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Integration Of Cognitive And Physical Factors To Model Human Performance In Fluid Power Systems

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INTEGRATION OF COGNITIVE AND PHYSICAL FACTORS
TO MODEL HUMAN PERFORMANCE
IN FLUID POWER SYSTEMS

by

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ABSTRACT

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Fluid power technology is constantly evolving as a result of the interaction between the human and the system. Systems such as the hydraulic excavator utilize this technology in order to deliver safe, efficient, and effective performance. However, traditional research has placed much emphasis on technical performance rather than on human components. Imbalances of this nature demonstrate inadequate understanding, lack of knowledge, and limited research on the factors affecting performance. This research aims to address these shortcomings by using an integrated approach to better model human performance in fluid power systems.

Through the development of an integrative framework considering cognitive and physical components, procedures were developed to facilitate the integration of various performance factors and simulation tools. An empirical study was performed using a case study in fluid power to demonstrate the viability of an integrated human performance model. From those studies, control was found to have a significant effect on workload and the environment on completion time. In addition, a significant difference in workload was found between non-integrated and integrated models. Future work should concentrate on further utilization of the framework with newly enhanced simulation tools that offer a range of capabilities to fully model its defined parameters.

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BIOGRAPHICAL SKETCH

Khaliah K. Hughes was born on February 21, 1985, in Burlington, North Carolina. Graduating Summa Cum Laude, with highest honor, she received a Bachelor of Science degree in Industrial Engineering from North Carolina Agricultural and Technical State University in May 2007. Immediately following, she entered the direct track Ph.D. program at her alma mater in the fall of the same year. She is a member of Alpha Pi Mu Industrial Engineering Honor Society, the Human Factors and Ergonomics Society (HFES), and the Institute of Industrial Engineers (IIE). During her tenure as a graduate student, she has worked as a research assistant for the National Science Foundation (NSF) Center for Compact and Efficient Fluid Power (CCEFP) and as a usability intern at SAS Institute in research and development for the Department of Business Intelligence Clients (BIC) in the Client User Interface (CUI) group. In 2010, she received the Department of Industrial and Systems Engineering Outstanding Researcher Award for her work in human factors and the Wadaran L. Kennedy 4.0 Scholar Award from the School of Graduate Studies for her academic excellence. Her research has been published in the Journal of Human Factors and Ergonomics in Manufacturing and Service Industries as well as in conference proceedings for the Industrial Engineering Research Conference (IERC), the Applied Ergonomics Conference (AEC), and the Symposium on Human Interaction with Complex Systems (HICS). She is a candidate for the Ph.D. in Industrial and Systems Engineering. Upon completion, she will be the first female candidate to complete the direct track Ph.D. program.

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EG	Electronic Control-Gravel Terrain
ES	Electronic Control-Soil Terrain
HG	Hydraulic Control-Gravel Terrain
HS	Hydraulic Control-Soil Terrain
HPM	Human Performance Modeling
HPMs	Human Performance Models
iHPMs	Integrated Human Performance Models
IPME	Integrated Human Performance Modeling Environment
e, f, r	Physical performance variables, i.e. energy, fatigue, and recovery
E_h , E_s	Effort exerted, i.e. human and system
fE_h	Effort exerted (E_h) subject to physical fatigue *(f)*
M_T, O_T, S_T	Performance tasks, i.e. movement, operational, and system
T_a, T_n	Recovery time variables, i.e. available and needed
W_K, iW_K	Workload estimates, i.e. non-integrated and integrated

CHAPTER 1

INTRODUCTION

1.1 Background

Fluid power technology has been used primarily in larger machinery, providing power in the form of hydraulics (i.e. liquids) and pneumatics (i.e. gasses) since the 1940's (Maskrey & Thayer, 1978). Being one of the three major types of control-transfer, this technology is most often used in systems where the fluid properties are pressurized and exploited to generate, transmit, and control power. With this technology, power is transferred from a prime mover or source to an actuator to complete required work tasks, allowing systems to operate with increased power, flexibility, and performance capability (Hutter, 2009). Thus, fluid power systems have become fundamental in many domains based on their versatility in a wide range of consumer and industrial applications.

One such system is the hydraulic excavator (Figure 1.1). Its primary components consist of a pivoting cab, rotary tracks, extendable arm, and a retractable bucket. High pressure forces fluid through hoses and tubes to control the machine's motor and hydraulic components such as the boom, cylinders, swing, and track-drive. Each of these hydraulic components is managed through operator controls which regulate system statics and dynamics. Furthermore, hydraulic excavators are available in various sizes, ranging from compact to large scale. They have also been used in a variety of industries such as transportation and manufacturing where they are favored for their cost, precision, and safety (Rowe, 1999). These systems are most recognized in the construction industry where they are often referred to as diggers or backhoes, denoting their most common work application (e.g. excavation or digging processes). However, they can also be specialized with tooling attachments for applications such as material handling, demolition, and heavy lifting (Boyanovsky, 2005).

