (Model C)				
	N	Mean	StDev	SE Mean
$\%VO_{2max}$ (actual)	132	0.491	0.106	0.0092
$\%VO_{2max}$ (Model C)	132	0.486	0.0897	0.0078

Difference = mu (%VO2max (actual)) - mu (%VO2max (Model C))
Estimate for difference: 0.004937
95% CI for difference: (-0.018821, 0.028694)
T-Test of difference = 0 (vs not =): T-Value = 0.41 P-Value = 0.683 DF = 255

Table IV.17 Paired T-test and P value for $\%VO_{2max}$

The paired t-test results in a t-value and a p-value of 0.41 and 0.683, respectively. Consequently, the null-hypothesis cannot be rejected (p-value >0.05), indicating that there is no significant difference in the actual and predicted values of $\%VO_{2max}$ for the validation subjects.

A similar t-test was performed for the VO_{2max} values. The test reveled a t-value of –0.08, and a p-value of 0.938. Again, the p-value > 0.05, indicates that the null hypothesis cannot be rejected. Hence, it can be concluded that there is no significant difference in the prediction value and actual measurements of VO_{2max} for the validation subjects.

Two-sample T for VO2max (actual) vs VO2max (Model C)				
	N	Mean	StDev	SE Mean
VO_{2max} (actual)	132	3.547	0.875	0.076
VO_{2max} (Model C)	132	3.556	0.893	0.078
Difference = μ (VO2max (actual)) - μ (VO2max (Model C)) Estimate for difference: -0.008423 95% CI for difference: (-0.222630, 0.205784) T-Test of difference = 0 (vs not =): T-Value = -0.08 P-Value = 0.938 DF = 261				

Table IV.18 Paired T-test and P value for VO_{2max}

The validation results indicate that the multiple regression model C produces acceptable prediction values for both relative and maximum oxygen uptake values. It also greatly improves the accuracy of the prediction results compared to the model described by the RWP equation.

CHAPTER V

CONCLUSION AND FUTURE WORK

V.1 Conclusion

This research introduced a methodology for predicting relative workload from sub-maximal oxygen uptake data collected in-situ, using multiple linear regression models and without the need to determine maximum oxygen uptake. In this research, the method developed by Abdelhamid (1999) to predict relative workload from in-situ collected sub-maximal oxygen uptake data was reconstructed for 100 experimental subjects from Michigan State University. As in the original technique, a strong linear relation was found between the Energy of the Green's function and relative workload ($\%VO_{2max}$). A relative workload prediction equation (RWP equation) was developed based on the collected data. The standard error of prediction for $\%VO_{2max}$ and VO_{2max} was estimated at ±7.6% and ±0.65 $liter \cdot min^{-1}$, respectively.

In an effort to improve the accuracy of predictions using the RWP equation, multiple linear regression modeling was considered. This led to the development of a number of regression models, which incorporated the Energy of the Green's function, relative heart rate, body surface area, and age as explanatory variables. A statistical comparison between the different MLR models indicated that the best prediction results would be attained when the Energy of the Green's function, relative heart rate, and body surface area were used as predictors. Using multiple regression methods to combine these predictors resulted in a model with a standard error of prediction for $\%VO_{2max}$ and VO_{2max} equal to ±4.9% and ±0.53 $liter \cdot min^{-1}$, respectively.

All regression models have been validated using non-steady state oxygen uptake and heart rate data measured for 100 validation subjects. No significant differences between measured and predicted $\%VO_{2max}$ (or VO_{2max}) are found. The validation results indicated that the multiple regression model developed in this research produced acceptable prediction values for both relative and maximum oxygen uptake values and greatly improves the accuracy of the prediction results compared to the single regression model developed by Abdelhamid (1999).

V.2 Thesis Contribution

This thesis makes the following important contributions:

1. Validating the time series analysis technique developed by Abdelhamid (1999) on a larger pool of subjects.
2. Improving the accuracy of the technique developed by Abdelhamid (1999) through the development and validation of a multiple regression model that includes heart rates and body dimensions.
3. Preserving the benefits of the single regression model advanced by Abdelhamid (1999), such as subject safety and ease of application.
4. Developing a model that provides acceptable prediction values in comparison with other quantitative prediction methods.
5. Providing a robust, efficient and reliable statistical methodology capable of predicting relative workloads from submaximal oxygen uptake and heart rate data collected in-situ.

V.2.1 Contributions to Construction

Construction work is physically demanding work. The construction industry has assumed that a high level of physical effort is an inherent part of doing the work. In fact, the culture of the construction industry has evolved such that contractors rely heavily on hand labor with small, relatively inexpensive, multipurpose tools. Contractors seldom consider the physical demands of work or a worker's physical qualifications to perform a given task.

Understanding the physical demands of construction work is of great importance in protecting the workforce's safety, health, and productivity. It is key to solving the problem of designing jobs that workers can safely perform. Improvements in performance can be attained when the workload is matched to the abilities of the individual worker, because this matching prevents the development of physical fatigue.

By using the methods developed and results advanced in this research and by promoting and applying concepts of work physiology at the workplace, many improvements will find their way to the occupational health and safety of the construction workforce. The methods described in this research will be critical to the success of many field studies focusing on:

1) Reliable evaluation of workloads to which workers are subjected, so that engineering or administrative interventions may be more effectively implemented by management to reduce workloads and injuries.
2) Expanding job opportunities for women, older workers, and workers who are partially disabled, by placing them in jobs according to their capabilities.

3) Evaluation of the effectiveness of rehabilitation programs for construction workers who previously suffered overexertion injuries.

V.3 Limitations and Future Work

Maximum oxygen uptake values are difficult, if not dangerous, to measure, but would lead to a better assessment of physical fatigue. Much research is needed to arrive at simple and reliable ways to achieve such measurements. The multiple regression model developed in this research proved promising in predicting relative workload. However, the model has some limitations which are worth noting. Firstly, the model was developed for a relatively homogeneous college-age group of predominantly white males. The effects of a wider range of ages, different racial backgrounds, and gender on the accuracy of the developed regression model need to be investigated. Secondly, many factors such as general health conditions, smoking habits, alcohol intake, and conditioning are explanatory variables that may increase the accuracy of the prediction.

Thirdly, because real construction environments and tasks were quite difficult to simulate in the lab, the results and findings of this study lose ecological (external) validity. Hence, the higher or lower limits of the prediction intervals as estimated by the model should not be respectively used to justify critical decisions regarding a worker's suitability for a particular work activity.

Additional development of the model presented in this research will be of great importance in better understanding the physical demands on today's workforce doing today's work. It will have widespread application in identifying excessively demanding tasks so they can be better matched to the abilities of subjects. Future research efforts should consider the following:

- Investigating the effects of gender, age, racial background, and overall health condition (smoking, fitness, stress, etc) on the model's accuracy.
- Validating the model on subjects from construction trades while performing various types of construction work.
- Investigating the use of other techniques/models to predict relative workload.

APPENDIX A
TIME SERIES ANALYSIS

A.1 Introduction[14]

When a sequence of data is observed with respect to time and space, the collected data is called a time series. In statistical theory, an observed time series is considered as one possible realization of a stochastic process (Pandit and Wu 1993, Anderson 1971). An observed stochastic process or time series is called strictly stationary when the probability distribution and all of its moments, i.e., mean, variance, etc., are independent of the origin. However, when the first and second moments are only assumed to be independent of the origin, the series is called wide sense stationary. Series that do not satisfy the mentioned conditions are considered to be non-stationary and are caused by trends or seasonalities in the data (Anderson 1971, Brockwell and Davis 1996).

The basic idea of time series analysis is to find a regression model that can represent an observation in time *t*, denoted as X_t, as the sum of two uncorrelated and independent parts: one dependent on preceding observed data and the other an independent sequence of unmeasured inputs (Pandit and Wu 1993).

A.2 Fitting and Finding Adequate ARMA(p,q) Models

Discrete or continuous Autoregressive Moving Average models, denoted as ARMA(p,q) models, are the family of regression models that can be fitted to time series data. The variables p and q describe the order of the ARMA(p,q) model to be

[14] Most content of this appendix is from Abdelhamid (1999).

used. The value of p represents how many preceding observations X_t depends on, and the value of q represents how many preceding disturbances affect X_t.

A general discrete Autoregressive Moving Average model, ARMA(p,q), has a linear stochastic difference equation of the form:

$$X_t - \varphi_1 X_{t-1} - \varphi_2 X_{t-2} - \ldots - \varphi_p X_{t-p} = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \ldots - \theta_q a_{t-q} \qquad \text{(A.1)}$$

The left-hand side of A.1 is the autoregressive part, and the right hand side is the moving average part. The basic assumptions of the ARMA(p,q) model represented by (A.1) are as follows: a_t = NID $(0,\sigma_a^2)$.i.e. a_t are normally and identically distributed random variables, i.e., a_t is independent of a_{t-p}, a_{t-p-1},...,and of X_{t-p-1}, X_{t-p-2}....

Given that ARMA(p,q) models are considered as conditional regression models, the parameters φ_1, $\varphi_2, \ldots, \varphi_p$ and θ_1, $\theta_2, \ldots, \theta_q$ can be estimated using the methods of least squares. Minimizing the nonlinear function S is performed in a stepwise fashion. Initial values of the parameters obtained through rough algorithms are used to compute a_t's recursively and to obtain the value of S. The direction along which S will be smaller is then found by methods of linearization and/or steepest descent. The new values of parameters with this smaller S are then taken as initial values and the routine continues until the minimum S is obtained (Pandit and Wu 1993).

A.3 Time Series Analysis

For each subject in this research, ARMA(p,q) models were fitted to oxygen uptake data collected during sessions 1,2 and 3, and the random sessions using the time series analysis packages ITSM 2000 version 7.0 (Brockwell and Davis 1996). Final model parameters were obtained using maximum likelihood methods of estimation.

After the adequate model was chosen, values of the Green's function were obtained. From the Green's function, the value of E_{G} was determined by sum the square of the Green's function.

A.4 Interpretation of the Green's Function

When a system is affected by disturbances a_t, it is important to understand how the system response or output at time t is affected by or depends on previous values of these disturbances. The Green's function summarizes the dependence or memory of an observed value X_t on previous a_t's. In essence, the Green's function characterizes how long a disturbance that affected the system at time t will be "remembered" by the system; or equivalently, how much time would the system require to "forget" the disturbance that affected it at time t. The shorter the time, the better the system is in coping with the disturbance and the more resistant it is to change. Therefore, by plotting the Green's function, an understanding of the "memory dynamics" or resistance to change from equilibrium in the system will be more easily visualized and quantified.

APPENDIX B

PHYSIOLOGICAL DATA FOR ALL SUBJECTS

The Green's function G_j and oxygen uptake data collected for subject 78 and 97 during the exercise session 3 discussed in Figure III.1 and III.2 are shown in Table B.1. The Energy of the Green's function is to sum the square of all the G_j for each subject.

	Subject 78 VO_2 (L/min)	Subject 97 VO_2 (L/min)	Subject 78 Gj^2	Subject 97 Gj^2
	0.16	0.15	1.000000	1.000000
	0.57	0.24	0.232247	0.929412
	0.88	0.44	0.382493	0.863803
	1.07	0.46	0.488573	0.802816
	1.27	0.61	0.533104	0.746133
	1.3	0.73	0.518083	0.693473
	1.59	1.04	0.457341	0.644520
	1.88	1.31	0.369688	0.599014
	1.7	1.16	0.273560	0.556725
	1.75	1.23	0.183724	0.517421
	1.77	1.28	0.109700	0.480901
	1.98	1.44	0.055734	0.446946
	1.53	1.52	0.021744	0.415393
	1.75	1.38	0.004683	0.386076
	1.69	1.42	0.000001	0.358813
	1.16	1.44	0.002878	0.333483
	2	1.4	0.009092	0.309948
	1.73	1.38	0.015500	0.288068
	1.81	1.4	0.020181	0.267734
	1.6	1.38	0.022308	0.248831
	1.85	1.39	0.021901	0.231265
	1.8	1.5	0.019505	0.214934
	1.53	1.35	0.015901	0.199764
	1.55	1.22	0.011870	0.185658

Table B.1 Subject 78 and 97 raw data on VO_2 and G_j

	Subject 78 VO$_2$ (L/min)	Subject 97 VO$_2$ (L/min)	Subject 78 Gj^2	Subject 97 Gj^2
	1.66	1.31	0.008053	0.172557
	1.78	1.5	0.004871	0.160376
	1.6	1.49	0.002522	0.149050
	1.65	1.45	0.001018	0.138533
	1.6	1.37	0.000240	0.128752
	1.8	1.48	0.000002	0.119661
	1.69	1.56	0.000100	0.111216
	1.69	1.56	0.000354	0.103362
	1.87	1.43	0.000627	0.096069
	1.63	1.41	0.000832	0.089281
	1.59	1.31	0.000933	0.082979
	1.5	1.52	0.000925	0.077123
	1.59	1.46	0.000831	0.071679
	1.74	1.52	0.000683	0.066621
	1.78	1.45	0.000515	0.061916
	1.73	1.39	0.000353	0.057547
	1.51	1.46	0.000216	0.053481
	1.48	1.46	0.000114	0.049707
	1.75	1.45	0.000047	0.046199
	1.64	1.4	0.000012	0.042936
	1.71	1.51	0.000000	0.039904
	1.58	1.49	0.000003	0.037087
	1.5	1.51	0.000014	0.034470
	1.57	1.53	0.000025	0.032037
	1.66	1.62	0.000034	0.029774
	1.7	1.49	0.000039	0.027672
	1.51	1.51	0.000023	0.025719
	1.68	1.2	0.000026	0.023904
	1.57	1.4	0.000015	0.022216
	1.82	1.62	0.000017	0.020647
	1.62	1.51	0.000010	0.019191
	1.59	1.53	0.000011	0.017836
	1.61	1.47	0.000006	0.016577
	1.73	1.52	0.000007	0.015406
	1.48	1.42	0.000004	0.014319
	1.64	1.58	0.000005	0.013308
	1.56	1.5	0.000003	0.012368

Table B.1 Subject 78 and 97 raw data on VO$_2$ and G$_j$ (continued)

	Subject 78 VO2 (L/min)	Subject 97 VO2 (L/min)	Subject 78 Gj^2	Subject 97 Gj^2
	1.66	1.39	0.000003	0.011496
	1.61	1.55	0.000002	0.010683
	1.8	1.65	0.000002	0.009930
	1.64	1.54	0.000001	0.009229
	1.44	1.55	0.000001	0.008577
	1.57	1.49	0.000001	0.007971
	1.68	1.46	0.000001	0.007410
	1.64	1.49	0.000001	0.006886
	1.4	1.5	0.000001	0.006400
	1.71	1.53		0.005947
	1.6	1.6		0.005528
	1.83	1.52		0.005138
	1.73	1.46		0.004775
	1.69	1.47		0.004438
	1.55	1.54		0.004124
	1.7	1.41		0.003834
	1.5	1.36		0.003563
	1.67	1.37		0.003311
	1.6	1.69		0.003078
	1.24	1.66		0.002860
	1.38	1.61		0.002658
	1.69	1.62		0.002471
	1.64	1.49		0.002296
	1.72	1.46		0.002134
	1.51	1.31		0.001984
	1.85	1.42		0.001844
	1.47	1.55		0.001713
	1.51	1.57		0.001593
	1.57	1.45		0.001480
	1.64	1.45		0.001376
	1.62	1.33		0.001279
VO_{2avg}	1.5758696	1.404915		
VO_{2max}	4.46	2.18		
$\%VO_{2max}$	0.353334	0.644457		
E_G			4.79	14.16

Table B.1 Subject 78 and 97 raw data on VO_2 and G_j (continued)

The physiological data including height, weight, BSA, age, heart rate, and actual oxygen uptake data collected in Session 2, 3 for the 100 experimental subjects discussed in Chapter IV Table IV.1 are shown in Table B.2.[15]

							Section 2			Section 3		
Sub	H	W	BSA	Age	HR max	VO_2 max	HR avg	VO_2 avg	% VO_2 max	HR avg	VO_2 avg	% VO_2 max
5	68	129	1.7	20	200	2.56	110.96	0.55	0.21	N/A	N/A	N/A
6	63	135	1.64	19	201	2.35	88.47	0.58	0.25	N/A	N/A	N/A
7	68.5	137	1.75	20	200	2.8	88.26	0.67	0.24	133.8	1.33	0.47
9	66.5	162	1.84	18	202	2.84	101.26	0.65	0.23	N/A	N/A	N/A
10	65.5	146	1.74	24	196	4.24	81.83	0.72	0.17	110.63	1.49	0.35
12	61.5	105.6	1.45	21	199	2.36	N/A	N/A	N/A	159.1	0.89	0.38
13	65	126	1.63	20	200	2.91	N/A	N/A	N/A	139.6	1.29	0.44
14	68	147	1.79	32	188	3.19	83.04	0.65	0.2	N/A	N/A	N/A
15	70.5	150.7	1.86	29	191	3.61	83.45	0.71	0.2	137.77	1.42	0.39
16	67	160	1.84	28	192	3.31	101.29	0.7	0.21	N/A	N/A	N/A
18	71.25	176.66	2.01	18	202	3.21	98.21	0.85	0.26	138.26	1.92	0.6
22	70.5	181.06	2.01	20	200	2.63	99.01	0.57	0.22	N/A	N/A	N/A
23	74	212	2.23	18	202	4.87	99.99	0.99	0.2	114.05	2.08	0.43
26	69	131	1.73	21	199	3.05	97.71	0.58	0.19	146.45	1.32	0.43
27	67.25	160	1.84	37	183	2.74	101.35	0.77	0.28	N/A	N/A	N/A
28	62.5	123	1.56	22	198	2.4	92.62	0.52	0.22	N/A	N/A	N/A
30	65.5	154	1.78	20	200	3.31	92.6	0.74	0.22	N/A	N/A	N/A
31	67.25	125	1.66	23	197	2.61	95.98	0.61	0.23	141.78	1.32	0.51
33	68	175	1.93	25	195	3.51	109.61	0.74	0.21	N/A	N/A	N/A
36	67	126	1.66	21	199	2.22	N/A	N/A	N/A	152.22	1.29	0.58
38	71.25	176.5	2	20	200	4.73	76.47	0.85	0.18	110.27	1.67	0.35
39	67	142.78	1.75	24	196	2.32	101.9	0.48	0.21	N/A	N/A	N/A
40	64.5	121	1.59	19	201	2.89	92.65	0.53	0.18	N/A	N/A	N/A
41	67.5	133	1.71	20	200	2.95	87.79	0.64	0.22	N/A	N/A	N/A
42	70	147	1.83	21	199	1.98	95.04	0.28	0.14	N/A	N/A	N/A

Table B.2 Physiological data for 100 experimental subjects

[15] The table does not include subjects' with missing data due to experimental errors or machine malfunctions.

Sub	H	W	BSA	Age	HR max	VO2 max	Section 2 HR avg	Section 2 VO2 avg	Section 2 % VO2 max	Section 3 HR avg	Section 3 VO2 avg	Section 3 % VO2 max
44	71.75	160	1.93	20	200	4.6	94.25	0.83	0.18	128.65	1.68	0.37
45	67	163	1.85	32	188	4.1	80.18	0.71	0.17	N/A	N/A	N/A
46	62.5	141	1.66	20	200	2.22	99.34	0.53	0.24	N/A	N/A	N/A
48	63	126	1.59	19	201	2.16	108.32	0.62	0.29	N/A	N/A	N/A
49	76.75	214	2.3	22	198	4.07	N/A	N/A	N/A	121.5	1.99	0.49
50	68.5	187	2	23	197	4.11	92.59	0.91	0.22	131.78	1.77	0.43
51	72.5	157.7	1.94	20	200	5.06	93.5	0.63	0.12	125.36	1.41	0.28
52	69.5	150	1.84	25	195	3.86	N/A	N/A	N/A	108.93	1.3	0.34
53	68	167	1.89	21	199	2.42	118.11	0.71	0.29	157.85	1.59	0.66
54	69.25	176	1.96	21	199	2.78	108.4	0.8	0.29	148.47	1.65	0.59
56	76	231	2.36	28	192	4.67	90.7	0.96	0.21	N/A	N/A	N/A
57	65	133	1.66	21	199	2.78	98.78	0.55	0.2	N/A	N/A	N/A
58	69	163	1.89	19	201	3.75	98.71	0.81	0.22	N/A	N/A	N/A
60	74	192	2.14	30	190	4.74	69.27	0.7	0.15	95.14	1.69	0.36
62	69	203	2.08	27	193	4	79.86	0.86	0.21	N/A	N/A	N/A
63	66	145	1.74	28	192	3.21	92.36	0.68	0.21	125.54	1.39	0.43
66	69.25	176	1.96	21	199	4.27	108.4	0.85	0.2	N/A	N/A	N/A
67	57.5	140	1.56	22	198	2.9	98.45	0.69	0.24	N/A	N/A	N/A
69	66	172	1.88	20	200	3.31	113.01	0.9	0.27	147.48	1.65	0.5
70	68.5	147	1.8	21	199	4.15	89.2	0.71	0.17	121.07	1.52	0.37
72	63	140	1.66	28	192	2.61	108.88	0.6	0.23	173.67	1.45	0.56
73	66.5	165	1.85	27	193	3.33	99.96	0.73	0.22	132.55	1.62	0.49
74	68.25	198	2.04	25	195	3.92	81.74	1.01	0.26	124.91	1.93	0.49
76	73	161	1.96	24	196	3.49	138.86	1.6	0.46	140.89	1.59	0.46
77	64.5	118	1.57	26	194	3.07	78.69	0.6	0.2	110.44	1.21	0.39
78	73.5	176	2.05	27	193	4.46	78.91	0.82	0.18	95.61	1.59	0.36
79	62.5	127	1.59	28	192	2.65	97.26	0.68	0.26	142.01	1.29	0.49
80	64	155	1.76	34	186	2.99	95.24	0.65	0.22	152.71	1.46	0.49
81	72.5	168	1.99	34	186	3.98	74.97	0.88	0.22	101.69	1.51	0.38
82	64	141	1.69	27	193	2.67	99.07	0.7	0.26	127.95	1.19	0.44
83	67	135	1.71	25	195	2.47	88.06	0.56	0.23	137.42	1.35	0.55
84	73.5	199	2.16	26	194	3.86	90.58	0.79	0.2	124.37	1.71	0.44
85	65	139	1.69	34	186	3	85.6	0.61	0.2	N/A	N/A	N/A
88	69	134	1.74	24	196	3.37	101.91	0.61	0.18	140.83	1.4	0.42

Table B.2 Physiological data for 100 experimental subjects (Continued)

Sub	H	W	BSA	Age	HR max	VO_2 max	Section 2 HR avg	Section 2 VO_2 vag	Section 2 % VO_2 max	Section 3 HR avg	Section 3 VO_2 vag	Section 3 % VO_2 max
89	69.5	142	1.8	25	195	3.81	99.27	0.75	0.2	93.55	1.44	0.38
90	66	149	1.76	24	196	2.71	103.13	0.75	0.28	N/A	N/A	N/A
91	72	167	1.97	22	198	4.36	90.33	0.77	0.18	121.98	1.57	0.36
93	70.5	163	1.92	24	196	3.42	106.14	0.77	0.22	155.36	1.43	0.4
94	64.5	137	1.67	24	196	4.02	81.96	0.64	0.16	142.89	1.72	0.5
95	69	150	1.83	27	193	2.86	110.37	0.7	0.24	162.43	1.46	0.51
96	66.5	158	1.82	25	195	3.4	81.51	0.9	0.27	N/A	N/A	N/A
97	69	150	1.83	37	183	2.18	101.33	0.6	0.27	N/A	N/A	N/A
98	67.5	162	1.86	37	183	3.36	88.03	0.75	0.22	N/A	N/A	N/A
100	68.5	171	1.92	25	195	3.9	95.36	0.99	0.25	128.96	1.84	0.47

Table B.2 Physiological data for 100 experimental subjects (Continued)

The physiological data including height, weight, BSA, age, heart rate, and actual oxygen uptake data for the 100 validation subjects discussed in Chapter IV Table IV.1 are shown in Table B.3[16].