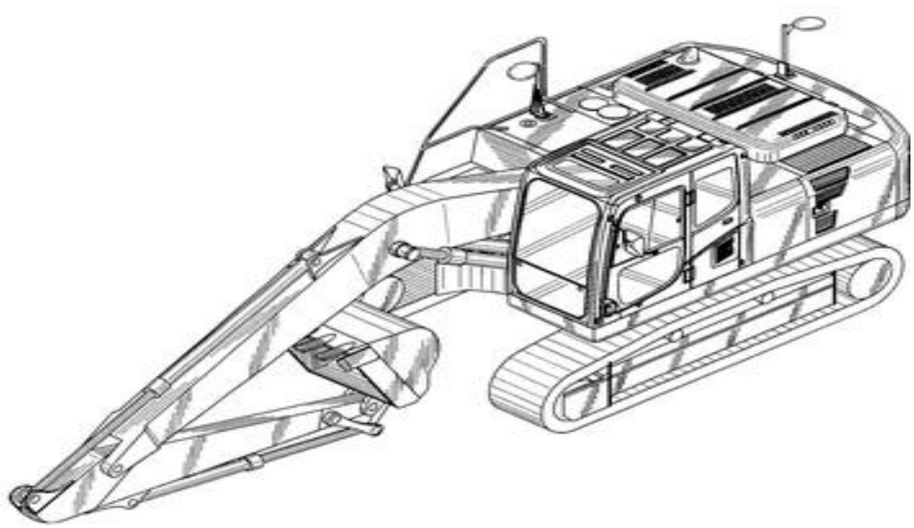

Figure 1.1. Modern Hydraulic Excavator System (Yanagida, 2007).

Over the years, fluid power systems have progressively advanced in order to meet the constant demand for new technology that accomplishes work tasks more easily, efficiently, and economically (Barrow-Williams, 2006). Therefore, with regard to these demands and the increased appeal of this technology, emergent hydraulic excavators are becoming more advanced and complex than ever before. In modern designs, manufacturers have begun producing excavator systems that retain many of the basic functions of their predecessors, yet incorporate new innovative features that provide increased safety, efficiency, and comfort to the human operator (Boyanovsky, 2005;

Carter, 2008). Some important improvements to excavator design include: engine performance for faster hydraulics, better operator interfaces, as well as an ergonomically redesigned cab (Singh, 1997).

Excavators, more importantly, have evolved in technical design, transitioning from hydraulic to electronic control (Figure 1.2). These systems are generally controlled by a human operator who executes sequential and organized operations to reach desired performance goals (Torres-Rodriguez et. al, 2004). In most systems, hydraulic control, which is also referred to as manual or iso-control, remains the standard operating mechanism. With this design, controls consist of manual joysticks and floor-mounted levers. Each joystick controller offers six degrees of freedom in a quadrant design known as the H-pattern. This pattern allows operators to control the system through horizontal (i.e. left and right), vertical (i.e. forward and backward), or diagonal movements. Levers in the front of the cab allow operators to move and position the excavator at various locations. Hydraulic control patterns not only offer simplicity, but also provide a high level of feedback to the operator.

With newly implemented electronic control, which is also referred to as servo or selectable joystick control, operators are given the option of using dual control patterns (Johnson, 2006). The primary difference between these and the traditional hydraulic controllers is that operators can switch from the traditional H-pattern control to a sub-control pattern of functional joystick buttons. Like hydraulic systems, when the traditional control pattern is selected, the system is controlled by horizontal, vertical, and diagonal joystick movements. In contrast, when the electronic control pattern is selected, joystick buttons control the system's mechanical movements as well as engine dynamics such as horsepower and speed. Electronic control mechanisms are thought to be more comfortable and less fatiguing to the human operator over long periods of time (Berndtson, 2007).