							Random exercise test			VO_{2max} test		
Sub	H	W	BSA	Age	HR max	VO_2 max	HR avg	VO_2 avg	% VO_2 max	HR avg	VO_2 avg	% VO_2 max
1	65	134	1.67	23	197	3.22	122.9	1.24	0.38	N/A	N/A	N/A
2	67.75	124	1.66	22	198	3.06	121.25	0.91	0.3	143.37	1.62	0.53
3	68.5	132	1.72	38	182	2.52	100.71	1.09	0.43	N/A	N/A	N/A
4	75.5	194	2.18	21	199	4.52	117.96	1.57	0.35	149.94	2.6	0.57
5	71.5	155	1.9	24	196	3.52	N/A	N/A	N/A	136.37	1.72	0.49
8	65.5	116	1.58	23	197	2.09	134.28	1.04	0.5	152.58	1.27	0.61
10	74	200	2.26	26	194	4.96	111.26	1.99	0.4	143.52	2.8	0.56
11	70.5	195	2.08	33	187	3.35	143.97	1.89	0.56	140.29	1.94	0.58
12	65.5	140	1.71	21	199	2.27	150.42	1.3	0.57	145.6	1.45	0.64
13	68	139	1.75	34	186	2.75	123.57	1.05	0.38	N/A	N/A	N/A
14	66.75	155	1.81	19	201	2.86	122.1	1.2	0.42	127.66	1.64	0.57
15	71.5	161	1.93	22	198	5.04	115.22	1.31	0.26	151.86	2.58	0.51
16	64	125	1.6	23	197	3.11	140.14	1.07	0.34	166.35	1.67	0.54
17	73	188	2.1	23	197	4.23	118.15	1.69	0.4	158.39	2.52	0.6
18	70	145	1.82	25	195	3	134.13	1.28	0.43	156.43	1.73	0.58
23	67	185	1.96	24	196	4.05	147.47	1.79	0.44	155.63	2.32	0.57
24	63	140	1.66	27	193	2.27	159.66	1.06	0.47	N/A	N/A	N/A
25	68	142	1.77	21	199	4.07	N/A	N/A	N/A	166.71	2.21	0.54
26	67	166	1.87	22	198	3.05	156.49	1.55	0.51	153.35	1.75	0.57
28	70	152	1.86	22	198	4.24	110.24	1.2	0.28	143.28	2.15	0.51
29	80.5	209	2.35	21	199	4.64	119.81	1.64	0.35	144.85	2.58	0.56
30	73	182	2.07	26	194	4.01	112.97	1.46	0.37	147.83	2.35	0.59
31	68	160	1.86	22	198	4.32	N/A	N/A	N/A	139.47	2.31	0.54
33	68.5	152	1.83	27	193	2.39	136.47	1.08	0.45	139.7	1.45	0.61
34	69.5	174	1.96	21	199	5.05	107.66	1.55	0.31	141.51	2.78	0.55
35	66.5	150	1.78	30	190	3.01	121.3	1.36	0.45	147.86	1.93	0.64

Table B.3 Physiological data for 100 validation subjects

16 Same as notes 14.

							Random exercise test			VO_{2max} test		
Sub	H	W	BSA	Age	HR max	VO_2 max	HR avg	VO_2 avg	% VO_2 max	HR avg	VO_2 avg	% VO_2 max
36	64	112	1.53	31	189	2.54	127.82	0.84	0.33	137.9	1.27	0.5
39	73	204	2.17	24	196	4.16	114.9	1.47	0.35	137.81	2.29	0.55
40	72	175	2.01	23	197	3.78	109.75	1.42	0.38	131.03	2.02	0.54
41	65.5	152	1.77	20	200	3.75	121.24	1.24	0.33	143.27	2.11	0.56
42	72.5	222	2.24	26	194	3.23	128.31	1.65	0.51	135.44	2.04	0.63
44	76	204	1.58	22	198	2.78	121.91	0.97	0.35	141	1.43	0.52
45	63	125	2.05	28	192	4.23	125.18	1.4	0.33	N/A	N/A	N/A
46	61	111	1.47	23	197	1.69	151.22	0.93	0.55	154.65	1.11	0.66
47	64	126	1.61	35	185	2.75	111.09	1.06	0.38	N/A	N/A	N/A
48	62	146	1.67	21	199	2.95	130.05	1.34	0.45	134.36	1.66	0.56
49	68	157	1.48	31	189	3.98	126.46	1.16	0.29	147.6	2.1	0.53
50	68	149	1.8	21	199	5.93	N/A	N/A	N/A	140.95	2.67	0.45
51	71.5	155	1.9	24	196	3.76	124.17	1.43	0.38	146.06	2.21	0.59
52	69	179	1.97	36	184	4.95	100.94	1.55	0.31	141.12	2.78	0.56
53	72	173	2	27	193	4.24	109.4	1.49	0.35	140.24	2.41	0.57
54	72	170	1.99	22	198	4.12	132.79	1.55	0.38	158.55	2.47	0.6
55	64	148	1.72	20	200	1.74	N/A	N/A	N/A	161.72	1.17	0.67
56	63	130	1.63	23	197	2.71	122.39	1.02	0.38	144.14	1.55	0.57
57	72	182	2.05	23	197	4.31	N/A	N/A	N/A	167.71	2.47	0.57
58	71.5	183	2.04	27	193	3.92	133.37	1.54	0.39	161.87	2.38	0.61
59	66.5	136	1.71	29	191	2.77	127.2	0.98	0.35	146.49	1.69	0.61
60	67	180	1.93	37	183	3.23	122.67	1.52	0.47	151.54	1.93	0.6
62	76	239	2.39	34	186	4.68	124.99	1.99	0.43	154.77	2.87	0.61
64	67.5	154	1.91	43	177	2.38	142.22	1.56	0.66	N/A	N/A	N/A
65	66	180	1.75	39	181	2.64	117.96	1.26	0.48	128.83	1.62	0.61
66	70	173	1.96	25	195	3.64	138.46	1.94	0.53	165.6	2.19	0.6
67	71	192.5	2.07	28	192	2.9	151.9	1.64	0.57	164.2	1.87	0.64
68	67.5	166	1.88	32	188	3.42	127.67	1.4	0.41	140.99	1.95	0.57
69	70.25	151	1.86	25	195	3.55	121.7	1.05	0.3	145.8	1.91	0.54
70	69	200	2.07	28	192	3.85	120.05	1.81	0.47	N/A	N/A	N/A
71	60.5	133	1.58	35	185	1.52	159.84	0.94	0.62	156.25	0.92	0.61
72	66	156	1.8	23	197	3.42	129.05	1.31	0.38	145.96	1.87	0.55
74	71	177	2	21	199	3.83	109.13	1.39	0.36	128.91	2.08	0.54
76	70	166	1.93	24	196	4.19	N/A	N/A	N/A	127.84	2.38	0.57

Table B.3 Physiological data for 100 validation subjects (Continued)

Sub	H	W	BSA	Age	HR max	VO_2 max	Random exercise test			VO_{2max} test		
							HR avg	VO_2 avg	% VO_2 max	HR avg	VO_2 avg	% VO_2 max
77	72	216	2.2	21	199	4.21	103.61	2.03	0.48	N/A	N/A	N/A
78	65.5	145	1.74	19	201	2.72	138.35	1.26	0.46	153.06	1.55	0.57
82	77	205	2.26	31	189	4.25	124.34	1.5	0.35	N/A	N/A	N/A
83	67	149	1.78	24	196	2.73	137.88	1.27	0.46	150.66	1.66	0.61
85	69.5	166	1.92	22	198	3.98	111.13	1.6	0.4	141.78	2.3	0.58
86	70.5	202	2.11	28	192	4.37	107.09	1.73	0.4	141.73	2.69	0.62
88	71	184	2.04	29	191	2.58	N/A	N/A	N/A	129.18	1.72	0.67
89	68	182	1.96	34	186	3.31	134.92	1.31	0.4	144.88	1.93	0.58
90	71	191	2.07	26	194	5.11	109.88	1.39	0.27	146.95	2.87	0.56
91	73.5	194	2.13	22	198	4.49	104.69	1.78	0.4	133.54	2.52	0.56
94	73	191	2.11	21	199	4.18	124.78	1.37	0.33	149.65	2.28	0.55
95	63	154	1.73	30	190	3.33	N/A	N/A	N/A	168.58	1.69	0.51
96	66	134	1.69	24	196	2.89	N/A	N/A	N/A	163.89	1.61	0.56
97	70.5	154	1.88	27	193	3.97	N/A	N/A	N/A	172.35	2.12	0.53
98	65	171	1.85	29	191	3.55	143.53	1.57	0.44	157.41	2	0.56
100	69	167	1.91	20	200	3.93	111.91	1.32	0.34	146.44	2.15	0.55

Table B.3 Physiological data for 100 validation subjects (Continued)

Table B.4 lists the data used to depict Figure IV.1 between E_G and $\%VO_{2max}$, and to generate the RWP and Model A and C based on the predictors of E_G, RHR and BSA from the experimental subjects, and the predicted $\%VO_{2max}$ and VO_{2max} values based on these models. Table B.4 (a) refers to section 2 exercise and (b) to section 3.

Sub	$E_{(G)}$	$Ln(E_G)$	BSA	RHR	$\%VO_2$ max (actual)	$\%VO_2$ max (RWP)	$\%VO_2$ max (A)	$\%VO_2$ max (C)	VO_2 max (RWP)	VO_2 max (A)	VO_2 max (C)
5	1.06	0.06	1.7	0.55	0.21	0.23	0.26	0.26	2.35	2.08	2.15
6	1.12	0.11	1.64	0.44	0.25	0.24	0.20	0.18	2.38	2.90	3.16
7	1.00	0.00	1.75	0.44	0.24	0.22	0.19	0.18	3.00	3.56	3.71
9	1.11	0.10	1.84	0.5	0.23	0.24	0.24	0.24	2.71	2.76	2.76
10	1.09	0.09	1.74	0.42	0.17	0.24	0.18	0.17	3.01	3.90	4.11
14	1.23	0.21	1.79	0.44	0.20	0.26	0.21	0.20	2.53	3.15	3.24
15	1.13	0.12	1.86	0.44	0.20	0.24	0.20	0.20	2.93	3.57	3.58
16	1.37	0.31	1.84	0.53	0.21	0.27	0.27	0.27	2.56	2.57	2.58
18	1.07	0.07	2.01	0.49	0.26	0.24	0.23	0.24	3.60	3.73	3.55
22	1.02	0.02	2.01	0.5	0.22	0.23	0.23	0.24	2.51	2.49	2.37
23	1.13	0.13	2.23	0.5	0.20	0.24	0.24	0.26	4.07	4.18	3.76
26	1.10	0.09	1.73	0.49	0.19	0.24	0.23	0.22	2.45	2.56	2.65
27	1.00	0.00	1.84	0.55	0.28	0.22	0.26	0.26	3.45	2.98	2.97
28	1.57	0.45	1.56	0.47	0.22	0.30	0.25	0.22	1.77	2.13	2.33
30	1.28	0.25	1.78	0.46	0.22	0.26	0.22	0.22	2.80	3.31	3.40
31	1.00	0.00	1.66	0.49	0.23	0.22	0.22	0.21	2.73	2.76	2.93
33	1.12	0.12	1.93	0.56	0.21	0.24	0.27	0.28	3.05	2.69	2.62
38	1.22	0.20	2	0.38	0.18	0.26	0.17	0.18	3.33	5.07	4.87
39	1.01	0.01	1.75	0.52	0.21	0.23	0.24	0.24	2.14	2.01	2.05
40	1.18	0.17	1.59	0.46	0.18	0.25	0.22	0.20	2.11	2.44	2.68
41	1.30	0.26	1.71	0.44	0.22	0.27	0.21	0.20	2.39	3.01	3.19
42	1.11	0.11	1.83	0.48	0.14	0.24	0.22	0.22	1.14	1.23	1.24
44	1.74	0.55	1.93	0.47	0.18	0.31	0.25	0.26	2.67	3.28	3.23
45	1.37	0.31	1.85	0.43	0.17	0.27	0.21	0.21	2.58	3.38	3.42
46	1.69	0.53	1.66	0.5	0.24	0.31	0.27	0.26	1.71	1.94	2.05
48	1.40	0.34	1.59	0.54	0.29	0.28	0.28	0.26	2.23	2.20	2.35
50	2.96	1.08	2	0.47	0.22	0.40	0.30	0.30	2.28	3.04	2.98
51	1.04	0.04	1.94	0.47	0.12	0.23	0.21	0.22	2.75	2.99	2.90
53	1.18	0.17	1.89	0.59	0.29	0.25	0.30	0.30	2.83	2.38	2.34

Table B.4 (a) Actual/predicted values for $\%VO_{2max}$ & VO_{2max} for experimental subjects