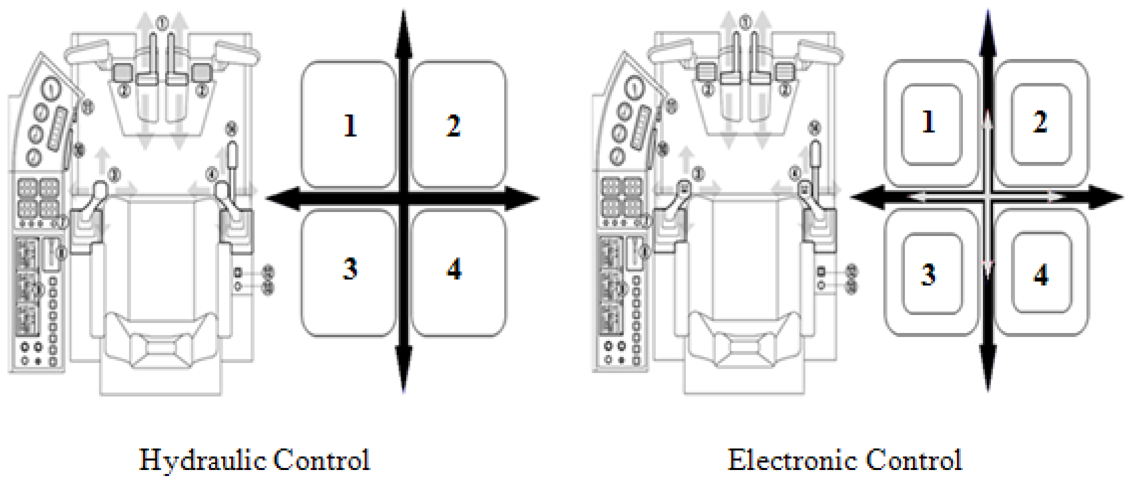

Figure 1.2. Excavator System Designs and Control Patterns (Hitachi, 2004).

In addition to control, various electro-hydraulic tooling attachments have also been added to excavators to offer versatility in work applications and for adaptability in multiple tasks. These improvements have led to hydraulic excavators becoming one of the most useful tools in the construction industry, yielding in higher productivity and decreased costs (Singh, 1997). The introduction of such improvements now allow excavator operators to alternate between control patterns to best suit their particular operation style and job type (Boyanovsky, 2005; Zubko, 2007).

1.2 Problem Statement

Despite advantages, many of these advancements have perpetuated existing problems and have also led to new difficulties concerning performance and design. Fluid power issues such as high pressure, friction, containment, and constant movement continue to present issues with control, leaks, and losses of efficiency within these systems. In addition, these systems are still manually operated by a human operator, requiring excessive amounts of energy, intense task concentration, and high skill level. Complex interactions between the operator and the system due to these requirements can lead to errors and misunderstandings (Rowe, 1999). Therefore, operators of fluid power systems must not only be aware of the system and how it operates, but also of its performance limitations. Aforementioned, excavators have evolved in technical design, transitioning from hydraulic to electronic control. These mechanisms are perceived to be more comfortable, less fatiguing, and allow operators to select control patterns based on personal preference, operation style, and job type (Boyanovsky, 2005; Zubko, 2007). Such changes, however, have brought about criticism from operators who prefer the original operating mechanism (e.g. hydraulic control) due to a lack of feedback in the electronic controllers. This lack of feedback gives operators a remote sense of the actual work environment, making decision processes more complex.

These and other matters have begun to compel researchers to investigate design changes and their impact on performance. With a wide variety of modeling tools available, efforts have yielded insights not only on human performance, but also on task efficiency, workload, and job re-design as well. Many of these models, however, are limited in applicability due to the complexities of human performance. Not only have many existing performance models and research efforts placed inappropriate concentration on technical performance, but they have also failed to recognize the various factors contributing to human performance. Specifically, the majority of models rely on either cognitive or physical performance alone; when in fact, both areas interact to produce human behavior. Shortcomings and oversights in this aspect have led to research gaps and inaccurate performance models which cause designs not to perform as expected in the real world. As a result, research credibility and model accuracy is lost. In spite of this issue, there is a lack of effort among researchers to integrate both cognitive and physical performance. Until issues of this nature are addressed in current and future research, shortcomings of human performance models will continue to perpetuate. Therefore, immense concentration and efforts are needed in this area in order to truly enhance the quality of predictive human performance models.

1.3 Motivation

Since system performance depends on the machine and the operator, the effectiveness of design advancements need to be investigated in order to better understand human-machine interaction. Human performance modeling provides a means to simulate these design changes and to evaluate their impact on the human operator without developing costly prototypes. Specifically, human performance is defined by its ability to perceive, plan, and carry out tasks or sub-tasks in response to the demands of the environment (Chapparo & Ranka, 1996). Models of human performance act as representations that simulate aspects of performance in real world systems. Modeling approaches can be either data-driven to predict human behavior, or cognitive architectures to simulate mental processes (Campbell & Bowers, 2000). Human performance models have been used in disciplines such as psychology and medicine, as well as engineering. These models have also attempted to integrate the human as well as the system in the design process, optimize or show deviation from normal models, and predict future outcomes (Feyen, 2007). Although these studies recognize the importance of human performance, most have placed an inappropriate amount of concentration on technical performance rather than on human components (Laughery, 1998). This imbalance is attributed to by the difficultly of modeling the complexity and variability of human behavior.