Sub	E(G)	Ln(E_G)	BSA	RHR	%VO_2 max (actual)	%VO_2 max (RWP)	%VO_2 max (A)	%VO_2 max (C)	VO_2 max (RWP)	VO_2 max (A)	VO_2 max (C)
54	1.14	0.14	1.96	0.54	0.29	0.25	0.26	0.27	3.25	3.02	2.92
56	1.09	0.08	2.36	0.47	0.21	0.24	0.22	0.25	4.05	4.47	3.84
57	1.14	0.13	1.66	0.5	0.20	0.25	0.24	0.23	2.25	2.31	2.44
58	1.26	0.23	1.89	0.49	0.22	0.26	0.24	0.24	3.13	3.39	3.36
60	1.17	0.16	2.14	0.36	0.15	0.25	0.15	0.17	2.79	4.58	4.13
62	1.25	0.22	2.08	0.41	0.21	0.26	0.19	0.20	3.30	4.53	4.23
63	1.04	0.04	1.74	0.48	0.21	0.23	0.22	0.21	2.96	3.13	3.24
66	1.63	0.49	1.96	0.54	0.20	0.30	0.29	0.30	2.81	2.89	2.82
67	1.07	0.07	1.56	0.5	0.24	0.24	0.23	0.21	2.93	2.96	3.23
69	1.13	0.12	1.88	0.57	0.27	0.24	0.28	0.29	3.69	3.19	3.14
70	1.01	0.01	1.8	0.45	0.17	0.23	0.20	0.19	3.13	3.60	3.67
72	1.27	0.24	1.66	0.57	0.23	0.26	0.29	0.28	2.30	2.06	2.15
73	1.54	0.43	1.85	0.52	0.22	0.29	0.28	0.28	2.50	2.65	2.65
74	1.03	0.03	2.04	0.42	0.26	0.23	0.18	0.19	4.43	5.65	5.30
76	1.89	0.63	1.96	0.71	0.46	0.33	0.41	0.43	4.90	3.86	3.75
77	1.11	0.11	1.57	0.41	0.20	0.24	0.18	0.16	2.50	3.36	3.82
78	1.12	0.11	2.05	0.41	0.18	0.24	0.18	0.19	3.40	4.57	4.29
79	1.17	0.16	1.59	0.51	0.26	0.25	0.25	0.23	2.73	2.76	2.97
80	1.01	0.01	1.76	0.51	0.22	0.23	0.23	0.23	2.85	2.75	2.81
81	1.07	0.07	1.99	0.4	0.22	0.23	0.17	0.18	3.76	5.21	4.98
82	1.01	0.01	1.69	0.51	0.26	0.22	0.23	0.22	3.10	2.98	3.11
83	1.18	0.16	1.71	0.45	0.23	0.25	0.21	0.20	2.25	2.68	2.83
84	1.21	0.19	2.16	0.47	0.20	0.25	0.22	0.25	3.08	3.50	3.20
85	1.11	0.11	1.69	0.46	0.20	0.24	0.21	0.20	2.53	2.89	3.06
88	1.42	0.35	1.74	0.52	0.18	0.28	0.27	0.26	2.18	2.26	2.33
89	1.21	0.19	1.8	0.51	0.20	0.25	0.25	0.25	2.94	3.00	3.03
90	1.38	0.32	1.76	0.53	0.28	0.28	0.27	0.27	2.73	2.75	2.81
91	1.19	0.17	1.97	0.46	0.18	0.25	0.22	0.22	3.04	3.54	3.42
93	1.01	0.01	1.92	0.54	0.22	0.23	0.25	0.26	3.40	3.03	2.95
94	1.56	0.44	1.67	0.42	0.16	0.29	0.21	0.20	2.17	3.00	3.24
95	1.07	0.07	1.83	0.57	0.24	0.24	0.28	0.28	2.96	2.51	2.50
96	1.02	0.02	1.82	0.42	0.27	0.23	0.18	0.17	3.98	5.07	5.17
97	1.19	0.17	1.83	0.55	0.27	0.25	0.27	0.27	2.36	2.18	2.17
98	1.11	0.10	1.86	0.48	0.22	0.24	0.22	0.22	3.10	3.34	3.33
100	1.17	0.16	1.92	0.49	0.25	0.25	0.23	0.24	3.95	4.21	4.12

Table B.4 (a) Actual/predicted values for %VO_{2max} & VO_{2max} for experimental subjects (continued)

Sub	E(G)	Ln(EG)	BSA	RHR	%VO2 max (actual)	%VO2 max (RWP)	%VO2 max (A)	%VO2 max (C)	VO2 max (RWP)	VO2 max (A)	VO2 max (C)
7	1.79	0.58	1.75	0.67	0.47	0.32	0.38	0.38	4.18	3.46	3.49
10	1.22	0.20	1.74	0.56	0.35	0.26	0.28	0.28	5.81	5.28	5.39
12	1.86	0.62	1.45	0.8	0.38	0.32	0.47	0.45	2.77	1.91	2.00
13	2.02	0.70	1.63	0.7	0.44	0.34	0.41	0.40	3.83	3.12	3.21
15	1.35	0.30	1.86	0.72	0.39	0.27	0.39	0.40	5.22	3.63	3.57
18	6.65	1.89	2.01	0.68	0.60	0.53	0.50	0.51	3.65	3.86	3.78
23	1.60	0.47	2.23	0.56	0.43	0.30	0.30	0.33	6.95	6.83	6.27
26	1.65	0.50	1.73	0.74	0.43	0.30	0.42	0.42	4.33	3.13	3.14
31	4.55	1.51	1.66	0.72	0.51	0.47	0.49	0.48	2.84	2.68	2.75
36	7.47	2.01	1.66	0.76	0.58	0.55	0.56	0.55	2.36	2.30	2.35
38	1.41	0.35	2	0.55	0.35	0.28	0.29	0.30	5.96	5.79	5.57
44	4.01	1.39	1.93	0.64	0.37	0.45	0.43	0.44	3.77	3.90	3.86
49	6.44	1.86	2.3	0.61	0.49	0.52	0.45	0.48	3.81	4.40	4.14
50	1.23	0.20	2	0.67	0.43	0.26	0.35	0.37	6.90	5.03	4.82
51	1.18	0.17	1.94	0.63	0.28	0.25	0.32	0.33	5.64	4.37	4.24
52	1.84	0.61	1.84	0.56	0.34	0.32	0.32	0.32	4.04	4.11	4.12
53	15.89	2.77	1.89	0.79	0.66	0.67	0.64	0.64	2.39	2.48	2.48
54	9.78	2.28	1.96	0.75	0.59	0.59	0.58	0.58	2.80	2.87	2.83
69	2.02	0.70	2.14	0.5	0.36	0.34	0.29	0.30	5.03	5.92	5.57
63	2.65	0.98	1.74	0.65	0.43	0.38	0.40	0.40	3.67	3.45	3.51
69	4.76	1.56	1.88	0.74	0.50	0.47	0.51	0.51	3.49	3.25	3.22
70	1.50	0.40	1.8	0.61	0.37	0.29	0.33	0.33	5.27	4.60	4.62
72	6.61	1.89	1.66	0.9	0.56	0.53	0.64	0.63	2.76	2.28	2.31
73	3.78	1.33	1.85	0.69	0.49	0.44	0.46	0.46	3.71	3.53	3.52
74	5.53	1.71	2.04	0.64	0.49	0.50	0.46	0.47	3.87	4.20	4.10
76	1.89	0.63	1.96	0.72	0.46	0.33	0.42	0.43	4.90	3.80	3.69
77	2.51	0.92	1.57	0.57	0.39	0.37	0.35	0.33	3.25	3.46	3.68
78	4.79	1.57	2.05	0.5	0.36	0.47	0.36	0.37	3.36	4.45	4.35
79	12.31	2.51	1.59	0.74	0.49	0.63	0.59	0.57	2.06	2.19	2.27
80	3.15	1.15	1.76	0.82	0.49	0.41	0.53	0.52	3.57	2.77	2.77
81	1.07	0.07	1.99	0.55	0.38	0.23	0.26	0.28	6.43	5.70	5.46
82	1.37	0.31	1.69	0.66	0.44	0.27	0.35	0.35	4.33	3.35	3.41
83	4.58	1.52	1.71	0.7	0.55	0.47	0.48	0.47	2.89	2.81	2.87
84	2.05	0.72	2.16	0.64	0.44	0.34	0.38	0.40	5.04	4.55	4.28

Table B.4 (b) Actual/predicted values for %VO_{2max} & VO_{2max} for experimental subjects (continued)

Sub	$E_{(G)}$	$Ln(E_G)$	BSA	RHR	%VO_2 max (actual)	%VO_2 max (RWP)	%VO_2 max (A)	%VO_2 max (C)	VO_2 max (RWP)	VO_2 max (A)	VO_2 max (C)
88	1.25	0.22	1.74	0.72	0.42	0.26	0.39	0.38	5.4	3.64	3.65
89	5.96	1.78	1.8	0.48	0.38	0.51	0.36	0.35	2.83	3.97	4.09
91	1.46	0.38	1.97	0.62	0.36	0.29	0.34	0.35	5.51	4.69	4.53
92	2.45	0.90	1.69	0.83	0.40	0.37	0.51	0.51	3.90	2.80	2.83
93	2.48	0.91	1.92	0.73	0.50	0.37	0.45	0.46	4.66	3.84	3.77
95	4.70	1.55	1.83	0.84	0.51	0.47	0.57	0.57	3.10	2.56	2.55
100	5.53	1.71	1.92	0.66	0.47	0.50	0.47	0.47	3.70	3.91	3.88

Table B.4 (b) Actual/predicted values for %VO_{2max} & VO_{2max} for experimental subjects (continued)

Table B.5 lists the actual $\%VO_{2max}$ and the predictecd $\%VO_{2max}$ and absolute VO_{2max} values of validation subjects using the developed RWP and MLR model A and C. Table B.5 (a) refers to validation subjects doing the random exercise test and (b) refers to the VO_{2max} test.

Sub	$E_{(G)}$	$Ln(E_G)$	BSA	RHR	%VO₂ max (actual)	%VO₂ max (RWP)	%VO₂ max (A)	%VO₂ max (C)	VO₂ max (RWP)	VO₂ max (A)	VO₂ max (C)
1	1.96	0.67	1.67	0.62	0.38	0.33	0.36	0.35	3.73	3.42	3.53
2	3.30	1.19	1.66	0.61	0.30	0.41	0.40	0.38	2.20	2.29	2.37
3	2.95	1.08	1.72	0.55	0.43	0.40	0.35	0.34	2.75	3.10	3.20
4	3.00	1.10	2.18	0.59	0.35	0.40	0.38	0.40	3.92	4.15	3.91
8	2.17	0.77	1.58	0.68	0.50	0.35	0.41	0.39	2.99	2.56	2.66
10	2.82	1.04	2.26	0.57	0.40	0.39	0.36	0.39	5.11	5.54	5.14
11	5.12	1.63	2.08	0.77	0.56	0.49	0.53	0.55	3.89	3.54	3.42
12	3.31	1.20	1.71	0.76	0.57	0.42	0.49	0.48	3.14	2.67	2.70
13	5.89	1.77	1.75	0.66	0.38	0.51	0.48	0.47	2.07	2.19	2.23
14	6.86	1.93	1.81	0.61	0.42	0.53	0.46	0.45	2.26	2.63	2.67
15	2.16	0.77	1.93	0.58	0.26	0.35	0.34	0.35	3.77	3.81	3.75
16	3.06	1.12	1.60	0.71	0.34	0.40	0.45	0.44	2.66	2.36	2.44
17	2.48	0.91	2.10	0.60	0.40	0.37	0.37	0.38	4.58	4.62	4.41
18	2.29	0.83	1.82	0.69	0.43	0.36	0.42	0.42	3.60	3.09	3.09
23	3.48	1.25	1.96	0.75	0.44	0.42	0.49	0.50	4.22	3.64	3.56
24	2.73	1.00	1.66	0.83	0.47	0.38	0.52	0.51	2.76	2.05	2.08
26	5.79	1.76	1.87	0.79	0.51	0.50	0.56	0.56	3.08	2.79	2.77
28	2.86	1.05	1.86	0.56	0.28	0.39	0.35	0.35	3.06	3.42	3.43
29	2.73	1.00	2.35	0.60	0.35	0.38	0.38	0.41	4.28	4.38	4.01
30	1.63	0.49	2.07	0.58	0.37	0.30	0.32	0.34	4.85	4.57	4.35
33	2.44	0.89	1.83	0.71	0.45	0.37	0.43	0.43	2.94	2.49	2.48
34	1.77	0.57	1.96	0.54	0.31	0.31	0.30	0.31	4.92	5.16	5.03
35	3.26	1.18	1.78	0.64	0.45	0.41	0.41	0.41	3.28	3.28	3.32
36	4.59	1.52	1.53	0.68	0.33	0.47	0.47	0.44	1.80	1.81	1.90
39	5.70	1.74	2.17	0.59	0.35	0.50	0.43	0,45	2.92	3.44	3.30
40	2.12	0.75	2.01	0.56	0.38	0.34	0.33	0.34	4.12	4.36	4.22
41	1.88	0.63	1.77	0.61	0.33	0.33	0.35	0.34	3.82	3.58	3.62

Table B.5 (a) Actual/predicted values for $\%VO_{2max}$ & VO_{2max} for validation subjects