Imbalances of this nature have resulted in less understanding of the factors which shape performance, a lack of significant knowledge, and limited research on interaction. More importantly, few studies concentrate on evaluating the human performance in fluid power systems such as the hydraulic excavator. Within these studies, there is a notable absence of research pertaining to the significance of design changes on system operation and the human operator. Such limitations in human performance models have led to gaps between real and anticipated performance, designs not performing as expected, and overestimation of efficiency (Baines et al., 2005). This is particularly true in the area of fluid power systems which are constantly evolving in design, placing new demands on human operators.

By studying human performance with fluid power systems such as the hydraulic excavator, there is the potential to gain insight on interaction, investigate the limitations of human performance, and better support the needs of operators (Laughery, 1998). Therefore, in order to better understand how tasks are accomplished with fluid power systems, modeling tools can be used to simulate performance under various conditions. Simulating human performance provides a way to overcome the limitations of past studies, fill the void of research on interaction with hydraulic excavators, and evaluate the impact of system design changes. In many research studies, simulation technology has been used to focus on the fundamental principles of modeling, to accurately represent systems, and to evaluate designs in complex settings. Although, this technology was initially used to improve the performance of various processes, a recent rise in competitiveness and costs has led to an increased awareness of its value in evaluating system complexities such as process definition, redesign, workload, and safety (Bloechle & Schunk, 2003). Through continual use and development, it can also be used to address new varieties of problems concerning complex human behavior, yielding in better decisions, decreased costs, and increased efficiency.

Over the years, the scope of problems addressed through human performance modeling has increased. Now, it can not only be used to simulate the inconsistencies of system performance, but also to address issues and provide solutions on complex human decision making (Bloechle & Schunk, 2003). Human performance modeling can help to ensure that problems associated with human performance are clearly identified and resolved during the design process before implementation. With fluid power systems such as the hydraulic excavator, modeling will enable the ability to determine operator performance in emergent system designs, eliminating the need for expensive mockups.

More importantly, it provides an opportunity for the development of better models which more accurately depict human performance. For instance, when simulation tools are used to independently assess components of performance; gaps are left in models, creating significant deviations from true performance with human-machine systems in real world settings. However, the flexibility offered in most simulation software allows for new approaches wherein predictive models can be developed based on the environment, system, and the human's cognitive and physical functioning.

1.4 Research Objectives

The aim of this research is to develop an integrated human performance model for a hydraulic excavator to better understand the interactions that occur in typical work processes. Simulation models are used to incorporate additional aspects of human performance by taking into consideration both cognitive and physical factors. Objectives concentrate on three primary areas: the creation of a theoretical framework, an empirical study on human performance, and an integrated human performance model.

The theoretical framework in this research acts as a set of procedures for better models of human performance to be developed. Specific goals with regard to this objective are to:

- Develop a set of procedures to accurately model human performance
- Describe the internal and external mechanisms that create performance

- Identify key performance metrics to consider when modeling performance
- Extract and correlate performance variables through various modeling tools
- Create a schema to facilitate an integrated model representation

The empirical study assesses both current and future issues with human performance in existing and emergent fluid power systems. Associated goals of this research objective are to:

- Provide descriptions of critical tasks during routine excavation processes
- Investigate the effects of various factors on human performance
- Assess the degree of workload experienced by the human operator
- Identify usability and ergonomic issues with excavator system designs
- Propose recommendations for improvements in emergent systems

Lastly, the integrated human performance model attempts to expand beyond the realm of past approaches and overcome modeling deficiencies to bridge the gaps in traditional research. The goals of this objective are to:

- Create an integrated performance model with multiple modeling tools
- Acknowledge the variety of interactions that produce human behaviors
- Represent various components contributing to human performance
- Identify the relationship between cognitive and physical performance
- Examine the benefits of integrated versus traditional performance models

1.5 Dissertation Organization

The following chapters describe the development and implementation of integrated models to assess human performance with fluid power systems. This dissertation is divided into nine chapters.

Chapter 1 provides a brief overview of the background, problem, motivation, and objectives to be addressed in this dissertation. Subsections of the chapter serve to describe the current challenges, contributions, and potential outcomes of the research.

Chapter 2 provides a literature review, giving insight on human performance modeling with fluid power systems and the techniques that have been utilized by researchers in past studies. It discusses the fundamentals of modeling and modeling approaches. Such techniques are described and compared in terms of their strengths and limitations when modeling human performance. Examples of simulation software, along with a description of modeling capabilities are also provided.