Sub	E(G)	Ln (E_G)	BSA	RHR	%VO_2 max (actual)	%VO_2 max (RWP)	%VO_2 max (A)	%VO_2 max (C)	VO_2 max (RWP)	VO_2 max (A)	VO_2 max (C)
42	4.48	1.50	2.24	0.66	0.51	0.46	0.45	0.48	3.56	3.63	3.43
44	5.96	1.79	1.58	0.62	0.35	0.51	0.45	0.43	1.91	2.17	2.28
45	1.94	0.66	2.05	0.65	0.33	0.33	0.38	0.40	4.24	3.69	3.54
46	6.64	1.89	1.47	0.77	0.55	0.53	0.55	0.53	1.77	1.68	1.77
47	1.75	0.56	1.61	0.60	0.38	0.31	0.34	0.32	3.37	3.13	3.28
48	5.68	1.74	1.67	0.65	0.45	0.50	0.47	0.46	2.66	2.85	2.94
49	2.30	0.83	1.48	0.67	0.29	0.36	0.40	0.38	3.25	2.88	3.05
51	1.49	0.40	1.90	0.63	0.38	0.29	0.35	0.35	4.97	4.15	4.07
52	1.68	0.52	1.97	0.55	0.31	0.31	0.30	0.31	5.06	5.16	5.01
53	2.03	0.71	2.00	0.57	0.35	0.34	0.33	0.34	4.41	4.53	4.39
54	4.30	1.46	1.99	0.67	0.38	0.46	0.46	0.47	3.38	3.38	3.31
56	6.07	1.80	1.63	0.62	0.38	0.51	0.45	0.44	1.99	2.25	2.34
58	2.86	1.05	2.04	0.69	0.39	0.39	0.44	0.45	3.92	3.52	3.40
59	2.31	0.84	1.71	0.67	0.35	0.36	0.40	0.39	2.74	2.44	2.48
60	4.86	1.58	1.93	0.67	0.47	0.48	0.47	0.47	3.19	3.26	3.23
62	1.67	0.51	2.39	0.67	0.43	0.31	0.38	0.42	6.51	5.25	4.73
64	6.10	1.81	1.91	0.80	0.66	0.51	0.57	0.58	3.04	2.74	2.71
65	3.92	1.37	1.75	0.65	0.48	0.44	0.44	0.43	2.85	2.88	2.93
66	3.45	1.24	1.96	0.71	0.53	0.42	0.46	0.47	4.59	4.18	4.09
67	4.73	1.55	2.07	0.79	0.57	0.47	0.54	0.56	3.47	3.03	2.93
68	6.66	1.90	1.88	0.68	0.41	0.53	0.50	0.50	2.65	2.81	2.80
69	2.77	1.02	1.86	0.62	0.30	0.39	0.39	0.39	2.72	2.70	2.69
70	4.35	1.47	2.07	0.63	0.47	0.46	0.43	0.44	3.93	4.21	4.07
71	3.57	1.27	1.58	0.86	0.62	0.43	0.56	0.55	2.21	1.67	1.71
72	7.39	2.00	1.80	0.66	0.38	0.54	0.49	0.49	2.40	2.66	2.69
74	2.25	0.81	2.00	0.55	0.36	0.35	0.33	0.34	3.92	4.26	4.14
77	3.73	1.32	2.20	0.52	0.48	0.43	0.35	0.37	4.66	5.79	5.47
78	2.92	1.07	1.74	0.69	0.46	0.40	0.44	0.43	3.19	2.90	2.94
82	2.45	0.90	2.26	0.66	0.35	0.37	0.40	0.43	4.07	3.72	3.46
83	2.06	0.72	1.78	0.70	0.46	0.34	0.42	0.42	3.73	3.04	3.05
85	2.07	0.73	1.92	0.56	0.40	0.34	0.33	0.33	4.71	4.91	4.84
86	1.70	0.53	2.11	0.56	0.40	0.31	0.31	0.33	5.62	5.63	5.31
89	2.52	0.93	1.96	0.73	0.40	0.37	0.45	0.46	3.53	2.94	2.86
90	2.31	0.84	2.07	0.57	0.27	0.36	0.34	0.35	3.88	4.09	3.92

Table B.5 (a) Actual/predicted values for %VO_{2max} & VO_{2max} for validation subjects (Continued)

Sub	E(G)	Ln (E_G)	BSA	RHR	%VO_2 max (actual)	%VO_2 max (RWP)	%VO_2 max (A)	%VO_2 max (C)	VO_2 max (RWP)	VO_2 max (A)	VO_2 max (C)
91	1.95	0.67	2.13	0.53	0.4	0.33	0.3	0.32	5.37	5.9	5.55
94	2.60	0.96	2.11	0.63	0.33	0.38	0.39	0.41	3.64	3.54	3.38
98	1.38	0.32	1.85	0.75	0.44	0.28	0.41	0.42	5.70	3.80	3.73
100	1.69	0.53	1.91	0.56	0.34	0.31	0.31	0.31	4.30	4.29	4.22

Table B.5 (a) Actual/predicted values for %VO_{2max} & VO_{2max} for validation subjects (Continued)

Sub	$E_{(G)}$	Ln (E_G)	BSA	RHR	$\%VO_2$ max (actual)	$\%VO_2$ max (RWP)	$\%VO_2$ max (A)	$\%VO_2$ max (C)	VO_2 max (RWP)	VO_2 max (A)	VO_2 max (C)
2	2.95	1.08	1.66	0.72	0.53	0.40	0.46	0.45	4.08	3.53	3.61
4	10.88	2.39	2.18	0.75	0.57	0.61	0.59	0.61	4.29	4.43	4.27
5	3.00	1.10	1.90	0.70	0.49	0.40	0.44	0.45	4.31	3.89	3.84
8	4.41	1.48	1.58	0.77	0.61	0.46	0.52	0.51	2.74	2.41	2.49
10	7.73	2.05	2.26	0.74	0.56	0.55	0.55	0.58	5.07	5.09	4.84
11	6.27	1.84	2.08	0.75	0.58	0.52	0.54	0.56	3.75	3.61	3.50
12	7.71	2.04	1.74	0.73	0.64	0.55	0.54	0.54	2.64	2.67	2.72
14	12.96	2.56	1.81	0.64	0.57	0.63	0.53	0.52	2.59	3.12	3.17
15	7.15	1.97	1.93	0.77	0.51	0.54	0.56	0.57	4.78	4.60	4.55
16	8.61	2.15	1.60	0.84	0.54	0.57	0.62	0.61	2.94	2.68	2.75
17	5.66	1.73	2.10	0.80	0.60	0.50	0.56	0.58	5.02	4.46	4.31
18	5.32	1.67	1.82	0.80	0.58	0.49	0.56	0.56	3.52	3.11	3.10
23	5.81	1.76	1.96	0.79	0.57	0.51	0.56	0.57	4.60	4.15	4.08
25	6.83	1.92	1.77	0.84	0.54	0.53	0.60	0.60	4.15	3.67	3.68
26	5.16	1.64	1.87	0.77	0.57	0.49	0.54	0.54	3.59	3.25	3.23
27	6.85	1.92	1.81	0.82	0.50	0.53	0.59	0.59	3.81	3.42	3.42
28	5.07	1.62	1.86	0.72	0.51	0.48	0.50	0.51	4.44	4.27	4.25
29	8.03	2.08	2.35	0.73	0.56	0.56	0.54	0.58	4.63	4.73	4.45
30	12.35	2.51	2.07	0.76	0.59	0.63	0.60	0.62	3.76	3.91	3.82
31	10.84	2.38	1.86	0.70	0.54	0.61	0.56	0.55	3.82	4.17	4.18
33	6.56	1.88	1.83	0.72	0.61	0.52	0.53	0.52	2.77	2.76	2.77
34	4.96	1.60	1.96	0.71	0.55	0.48	0.49	0.50	5.78	5.62	5.53
35	5.63	1.73	1.78	0.78	0.64	0.50	0.55	0.54	3.85	3.52	3.54
36	5.24	1.66	1.53	0.73	0.50	0.49	0.51	0.49	2.59	2.48	2.59
39	4.96	1.60	2.17	0.70	0.55	0.48	0.49	0.51	4.76	4.67	4.47
40	6.59	1.89	2.01	0.67	0.54	0.53	0.49	0.50	3.85	4.14	4.06
41	6.77	1.91	1.77	0.72	0.56	0.53	0.52	0.52	3.99	4.03	4.08
42	12.39	2.52	2.24	0.70	0.63	0.63	0.56	0.59	3.25	3.62	3.48
44	6.47	1.87	1.58	0.71	0.52	0.52	0.52	0.50	2.74	2.77	2.88
46	12.35	2.51	1.47	0.79	0.66	0.63	0.62	0.59	1.77	1.80	1.88
48	7.57	2.02	1.67	0.68	0.56	0.55	0.51	0.49	3.03	3.27	3.37
49	6.65	1.90	1.48	0.78	0.53	0.53	0.56	0.54	3.99	3.74	3.91
50	5.25	1.66	1.80	0.71	0.45	0.49	0.50	0.49	5.45	5.36	5.40
51	6.93	1.94	1.90	0.75	0.59	0.53	0.54	0.55	4.15	4.07	4.04

Table B.5 (b) Actual/predicted values for $\%VO_{2max}$ & VO_{2max} for validation subjects

Sub	E(G)	Ln (E_G)	BSA	RHR	%VO_2 max (actual)	%VO_2 max (RWP)	%VO_2 max (A)	%VO_2 max (C)	VO_2 max (RWP)	VO_2 max (A)	VO_2 max (C)
52	9.79	2.28	1.97	0.77	0.56	0.59	0.59	0.59	4.73	4.75	4.69
53	9.58	2.26	2.00	0.73	0.57	0.59	0.56	0.57	4.11	4.30	4.24
54	4.86	1.58	1.99	0.80	0.60	0.48	0.55	0.56	5.17	4.49	4.39
55	7.15	1.97	1.72	0.81	0.67	0.54	0.59	0.58	2.17	1.99	2.02
56	12.41	2.52	1.63	0.73	0.57	0.63	0.58	0.57	2.47	2.66	2.74
57	5.54	1.71	2.05	0.85	0.57	0.50	0.59	0.61	4.96	4.17	4.05
58	10.64	2.36	2.04	0.84	0.61	0.60	0.64	0.65	3.95	3.73	3.64
59	6.04	1.80	1.71	0.77	0.61	0.51	0.55	0.54	3.31	3.10	3.15
60	5.30	1.67	1.93	0.83	0.60	0.49	0.57	0.58	3.93	3.36	3.30
62	8.27	2.11	2.39	0.83	0.61	0.56	0.61	0.65	5.10	4.67	4.39
65	6.68	1.90	1.75	0.71	0.61	0.53	0.52	0.51	3.07	3.12	3.17
66	12.70	2.54	1.96	0.85	0.60	0.63	0.66	0.67	3.48	3.32	3.28
67	4.08	1.40	2.07	0.86	0.64	0.45	0.57	0.59	4.16	3.28	3.16
68	12.08	2.49	1.88	0.75	0.57	0.62	0.59	0.59	3.12	3.28	3.28
69	10.30	2.33	1.86	0.75	0.54	0.60	0.58	0.58	3.20	3.30	3.30
71	5.90	1.77	1.58	0.84	0.61	0.51	0.59	0.58	1.81	1.55	1.59
72	10.82	2.38	1.80	0.74	0.55	0.60	0.58	0.57	3.08	3.23	3.26
74	5.68	1.74	2.00	0.65	0.54	0.50	0.47	0.47	4.15	4.48	4.40
76	6.00	1.79	1.93	0.65	0.57	0.51	0.47	0.48	4.66	5.03	4.99
78	4.05	1.40	1.74	0.76	0.57	0.45	0.51	0.50	3.45	3.04	3.07
83	4.78	1.57	1.78	0.77	0.61	0.47	0.53	0.53	3.51	3.15	3.17
85	10.65	2.37	1.92	0.72	0.58	0.60	0.56	0.56	3.82	4.10	4.08
86	3.15	1.15	2.11	0.74	0.62	0.41	0.47	0.50	6.60	5.68	5.43
88	12.93	2.56	2.04	0.68	0.67	0.63	0.55	0.56	2.72	3.12	3.07
89	4.17	1.43	1.96	0.78	0.58	0.45	0.52	0.53	4.27	3.70	3.62
90	4.07	1.40	2.07	0.76	0.56	0.45	0.51	0.53	6.40	5.66	5.47
91	4.42	1.49	2.13	0.67	0.56	0.46	0.46	0.48	5.47	5.47	5.25
94	7.59	2.03	2.11	0.75	0.55	0.55	0.56	0.57	4.17	4.11	3.98
95	3.50	1.25	1.73	0.89	0.51	0.42	0.58	0.58	3.98	2.93	2.93
96	5.85	1.77	1.69	0.84	0.56	0.51	0.59	0.58	3.19	2.75	2.78
97	4.44	1.49	1.88	0.89	0.53	0.46	0.60	0.61	4.59	3.54	3.49
98	4.74	1.56	1.85	0.82	0.56	0.47	0.56	0.57	4.23	3.56	3.53
100	8.82	2.18	1.91	0.73	0.55	0.57	0.56	0.56	3.76	3.87	3.85

Table B.5 (b) Actual/predicted values for %VO_{2max} & VO_{2max} for validation subjects (Continued)

#	%VO_2 max (actual)	RWP	A	C	J	VO_2 max (actual)	RWP	A	C	J
1	0.38	0.33	0.36	0.35	0.44	3.22	3.73	3.42	3.53	2.80
2	0.30	0.41	0.40	0.38	0.29	3.06	2.20	2.29	2.37	3.14
3	0.43	0.40	0.35	0.34	0.38	2.52	2.75	3.10	3.20	2.90
4	0.35	0.40	0.38	0.40	0.38	4.52	3.92	4.15	3.91	4.07
8	0.50	0.35	0.41	0.39	0.36	2.09	2.99	2.56	2.66	2.86
10	0.40	0.39	0.36	0.39	0.53	4.96	5.11	5.54	5.14	3.79
11	0.56	0.49	0.53	0.55	0.58	3.35	3.89	3.54	3.42	3.23
12	0.57	0.42	0.49	0.48	0.45	2.27	3.14	2.67	2.70	2.90
13	0.38	0.51	0.48	0.47	0.36	2.75	2.07	2.19	2.23	2.92
14	0.42	0.53	0.46	0.45	0.39	2.86	2.26	2.63	2.67	3.09
15	0.26	0.35	0.34	0.35	0.37	5.04	3.77	3.81	3.75	3.58
16	0.34	0.40	0.45	0.44	0.40	3.11	2.66	2.36	2.44	2.68
17	0.40	0.37	0.37	0.38	0.45	4.23	4.58	4.62	4.41	3.74
18	0.43	0.36	0.42	0.42	0.38	3.00	3.60	3.09	3.09	3.34
23	0.44	0.42	0.49	0.50	0.59	4.05	4.22	3.64	3.56	3.01
24	0.47	0.38	0.52	0.51	0.43	2.27	2.76	2.05	2.08	2.48
26	0.51	0.50	0.56	0.56	0.51	3.05	3.08	2.79	2.77	3.06
28	0.28	0.39	0.35	0.35	0.35	4.24	3.06	3.42	3.43	3.41
29	0.35	0.38	0.38	0.41	0.35	4.64	4.28	4.38	4.01	4.65
30	0.37	0.30	0.32	0.34	0.40	4.01	4.85	4.57	4.35	3.67
33	0.45	0.37	0.43	0.43	0.34	2.39	2.94	2.49	2.48	3.13
34	0.31	0.31	0.30	0.31	0.46	5.05	4.92	5.16	5.03	3.37
35	0.45	0.41	0.41	0.41	0.48	3.01	3.28	3.28	3.32	2.83
36	0.33	0.47	0.47	0.44	0.33	2.54	1.80	1.81	1.90	2.52
39	0.35	0.50	0.43	0.45	0.40	4.16	2.92	3.44	3.30	3.72
40	0.38	0.34	0.33	0.34	0.39	3.78	4.12	4.36	4.22	3.62
41	0.33	0.33	0.35	0.34	0.43	3.75	3.82	3.58	3.62	2.92
42	0.51	0.46	0.45	0.48	0.46	3.23	3.56	3.63	3.43	3.61
44	0.35	0.51	0.45	0.43	0.24	2.78	1.91	2.17	2.28	4.11
45	0.33	0.33	0.38	0.40	0.57	4.23	4.24	3.69	3.54	2.46
46	0.55	0.53	0.55	0.53	0.40	1.69	1.77	1.68	1.77	2.33

Table B.6 (a)[17] MSPR check and Jones' equation comparison on validation subjects

[17] Table B.6 (a) refers to the random exercise test and (b) refers to VO_2max test for all validation subjects.

#	$e_i^2(\%)$				e_i^2			
	RWP	A	C	J	RWP	A	C	J
1	0.00	0.00	0.00	0.00	0.26	0.04	0.10	0.18
2	0.01	0.01	0.01	0.00	0.75	0.59	0.47	0.01
3	0.00	0.01	0.01	0.00	0.05	0.34	0.47	0.14
4	0.00	0.00	0.00	0.00	0.37	0.14	0.37	0.20
8	0.02	0.01	0.01	0.02	0.81	0.22	0.32	0.59
10	0.00	0.00	0.00	0.02	0.02	0.33	0.03	1.37
11	0.01	0.00	0.00	0.00	0.29	0.03	0.00	0.01
12	0.02	0.01	0.01	0.01	0.76	0.16	0.19	0.40
13	0.02	0.01	0.01	0.00	0.47	0.31	0.27	0.03
14	0.01	0.00	0.00	0.00	0.37	0.05	0.04	0.05
15	0.01	0.01	0.01	0.01	1.62	1.51	1.67	2.13
16	0.00	0.01	0.01	0.00	0.21	0.57	0.45	0.18
17	0.00	0.00	0.00	0.00	0.12	0.16	0.03	0.24
18	0.01	0.00	0.00	0.00	0.36	0.01	0.01	0.12
23	0.00	0.00	0.00	0.02	0.03	0.17	0.24	1.07
24	0.01	0.00	0.00	0.00	0.24	0.05	0.04	0.05
26	0.00	0.00	0.00	0.00	0.00	0.07	0.08	0.00
28	0.01	0.01	0.00	0.01	1.40	0.68	0.66	0.69
29	0.00	0.00	0.00	0.00	0.13	0.07	0.40	0.00
30	0.00	0.00	0.00	0.00	0.70	0.32	0.11	0.11
33	0.01	0.00	0.00	0.01	0.30	0.01	0.01	0.54
34	0.00	0.00	0.00	0.02	0.02	0.01	0.00	2.82
35	0.00	0.00	0.00	0.00	0.07	0.07	0.10	0.03
36	0.02	0.02	0.01	0.00	0.55	0.54	0.41	0.00
39	0.02	0.01	0.01	0.00	1.53	0.52	0.75	0.20
40	0.00	0.00	0.00	0.00	0.12	0.33	0.19	0.03
41	0.00	0.00	0.00	0.01	0.01	0.03	0.02	0.68
42	0.00	0.00	0.00	0.00	0.11	0.16	0.04	0.15
44	0.03	0.01	0.01	0.01	0.76	0.38	0.25	1.76
45	0.00	0.00	0.00	0.06	0.00	0.29	0.48	3.12
46	0.00	0.00	0.00	0.02	0.01	0.00	0.01	0.42

Table B.6 (a) MSPR check and Jones' equation comparison on validation subjects (Continued)

#	%VO_2 max (actual)	RWP	A	C	J	VO_2 max (actual)	RWP	A	C	J
47	0.38	0.31	0.34	0.32	0.43	2.75	3.37	3.13	3.28	2.43
48	0.45	0.50	0.47	0.46	0.54	2.95	2.66	2.85	2.94	2.49
49	0.29	0.36	0.40	0.38	0.39	3.98	3.25	2.88	3.05	2.98
51	0.38	0.29	0.35	0.35	0.40	3.76	4.97	4.15	4.07	3.54
52	0.31	0.31	0.30	0.31	0.52	4.95	5.06	5.16	5.01	3.00
53	0.35	0.34	0.33	0.34	0.42	4.24	4.41	4.53	4.39	3.54
54	0.38	0.46	0.46	0.47	0.42	4.12	3.38	3.38	3.31	3.64
56	0.38	0.51	0.45	0.44	0.40	2.71	1.99	2.25	2.34	2.57
58	0.39	0.39	0.44	0.45	0.44	3.92	3.92	3.52	3.40	3.48
59	0.35	0.36	0.40	0.39	0.34	2.77	2.74	2.44	2.48	2.85
60	0.47	0.48	0.47	0.47	0.56	3.23	3.19	3.26	3.23	2.74
62	0.43	0.31	0.38	0.42	0.52	4.68	6.51	5.25	4.73	3.86
64	0.66	0.51	0.57	0.58	0.58	2.38	3.04	2.74	2.71	2.67
65	0.48	0.44	0.44	0.43	0.49	2.64	2.85	2.88	2.93	2.58
66	0.53	0.42	0.46	0.47	0.58	3.64	4.59	4.18	4.09	3.34
67	0.57	0.47	0.54	0.56	0.48	2.90	3.47	3.03	2.93	3.40
68	0.41	0.53	0.50	0.50	0.48	3.42	2.65	2.81	2.80	2.90
69	0.30	0.39	0.39	0.39	0.31	3.55	2.72	2.70	2.69	3.37
70	0.47	0.46	0.43	0.44	0.57	3.85	3.93	4.21	4.07	3.16
71	0.62	0.43	0.56	0.55	0.47	1.52	2.21	1.67	1.71	2.02
72	0.38	0.54	0.49	0.49	0.45	3.42	2.40	2.66	2.69	2.92
74	0.36	0.35	0.33	0.34	0.39	3.83	3.92	4.26	4.14	3.54
77	0.48	0.43	0.35	0.37	0.55	4.21	4.66	5.79	5.47	3.66
78	0.46	0.40	0.44	0.43	0.43	2.72	3.19	2.90	2.94	2.94
82	0.35	0.37	0.40	0.43	0.37	4.25	4.07	3.72	3.46	4.04
83	0.46	0.34	0.42	0.42	0.42	2.73	3.73	3.04	3.05	3.01
85	0.40	0.34	0.33	0.33	0.48	3.98	4.71	4.91	4.84	3.35
86	0.40	0.31	0.31	0.33	0.52	4.37	5.62	5.63	5.31	3.34
89	0.40	0.37	0.45	0.46	0.45	3.31	3.53	2.94	2.86	2.92
90	0.27	0.36	0.34	0.35	0.40	5.11	3.88	4.09	3.92	3.44
91	0.40	0.33	0.30	0.32	0.47	4.49	5.37	5.90	5.55	3.82
94	0.33	0.38	0.39	0.41	0.36	4.18	3.64	3.54	3.38	3.78
98	0.44	0.28	0.41	0.42	0.59	3.55	5.70	3.80	3.73	2.68
100	0.34	0.31	0.31	0.31	0.40	3.93	4.30	4.29	4.22	3.33

Table B.6 (a) MSPR check and Jones' equation comparison on validation subjects (continued)

#	e_i^2(%)				e_i^2			
	RWP	A	C	J	RWP	A	C	J
47	0.00	0.00	0.00	0.00	0.38	0.15	0.28	0.10
48	0.00	0.00	0.00	0.01	0.08	0.01	0.00	0.21
49	0.00	0.01	0.01	0.01	0.53	1.22	0.86	0.99
51	0.01	0.00	0.00	0.00	1.47	0.15	0.10	0.05
52	0.00	0.00	0.00	0.04	0.01	0.04	0.00	3.82
53	0.00	0.00	0.00	0.01	0.03	0.08	0.02	0.50
54	0.01	0.01	0.01	0.00	0.55	0.54	0.65	0.23
56	0.02	0.01	0.00	0.00	0.51	0.21	0.14	0.02
58	0.00	0.00	0.00	0.00	0.00	0.16	0.27	0.20
59	0.00	0.00	0.00	0.00	0.00	0.11	0.08	0.01
60	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.24
62	0.02	0.00	0.00	0.01	3.33	0.33	0.00	0.68
64	0.02	0.01	0.01	0.01	0.44	0.13	0.11	0.09
65	0.00	0.00	0.00	0.00	0.04	0.06	0.08	0.00
66	0.01	0.00	0.00	0.00	0.90	0.29	0.20	0.09
67	0.01	0.00	0.00	0.01	0.33	0.02	0.00	0.25
68	0.01	0.01	0.01	0.01	0.59	0.37	0.38	0.27
69	0.01	0.01	0.01	0.00	0.68	0.73	0.74	0.03
70	0.00	0.00	0.00	0.01	0.01	0.13	0.05	0.47
71	0.04	0.00	0.00	0.02	0.47	0.02	0.04	0.25
72	0.03	0.01	0.01	0.00	1.04	0.59	0.54	0.25
74	0.00	0.00	0.00	0.00	0.01	0.19	0.10	0.08
77	0.00	0.02	0.01	0.01	0.20	2.49	1.58	0.30
78	0.00	0.00	0.00	0.00	0.22	0.03	0.05	0.05
82	0.00	0.00	0.01	0.00	0.03	0.28	0.63	0.05
83	0.01	0.00	0.00	0.00	0.99	0.10	0.10	0.08
85	0.00	0.01	0.00	0.01	0.53	0.86	0.74	0.40
86	0.01	0.01	0.01	0.01	1.55	1.59	0.88	1.06
89	0.00	0.00	0.00	0.00	0.05	0.14	0.20	0.15
90	0.01	0.00	0.01	0.02	1.52	1.04	1.41	2.79
91	0.00	0.01	0.01	0.00	0.77	1.98	1.13	0.45
94	0.00	0.00	0.01	0.00	0.29	0.41	0.64	0.16
98	0.03	0.00	0.00	0.02	4.61	0.06	0.03	0.76
100	0.00	0.00	0.00	0.00	0.13	0.13	0.09	0.36

Table B.6 (a) MSPR check and Jones' equation comparison on validation subjects (continued)