Chapters 3 and 4 describe the research methodology for the development of an integrated human performance model. Chapter 3 presents methods for the theoretical modeling framework, integrating both cognitive and physical aspects of human performance. Procedures presented in the framework and their potential uses are identified to enhance human performance models with complex human-machine systems. Chapter 4 concentrates on procedures for an empirical study to facilitate the integration of human performance models as described in the prior chapter.

Chapter 5 presents the integrated human performance modeling framework. The integrated framework describes the modeling approach and required parameters for the creation of integrated human performance models. Its structure and the purpose of its components are described along with examples for implementation. Chapter 6 expands upon that framework and presents a case study in the fluid power domain to demonstrate a viable application for the integrative framework.

Chapter 7 presents results derived from the creation of an integrated human performance model with respect to cognitive and physical factors. Model results detail data (i.e. numerical and graphical) from cognitive, physical, and integrated performance models based on simulated output from various human-system configurations. Empirical results convey the significance of multiple independent variables on human performance.

Chapter 8 discusses implications of those results. It describes in detail, the value of the integrated framework and the correlation between cognitive and physical performance. Results from cognitive and physical performance models are examined both independently and collectively. Areas of divergence and concurrency between both models are used to discuss implications on human performance, the distribution of workload, and equipment design in existing and emergent fluid power systems.

Lastly, Chapter 9 provides a conclusive summary of the research presented in this dissertation, as well as potential areas for future work to extend the addressed topic. It demonstrates the contribution of using such an approach to investigate human performance by identifying the benefits of the developed framework and showing the limitations of existing performance modeling approaches. Examples of its potential use, further validate the framework which provides a foundation for the development of better human performance models.

CHAPTER 2

LITERATURE REVIEW

2.1 Hydraulic Excavators in Fluid Power Industry

In a variety of industries, fluid power is recognized for its extensive flexibility in a diverse range of work applications. In both of its forms, hydraulics and pneumatics, the technology is particularly favored for its effectiveness in decreasing costs as well as improving precision and safety (Rowe, 1999). A prime example of this technology is the excavator, one of the many forms of hydraulic machinery. Such systems utilize fluid power technology to control the system's motor and cylinders (Ding, Qian, & Pan, 2000). The principal functions of these systems are digging (i.e. material removal), ground leveling, and material transportation operations; however, with custom tooling, they can also be used in a variety of other applications, making work processes more manageable for the human operator (Torres-Rodriguez, Parra-Vega, & Ruiz-Sanchez, 2004; Boyanovsky, 2005).

2.1.1 Evolution of Fluid Power Systems

Despite use in a variety of applications, the basic structure of excavator systems are highly similar. The machines normally include a transmission system, crane, and an attachment with functional hydraulics (Kappi, 2000). Its exterior consists of mechanical components such as a pivoting cab, rotary tracks, extendable arm, and a retractable bucket. Its main hydraulics are the boom, cylinders, swing, and track-drive (Ding et al., 2000). Excavators are primarily operated via series of manual controls consisting of buttons, joysticks, pedals, and levers located on the interior of the cab. Push button controls allow the operator to activate power, monitor the system, and adjust additional settings; whereas, levers and pedals allow the operator to move the excavator to the desired location and to control action of the hydraulic tooling attachment. Most important of the system's controls are the joysticks which are located on each side of the operator's chair. These controls direct work performance through horizontal rotation and vertical motion of the system's hydraulic components.

2.1.2 Emergent Systems and Design Changes

With fluid power systems, there have been relatively few industry changes that have caused the need for significant design or process modifications (Kappi, 2000). Hydraulic hardware, however, has advanced tremendously in recent years, evolving from hydro-mechanic to electro-hydraulic mechanisms (Elton, Enes, & Book, 2009). The development of these new technologies have caused radical changes in the role of the human operator; a role which has shifted from monitoring and control in traditional systems to supervision in newer more automated systems. Although such systems were manufactured as early as the 1940s, their current design was not produced until the 1960s. Modern system designs maintain many of the primary functions of their predecessors, yet incorporate additional features that improve both human and system performance (Boyanovsky, 2005; Carter 1996). Such improvements have focused on faster performance, intuitive interfaces, and better aesthetics (Singh, 1997). Most significant of these changes are those with regard to the excavator's technical design, transforming traditional control mechanisms. Majority of past systems use hydraulic control as its primary operating mechanism. With this design, the system is controlled via manual joysticks and levers. The joystick controllers offer six degrees of freedom used for the translation of the machine and dynamics of its mechanical components. Since motion control is often complex and non-intuitive, this control pattern is particularly favored by many excavator operators because of its simplicity and quality of feedback (Torres-Rodriguez et al., 2004).

In contrast, newer electronic control systems offer dual control patterns that can be utilized based on the operator's preference, operation style, or job type (Boyanovsky, 2005; Zubko, 2007). Like hydraulic systems, the newer systems can be controlled by linear joystick movements; however, these systems can also be controlled by functional buttons embedded in the joystick controls which are believed to make work processes more comfortable and less fatiguing to the operator over long periods of time. Electronic controllers provide the opportunity to improve performance and enhance traditional hydraulic systems with new mechanisms that improve energy efficiency, enhance operator control, and increase productivity (Elton et al., 2009). Such advancements, however, often result in a tradeoff with system complexity, particularly in the area of system controls and interface design which impacts the human operator.

2.1.3 Hydraulic Excavator Operator Performance

Human performance has a significant impact on overall system performance. With regard to fluid power, the human operator is the most critical and complex component when determining the operational effectiveness of the system. Human operators manage and provide much of the information processing capability (i.e. cognitive performance); whereas, the excavator system itself contributes to physical performance. For instance, tasks of a hydraulic excavator operator usually involve receiving information, decision making, and control actions. In this process, operators receive information by sensing the environment, followed by making decisions based on the obtained information or prior knowledge. These decisions are then translated into cognitive or physical actions. Such processes vary among different operators; therefore, it is essential to understand the human factors that contribute to and affect performance in complex systems.

Despite many advantages, improvements in hydraulic excavator systems have perpetuated existing problems and have led to difficulties in terms of human performance. The productivity of the human operator is often determined by the qualities such as the level of system automation or design (Al-Masalha, 2004). In addition to past issues such as high pressure, friction, and control, operators are now faced with new systems that require excessive amounts of energy, intense task concentration, and high skill level. These requirements cause complex interactions between the operator and the system, imposing new cognitive demands (Nikolova, Valentin, & ColMircho, 1993).

Studies have shown evidence that operators need additional information to support tasks (Corker, 1999).

This need has occurred due to intellectual demands such as observation, attention, and memory, versus the physical abilities of the human operator (Miroljub et al., 2004). Such abilities vary among operators due to a host of individual factors ranging from age and gender to training and expertise. Operator skills can diverge immensely on simple tasks as well as complex procedures (Fisher, 2008). For instance, with an unskilled operator, it can be a difficult and time consuming to learn process and to master the skills necessary for efficient excavator system operations. Operator training is required in order to gain the necessary experience and the ability to understand the correlation between movement of the excavator and control of its joysticks. Therefore, newer less skilled operators encounter more difficulties with performance than proficient excavator operators having more experience (Kim et al., 2009).

These circumstances have caused many research, design, engineering, and user communities to recognize the importance and need to consider the human as a component during design (Laughery, 1999). Human performance modeling provides a timely and economically feasible method of assessment. Providing realistic models of operator performance in fluid power systems, however, presents numerous technical challenges. Both work processes and the environment change considerably according to the operator's training or skills as well as environmental conditions such as the temperature or terrain (Kappi, 2000). Furthermore, new control mechanisms and hydraulic components are highly nonlinear and difficult to model (Elton et al., 2009). In order to address such demands, sophisticated human performance modeling techniques must be applied to accurately and efficiently model human performance with fluid power systems (Fisher, 2008).

2.2 Human Performance Modeling (HPM)

Models are representations of complex phenomena that depict how components of a system function are coordinated to achieve desired outcomes to reduce, complexity, enhance understanding, and minimize assumptions (Chaffin, Anderson, & Martin, 2006). Models are defined as representations of systems embodied by words, pictures, or numbers. Generally, models are used to communicate how aspects of the human-machine system deviate from normal models or to predict future outcomes (Chapparo & Ranka, 1996). In contrast, human performance refers to “the effectiveness or skill to accomplish goals through operations associated with human behavior” (Hockey, 1997, p.77).

2.2.1 Definition of HPMs

Models of human performance in complex systems serve to predict performance by identifying deficiencies in the human-machine system under various scenarios and to make assumptions about the underlying process of human behavior (Corker, 1999). The key differentiator between a model and a human performance model is a representation of a system that simulates some aspect of human performance within a limited domain. Representations of human performance models can range from a simple written equation or mathematical statement to a complex computer simulation. Such models are beneficial when used as a precursor to design which aids in a better understanding of the concept, design, use, strengths or weaknesses, performance effectiveness, and costs of proposed systems (Allender, 2000).