#	$\%VO_2$ max (actual)	RWP	A	C	J	VO_2 max (actual)	RWP	A	C	J
2	0.53	0.40	0.46	0.45	0.52	3.06	4.08	3.53	3.61	3.14
4	0.57	0.61	0.59	0.61	0.64	4.52	4.29	4.43	4.27	4.07
5	0.49	0.40	0.44	0.45	0.49	3.52	4.31	3.89	3.84	3.54
8	0.61	0.46	0.52	0.51	0.44	2.09	2.74	2.41	2.49	2.86
10	0.56	0.55	0.55	0.58	0.74	4.96	5.07	5.09	4.84	3.79
11	0.58	0.52	0.54	0.56	0.60	3.35	3.75	3.61	3.50	3.23
12	0.64	0.55	0.54	0.54	0.50	2.27	2.64	2.67	2.72	2.90
14	0.57	0.63	0.53	0.52	0.53	2.86	2.59	3.12	3.17	3.09
15	0.51	0.54	0.56	0.57	0.72	5.04	4.78	4.60	4.55	3.58
16	0.54	0.57	0.62	0.61	0.62	3.11	2.94	2.68	2.75	2.68
17	0.60	0.50	0.56	0.58	0.67	4.23	5.02	4.46	4.31	3.74
18	0.58	0.49	0.56	0.56	0.52	3.00	3.52	3.11	3.10	3.34
23	0.57	0.51	0.56	0.57	0.77	4.05	4.60	4.15	4.08	3.01
25	0.54	0.53	0.60	0.60	0.69	4.07	4.15	3.67	3.68	3.19
26	0.57	0.49	0.54	0.54	0.57	3.05	3.59	3.25	3.23	3.06
27	0.50	0.53	0.59	0.59	0.61	4.02	3.81	3.42	3.42	3.31
28	0.51	0.48	0.50	0.51	0.63	4.24	4.44	4.27	4.25	3.41
29	0.56	0.56	0.54	0.58	0.55	4.64	4.63	4.73	4.45	4.65
30	0.59	0.63	0.60	0.62	0.64	4.01	3.76	3.91	3.82	3.67
31	0.54	0.61	0.56	0.55	0.73	4.32	3.82	4.17	4.18	3.17
33	0.61	0.52	0.53	0.52	0.46	2.39	2.77	2.76	2.77	3.13
34	0.55	0.48	0.49	0.50	0.82	5.05	5.78	5.62	5.53	3.37
35	0.64	0.50	0.55	0.54	0.68	3.01	3.85	3.52	3.54	2.83
36	0.50	0.49	0.51	0.49	0.50	2.54	2.59	2.48	2.59	2.52
39	0.55	0.48	0.49	0.51	0.62	4.16	4.76	4.67	4.47	3.72
40	0.54	0.53	0.49	0.50	0.56	3.78	3.85	4.14	4.06	3.62
41	0.56	0.53	0.52	0.52	0.72	3.75	3.99	4.03	4.08	2.92
42	0.63	0.63	0.56	0.59	0.56	3.23	3.25	3.62	3.48	3.61
44	0.52	0.52	0.52	0.50	0.55	2.78	2.74	2.77	2.88	2.59
46	0.66	0.63	0.62	0.59	0.47	1.69	1.77	1.80	1.88	2.33
48	0.56	0.55	0.51	0.49	0.66	2.95	3.03	3.27	3.37	2.49
49	0.53	0.53	0.56	0.54	0.70	3.98	3.99	3.74	3.91	2.98
50	0.45	0.49	0.50	0.49	0.83	5.93	5.45	5.36	5.40	3.19
51	0.59	0.53	0.54	0.55	0.62	3.76	4.15	4.07	4.04	3.54

Table B.6 (b) MSPR check and Jones' equation comparison on validation subjects

	$e_i^2(\%)$				e_i^2			
#	RWP	A	C	J	RWP	A	C	J
2	0.02	0.00	0.01	0.00	1.05	0.22	0.31	0.01
4	0.00	0.00	0.00	0.00	0.05	0.01	0.06	0.20
5	0.01	0.00	0.00	0.00	0.62	0.14	0.10	0.00
8	0.02	0.01	0.01	0.03	0.43	0.10	0.16	0.59
10	0.00	0.00	0.00	0.03	0.01	0.02	0.01	1.37
11	0.00	0.00	0.00	0.00	0.16	0.07	0.02	0.01
12	0.01	0.01	0.01	0.02	0.14	0.16	0.20	0.40
14	0.00	0.00	0.00	0.00	0.07	0.07	0.10	0.05
15	0.00	0.00	0.00	0.04	0.07	0.19	0.24	2.13
16	0.00	0.01	0.00	0.01	0.03	0.18	0.13	0.18
17	0.01	0.00	0.00	0.01	0.63	0.05	0.01	0.24
18	0.01	0.00	0.00	0.00	0.28	0.01	0.01	0.12
23	0.00	0.00	0.00	0.04	0.30	0.01	0.00	1.07
25	0.00	0.00	0.00	0.02	0.01	0.16	0.15	0.77
26	0.01	0.00	0.00	0.00	0.30	0.04	0.03	0.00
27	0.00	0.01	0.01	0.01	0.04	0.36	0.35	0.50
28	0.00	0.00	0.00	0.01	0.04	0.00	0.00	0.69
29	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.00
30	0.00	0.00	0.00	0.00	0.06	0.01	0.04	0.11
31	0.00	0.00	0.00	0.04	0.25	0.02	0.02	1.32
33	0.01	0.01	0.01	0.02	0.14	0.14	0.15	0.54
34	0.00	0.00	0.00	0.08	0.54	0.32	0.23	2.82
35	0.02	0.01	0.01	0.00	0.70	0.26	0.28	0.03
36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
39	0.00	0.00	0.00	0.00	0.36	0.26	0.09	0.20
40	0.00	0.00	0.00	0.00	0.00	0.13	0.08	0.03
41	0.00	0.00	0.00	0.03	0.06	0.08	0.11	0.68
42	0.00	0.00	0.00	0.00	0.00	0.16	0.06	0.15
44	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04
46	0.00	0.00	0.00	0.03	0.01	0.01	0.04	0.42
48	0.00	0.00	0.00	0.01	0.01	0.10	0.18	0.21
49	0.00	0.00	0.00	0.03	0.00	0.06	0.01	0.99
50	0.00	0.00	0.00	0.15	0.23	0.32	0.28	7.49
51	0.00	0.00	0.00	0.00	0.15	0.10	0.08	0.05

Table B.6 (b) MSPR check and Jones' equation comparison on validation subjects (continued)

#	%VO_2 max (actual)	RWP	A	C	J	VO_2 max (actual)	RWP	A	C	J
52	0.56	0.59	0.59	0.59	0.93	4.95	4.73	4.75	4.69	3.00
53	0.57	0.59	0.56	0.57	0.68	4.24	4.11	4.30	4.24	3.54
55	0.67	0.54	0.59	0.58	0.43	1.74	2.17	1.99	2.02	2.75
56	0.57	0.63	0.58	0.57	0.60	2.71	2.47	2.66	2.74	2.57
57	0.57	0.50	0.59	0.61	0.68	4.31	4.96	4.17	4.05	3.62
58	0.61	0.60	0.64	0.65	0.68	3.92	3.95	3.73	3.64	3.48
59	0.61	0.51	0.55	0.54	0.59	2.77	3.31	3.10	3.15	2.85
60	0.60	0.49	0.57	0.58	0.70	3.23	3.93	3.36	3.30	2.74
62	0.61	0.56	0.61	0.65	0.74	4.68	5.10	4.67	4.39	3.86
65	0.61	0.53	0.52	0.51	0.63	2.64	3.07	3.12	3.17	2.58
66	0.60	0.63	0.66	0.67	0.66	3.64	3.48	3.32	3.28	3.34
67	0.64	0.45	0.57	0.59	0.55	2.90	4.16	3.28	3.16	3.40
68	0.57	0.62	0.59	0.59	0.67	3.42	3.12	3.28	3.28	2.90
69	0.54	0.60	0.58	0.58	0.57	3.55	3.20	3.30	3.30	3.37
71	0.61	0.51	0.59	0.58	0.45	1.52	1.81	1.55	1.59	2.02
72	0.55	0.60	0.58	0.57	0.64	3.42	3.08	3.23	3.26	2.92
74	0.54	0.50	0.47	0.47	0.59	3.83	4.15	4.48	4.40	3.54
76	0.57	0.51	0.47	0.48	0.71	4.19	4.66	5.03	4.99	3.36
78	0.57	0.45	0.51	0.50	0.53	2.72	3.45	3.04	3.07	2.94
83	0.61	0.47	0.53	0.53	0.55	2.73	3.51	3.15	3.17	3.01
85	0.58	0.60	0.56	0.56	0.69	3.98	3.82	4.10	4.08	3.35
86	0.62	0.41	0.47	0.50	0.81	4.37	6.60	5.68	5.43	3.34
88	0.67	0.63	0.55	0.56	0.51	2.58	2.72	3.12	3.07	3.38
89	0.58	0.45	0.52	0.53	0.66	3.31	4.27	3.70	3.62	2.92
90	0.56	0.45	0.51	0.53	0.84	5.11	6.40	5.66	5.47	3.44
91	0.56	0.46	0.46	0.48	0.66	4.49	5.47	5.47	5.25	3.82
94	0.55	0.55	0.56	0.57	0.60	4.18	4.17	4.11	3.98	3.78
95	0.51	0.42	0.58	0.58	0.70	3.33	3.98	2.93	2.93	2.42
96	0.56	0.51	0.59	0.58	0.56	2.89	3.19	2.75	2.78	2.90
97	0.53	0.46	0.60	0.61	0.63	3.97	4.59	3.54	3.49	3.36
98	0.56	0.47	0.56	0.57	0.75	3.55	4.23	3.56	3.53	2.68
100	0.55	0.57	0.56	0.56	0.65	3.93	3.76	3.87	3.85	3.33

Table B.6 (b) MSPR check and Jones' equation comparison on validation subjects (continued)

#	e_i^2(%)				e_i^2			
	RWP	A	C	J	RWP	A	C	J
52	0.00	0.00	0.00	0.14	0.05	0.04	0.07	3.82
53	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.50
54	0.02	0.00	0.00	0.01	1.11	0.14	0.07	0.23
55	0.02	0.01	0.01	0.06	0.19	0.06	0.08	1.02
56	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.02
57	0.01	0.00	0.00	0.01	0.43	0.02	0.07	0.48
58	0.00	0.00	0.00	0.01	0.00	0.04	0.08	0.20
59	0.01	0.00	0.01	0.00	0.29	0.11	0.15	0.01
60	0.01	0.00	0.00	0.01	0.49	0.02	0.01	0.24
62	0.00	0.00	0.00	0.02	0.18	0.00	0.09	0.68
65	0.01	0.01	0.01	0.00	0.19	0.23	0.28	0.00
66	0.00	0.00	0.00	0.00	0.03	0.10	0.13	0.09
67	0.04	0.01	0.00	0.01	1.59	0.15	0.07	0.25
68	0.00	0.00	0.00	0.01	0.09	0.02	0.02	0.27
69	0.00	0.00	0.00	0.00	0.13	0.06	0.06	0.03
71	0.01	0.00	0.00	0.02	0.09	0.00	0.01	0.25
72	0.00	0.00	0.00	0.01	0.11	0.04	0.03	0.25
74	0.00	0.01	0.00	0.00	0.11	0.42	0.32	0.08
76	0.00	0.01	0.01	0.02	0.22	0.71	0.65	0.68
78	0.01	0.00	0.00	0.00	0.54	0.10	0.12	0.05
83	0.02	0.01	0.01	0.00	0.61	0.18	0.19	0.08
85	0.00	0.00	0.00	0.01	0.03	0.01	0.01	0.40
86	0.05	0.02	0.02	0.03	4.97	1.71	1.13	1.06
88	0.00	0.01	0.01	0.03	0.02	0.29	0.24	0.63
89	0.02	0.00	0.00	0.01	0.92	0.15	0.10	0.15
90	0.01	0.00	0.00	0.08	1.67	0.31	0.13	2.79
91	0.01	0.01	0.01	0.01	0.95	0.96	0.57	0.45
94	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.16
95	0.01	0.00	0.00	0.03	0.42	0.16	0.16	0.83
96	0.00	0.00	0.00	0.00	0.09	0.02	0.01	0.00
97	0.00	0.00	0.01	0.01	0.38	0.19	0.23	0.37
98	0.01	0.00	0.00	0.04	0.46	0.00	0.00	0.76
100	0.00	0.00	0.00	0.01	0.03	0.00	0.01	0.36
Σ	0.91	0.49	0.46	1.71	57.90	32.81	28.96	73.36
MSRP	0.69%	0.37%	0.35%	1.30%	0.44	0.25	0.22	0.56

Table B.6 (b) MSPR check and Jones' equation comparison on validation subjects (continued)

BIBLIOGRAPHY

Abdelhamid, T. S. (1999). *Measuring and Evaluating Physiological Demands of Construction Work.* Ph.D. Dissertation, University of Michigan, Ann Arbor, Michigan.