Over the years, human performance models have rapidly advanced in order to better predict and model human behavior (Campbell & Bowers 2000). These improvements have been made possible due to simulation models that more accurately approximate performance data within acceptable limits, allowing researchers to consider human performance-related risks on system performance. Output from human performance models come in many forms such as workload predictions and task timelines which can be found throughout a diverse range of disciplines such as psychology, cognitive science, engineering, artificial intelligence, computer science, biomechanics, physiology, and medicine (Gore & Smith, 2006; Feyen 2007).

2.2.2 Types of HPMs

Human performance models have been thought by researchers to involve two categories: reductionist models and first principle models. Reductionist models are characterized by their ability to reduce high level aspects of human-system behavior into smaller elements so that realistic predictions of human performance can be made. In contrast, first principle models describe the manner in which the system and environment interact with human processes; however, the primary difference between both performance models lies within their organization. Reductionist models use the human-system task sequence as its organizing structure to describe human behavior; whereas, first principle models are organized by a framework representing the underlying performance goals such as behavior, perception, or cognition (Laughery, 1998).

Other studies also classify human performance models in two categories, predictive models and process models. Predictive models attempt to assess performance before implementation in real world scenarios. Similarly, process models also predict performance; however, these models concentrate on representing specific human processes used to accomplish the task. Predictive models are beneficial because they accurately model performance without requiring extensive validation data as compared to process models which are applicable to a wider range of tasks and conditions (Feyen, 2007).

2.2.3 HPM Approaches

In order to evaluate human performance, it must be done systematically. Therefore, researchers have used a variety of modeling approaches to fully capture its dynamics and predict performance at the appropriate level of detail.

2.2.3.1 Qualitative and quantitative approach. Such approaches are both qualitative and quantitative, having a distinct purpose for modeling a unique aspect of performance (Bender, 2006). For instance, "data-driven approaches predict human behavior through recognition, decision making, and temporal planning; whereas, the task network modeling approach describes steps associated with human performance via flow diagrams" (Campbell & Bowers, 2000, p.1). The computational approach, describes representations of users which allow designers to simulate responses to various scenarios and design options based on task analyses which arrange data on human perception and cognition into sets of behavioral guides. These guides reduce the amount of psychological and methodological knowledge required to build models, allowing researchers to focus on the task rather than psychological theory and modeling methodology (Vera, Remington, Matessa, & Freed, 2001). The task network modeling approach has also been described as a subset of the computational approach because it defines sub-models of the human-machine system, making tasks more efficient and eliminating factors that reduce desired performance (Nickols, 2006).

2.2.3.2 Physical approach. Although a variety of approaches to human performance modeling exist, there are two general categories which as classified as either cognitive or physical based on the chosen modeling parameters. The physical approach to human performance modeling focuses on developing methods that enable researchers to specify, design, control, and build models of systems or objects. Unlike other modeling approaches, the physical approach is based on physical properties and their motion which is governed by the laws of physics (e.g. Newton's second law of motion). In general, physically-based modeling involves distinct steps such as mathematical modeling, rendering, and animation (Barzel, 1992). This approach enables models to produce realistic motion through dynamic simulation which incorporates physical characteristics to model create lifelike human behavior (Funge & Tu, 1999).

Physical models use calculations to model entities based on their representations, providing results in real-time 3D graphical form. These models are facilitated through mathematical representations of the simulated system as well as its environment wherein behaviors are defined according to the physical laws of statics and dynamics. For example, a physically-based model can describe the parts and components of the simulated system and determine system behavior based on mathematical algorithms. It can also include representations of physical objects that impact performance or interact with the system being modeled (Al-Masalha, 2004).

In recent years, the physical human performance modeling approach has become more realistic by describing motion that is subject to objects, forces, and constraints; hence, making the models perform as they would in real world environments (Skolnick, 1990; Beliveau, Dixit, & Dale, 1993; Park, 2002). These advantages can be summarized by the following:

- Facilitates the creation of realistic human motion models
- Adds additional levels of representation to modeled objects
- Uses geometry, forces, and other physical quantities to control models
- Models entity responses to one another and the simulated environment

Such models have renowned capabilities when predicting human performance from physiological aspects; however, the approach neglects the biological context of behavior that is necessary to adequately account for the variability of human performance under various conditions (Hockey, 1997).

2.2.3.3 Cognitive approach. Unlike physical approaches, which are reactive, cognitive approaches to human performance modeling are deliberative (Cacciabue, Decortis, Drozdowicz, Masson, & Nordvik, 1992). Cognitive approaches (Figure 2.1) model human performance according to the nature of behavioral processes by focusing on internal or mental representations and operations rather than on environmental elements (Kokinov, 1999). Such approaches attempt to extend beyond the realm of physical performance by modeling cognitive functions (e.g. working memory and human knowledge) as well as other inferential processes such as decision making (Funge & Tu, 1999; Parasuraman, Sheridan, & Wickens, 2000). The approach typically regards human performance as a set of condition-action rules that gather perceptual knowledge, perform cognitive functions, and issue motor commands. Its most important advantage is that it incorporates the capabilities and limitations of human cognition and performance, making models more psychologically plausible (Salvucci & Lee, 2003).