Abdelhamid, T. S., Patel, B., Howell, G. A., and Mitropoulos, P. (2003). "Signal detection theory: enabling work near the edge." *Proceedings of the 11th Annual Conference for Lean Construction,* 22-24 July 2003, Blacksburg, Virginia, 243-256.

Abdelhamid, T. S. and Everett, J. G. (2002). "Physiological demands during construction work." *Journal of Construction Engineering and Management*, ASCE, 128(5), 427-437.

Adams, G. M. (1998). *Exercise Physiology Laboratory Manual.* Boston, MA: The McGraw-Hill Companies. Inc., 147

Anderson, T. W. (1971). *The Statistical Analysis of Time Series.* Wiley, New York.

Aquilano, N. J. (1968). *Work Physiology: A physiological Evaluation of Time Standards and Work-Rest Design for Moderate to Strenuous Work.* Ph. D. Dissertation. The University of California, Los Angeles, California.

American College of Sports Medicine (1982). "Position statement on the use of alcohol in sport." *Med. Sci.Sports Exerc.* 14:ix-x.

American College of Sports Medicine (1995). *Guidelines for Exercise Testing and Prescription. (5th ed.)* Baltimore, Williams and Wilkins.

Aminoff, T., Smolander, J., Korhonen, O. and Louhevaara, V. (1998). "Prediction of acceptable physical work loads based on responses to prolonged arm and leg exercise." *Ergonomics.* 41,109-120.

Astorino Todd A., Robergs Robert A., Ghiasvand Farzaneh, Marks Derek and Burns Steve. "Incidence of the oxygen plateau at VO_{2max} during exercise testing to volitional fatigue." *JEPonline,* 3(4): 1-12, 2000.

Astrand, P.-O., and I. Ryhming (1954). "A nomogram for calculation of aerobic capacity (physical fitness) from pulse rate during submaximal work." *J. Appl. Physiol.*, 7, 218-221

Astrand, I. (1960). "Aerobic work capacity in men and women with special reference to age." *Acta Physiol Scand.* 1960; 49 (Suppl 169): 1-92

Astrand, I. (1967). " Degree of strain during building work as related to individual aerobic work capacity." *Ergonomics*, 1967 Vol. 10 No. 3, 293-303

Astrand, P. and Rodahl, K. (2003). *Textbook of Work Physiology, Physiological Bases of Exercise.* McGraw-Hill, New York.

Bassett, D. R. Jr. and Howley, E. T. (2000). "Limiting factors for maximum oxygen uptake and determinants of endurance performance." *Med. Sci. Sports Exerc.,* Vol. 32, No.1. 70-84,2000

Bink, B. (1962). "The physical working capacity in relation to working time and age." *Ergonomics.* 5, 25-28.

Bonjer, F. H. (1971). "Temporal factors and physiological load." *Measurement of Man at Work* (Editors: Singleton, W. T., Fox, J. G., and Whitfield, D. W., Taylor and Francis, London).

Bot, S. D. M. and Hollander, A. P. (2000). "The relationship between heart rate and oxygen uptake during non-steady state exercise." *Ergonomics* 2000 Vol. 43, No.10 1578-1592.

Brockwell, P. J. and Davis, R. A. (1996). *Introduction to Time Series and Forecasting.* Springer-Verlag, New York.

Brouha, L. (1967). *Physiology in Industry.* Pergamon Press, New York.

Brody, S. (1945). *Bioenergetics and Growth, with Special Reference to the Efficiency Complex in Domestic Animals.* (New York: Reinhold)

Bryant, Cedric X. and Peterson, James A. (1997). "The science of aerobic fitness need not be difficult to understand, and it can help both trainers and exercisers make workout decisions." *Fitness Management Magazine*, Los Angeles, Calif. Vol. 13, No. 9, pp.26-28, 30.

Chung, Min K., Inseok Lee and Yeo, Yoon S. (1999). "Physiological workload evaluation of screw driving tasks in automobile assembly jobs." *International Journal of Industrial Ergonomics* 28(2001) 181-188

Cooper, K. H. (1968). *Aerobics*. M. Evans and Company, New York.

Davies, C. T. M. (1968). "Limitations to the prediction of maximum oxygen intake from cardiac frequency measurements." *J. Appl. Physiol.*, 24, 700-706.

Everett, J. G. and Saito, H. (1996). "Construction Automation: Demands and Satisfiers in the United States and Japan." *Journal of Construction Engineering and Management*. Vol. 122, No. 2, pp. 147-151.

Fox, E. L. (1973). "A simple, accurate technique for predicting maximal aerobic power." *J. Appl. Physiol.*, 35, 914-916.

Glassford, R. G., Baycroft, G. H. Y., Sedgwick, A. W. and Macnab, R. B. J. (1965). "Comparison of maximal oxygen uptake values determined by predicted and actual methods." *J. Appl. Physiol.*, 20, 509-514.

George J. D., Stone W. J. and Burkett L.N. (1997). "Non-exercise VO_{2max} estimation for physically active college students." *Med Sci Sports Exerc.* 1997 Mar; 29(3):415-23.

Hanson, J.A. and Jones, E.P. (1970). Heart rate and small postural changes in man. *Ergonomics* 13:483-487.

Hansson, J. E. (1965). "The relationship between individual characteristics of the worker and output of work in logging operations." *Studia Forestalia Suecica* No. 29. Stockholm. 90 p.

Hermiston, R. T. and Faulkner, J. A. (1971). "Prediction of maximal oxygen uptake by a stepwise regression technique." *J. Appl. Physiol.*, 30, 833-837.

Ilmarinen, J. (1992) "Job design for the aged with regard to the decline in their maximal Aerobic capacity: Part I-Guidelines for the practitioner." *International Journal of Industrial Ergonomics*, 10, 53-63.

Janaro, R. E. (1982). *The Development and Implementation of Optimal Multi-rest Break Scheduling Models*, Ph. D. Dissertation, Florida State University, Florida.

Jessup, G. T., Tolston H. and Terry, J. W. (1974). "Prediction of maximal oxygen intake from Astrand-Rhyming test, 12 minute run and anthropometric variables using stepwise multiple regression." *Am. J. Phys. Med.*, 53, 200-207.

Jones, N. L., Makrides, L., Hitchcock, C., Chypchar, T. and McCartney, N. (1985). "Normal standard for an incremental progressive cycle ergometer test." *Am. Rev. Rspri. Dis.*,131, 700-708.

Jorgensen, K. (1985). "Permissible loads based on energy expenditure measurements." *Ergonomics*, 28(1), 365-369.

Juurup, A., and Murido, L. (1946). "On acute effects of cigarette smoking on oxygen consumption, pulse rate, breathing rate and blood pressure in working organisms." *Acta Physiol. Scand.* 11:48.

Kamon, E. (1979). "Scheduling cycles of work for hot ambient conditions." *Ergonomics*, 22(4), 427-439.

Kalsbeek, J. W. (1971). "Sinus arrhythmia and the dual task method in measuring mental Load." *In Measurement of Man at Work, an Appraisal of Physiological and Psychological Criteria in Man-Machine System.* (Editors: Singleton, W. T., Fox, J. G., and Whitfield, D. W.) (Taylor and Francis, London).

Kline, G. M., Porcari, J. P. and Hintermeister, R. (1987). "Estimation of VO_{2max} from a one-mile track walk, gender, age, and body weight." *Medical Science and Sports Exercise*, 19, 253.

Krantz, L. (2000). *The jobs rated almanac.* Pharos Books, New York.

Lear, S. A., Brozic A., Myers, J. N. and Ignaszewski, A. (1999). "Exercise stress testing: an overview of current guidelines." *Sports Medicine*, 27, 285-312.

Lehmann, G. (1962). *Praktische Arbeitsphysiologie*, 2nd ed. (Stuttgart: Thieme);quoted in Andersen, L. *et al.* 1971, *Fundamentals of Exercise Testing* (Geneva: WHO), 115.

Lynn A. Darby and Roberta L. Pohlman. (1999). "Prediction of max VO_2 for women: Adaptation of the Fox cycle ergometer protocol." *Journal of Exercises Physiology*, 2.

Maas, S., Kok, M. L., Westra, H.G. and Kemper, H. C. (1989). "The validity of the use of heart rate in estimating oxygen consumption in static and in combined static/dynamic exercise." *Ergonomics*, 32, 141.

Mastropaolo, J. A. (1970). "Prediction of maximal O_2 consumption in middle-aged men by multiple regression." *Med. Sci. Sports*, 2, 124-127.

McArdle, W. D., et al. (1971). "Aerobic capacity, heart rate, and estimated energy cost during women's competitive basketball." *Research Quarterly*, 42, 178.

McArdle, W. D., Katch, F. I. and Katch, V. L. (1996). *Exercise Physiology*. Williams & Wilkins, Baltimore.

McDonough, P. and Moffatt, R. J. (1999). "Smoking-induced elevation in blood carboxyhaemoglobin levels: effect on maximal oxygen uptake." *Sports Med.* 27: 275-283.

Michael. E. D., Hutton, K.E. and Horvath, S. M. (1961). "Cardio respiratory responses during prolonged exercise." *Journal of Applied Physiology*, 16.197

Mosteller (1987). "Simplified calculation of body-surface area in metric terms." *New England Journal of Medicine*.

Muller, E. A. (1950). "Ein Leistungs-Pulsindex als MaB Der Leistungsfhigkeit." *Arbeitphysiologie*, Vol. 14 pp 271-284,1950

Oglesby, C. H., Parker, H. W. and Howell, G. A. (1989). *Productivity Improvement in Construction*. McGraw-Hill, New York.

Pandit, S. M., and Wu, S. M. (1993). *Time Series and Systems Analysis with Applications*. Krieger, Malabar, Florida.

Poulsen, E. and Asmussen, E. (1962). "Energy requirements of practical jobs from pulse increase and ergometer test." *Ergonomics*, 5(1), 33-36

Rodahl, K., Vokac, Z., Fugelli, P., Vaage, O., and Maehlum, S. (1974). "Circulatory strain, estimated energy output and catecholamine excretion in Norwegian coastal fishermen." *Ergonomics*. 17, 585-602.

Rohmert, W. (1973). "Problems of determination of rest allowances; Part 2: Determining rest allowances in different human tasks." *Applied Ergonomics*, Vol. 4, No. 3, 158-162.

Rowell, J. S., Taylor, H. L. and Wang, Y. (1964). "Limitations to prediction of maximal oxygen intake." *J. Appl. Physiol.*, 19, 919-927.

Saha, P. N., Datta, S. R., Banerjee, P. K. and Narayane, G. (1979). "An acceptable workload for Indian workers." *Ergonomics*, 22, 1059-1071.

Shephard, R. J. (1977). *Endurance Fitness*. University of Toronto Press, Toronto.

Storer, T. W., Davis, J. A. and Caiozzo, V. J. (1990). "Accurate prediction of VO_{2max} in cycle ergometry." *Med. Sci. Sports Exerc.*, 22, 704-712

Tomlinson, R. W., and Manenica I. (1977). "A study of physiological and work study indices of forestry work." *Applied Ergonomics*, Vol. 8, no. 3, 165-172.

Verma S. S., Sen Gupta J. and Malhotra M.S. (1977). "Prediction of maximal aerobic power in man." *Eur. J. Appl. Physiol.*, 36, 15-222.

Verma, S. S., Bharadwaj, H. and Malhotra, M. S. (1980). "Prediction of maximal aerobic power in healthy Indian males from anthropometric measurements." *Z. Morphol. Anthropol.*, 71, 101-106.

Verma, S. S. (1994). "Prediction of maximal aerobic power in man: a monographic approach." *Ergonomics*, 37(9), 1491-1494.

Viljanen, A. (1982) "Reference values for spirometric, pulmonary diffusing capacity and body plethysmographic studies." *Scand, J. Clin, Lab. Inv. 42* (suppl. 159)

Von Dobeln, W., Astrand, I. and Bergstrom, A. (1967). "An analysis of age and other factors related to maximum oxygen uptake." *J. App. Physiol.*, 22, 934-938.

Wahren, J. E., Jequier, L. Acheson and Y. Schutz. (1983). "Influence of cigarette smoking on body oxygen consumption." *Clin. Phys.* 3:91.

Womack, C. J., Hyman, B. A. and Gardner, A. W. (1998) "Prediction of peak oxygen consumption in patients with intermittent claudication." *Angiology, the Journal of Vascular Disease* Aug 1998 Volume 49 No. 8 *s*

Wilmore, J. H. (1979). "The application of science to sport: physiological profiles of male and female athletes." *Can. J. Appl. Sport Sci.* 4:103-115.

Wyndham, C. H., Strydom, N. B., Morrison, J. F., Williams, C. G, Bredell, G., Peter, J., Cooke, H. M. and Joffe, A. (1962). "The influence of gross body weight on oxygen consumption and on physical working capacity of manual laborers." *Ergonomics*, 5(3), 267-286