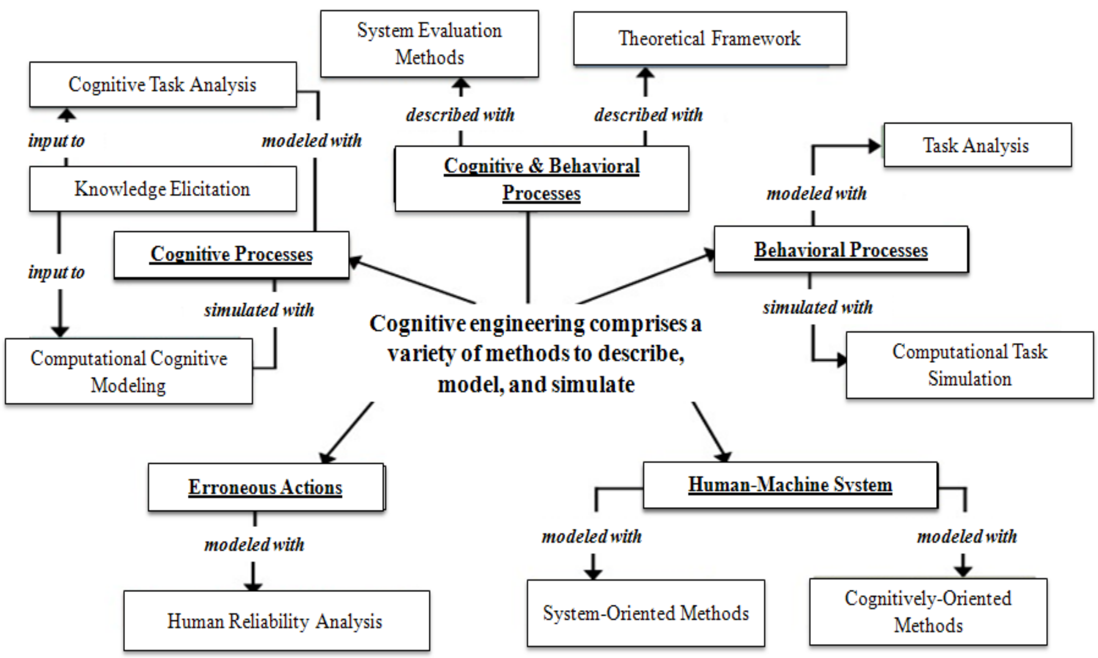

Figure 2.1. Cognitive Methods for Human Performance Modeling (MITRE, 2010).

With regard to cognitive approaches, a number of sub-models have also been developed such as the Goals, Operators, Methods, and Selection Rules (GOMS) and its variants: Keystroke Level Modeling (KLM), Cognitive Perceptual Model (CPM), Card, Moran, and Newell (CMN), as well as Natural GOMS Language (NGOMSL). Each model has a specific purpose in terms of human performance; however, each approach focuses on quantitative predictions of human behavior and cognitive processes associated with system design and evaluation (Gore & Smith, 2006; Wu & Liu, 2007). The GOMS modeling approach and its variants are popular for representing cognitive behavior, enabling researchers to successfully predict user behavior through efficient testing and evaluation. For instance, KLM-GOMS provides a simple method for describing expert behavior as linear sequence of steps. Such simplicity has proven benefits in the evaluation of interface designs and tasks. Such use demonstrates both the theoretical and practical benefits of cognitive modeling for human-machine interaction. Although the GOMS modeling approaches facilitate rapid model development, they are limited by their inability to model detailed user behavior (i.e. expert behavior) and yield little value with lower-level user behavior (Salvucci & Lee, 2003).

Since many new technological systems are highly autonomous, cognitive modeling approaches play a critical role in assessing human performance. In order to ensure that human performance models appropriately predict human reactions to environmental stimuli, cognitive approaches must incorporate a variety of other constructs to bring together contemporary approaches along with traditional approaches to modeling performance (Hockey, 1997; Funge & Tu, 1999). Over the years, there have been many theoretical advances in cognitive approaches, causing it to emerge as a useful tool in the development of real world systems and in understanding human interaction and behavior (Salvucci & Lee, 2003). A prime example is its ability to identify and model cognitive functions (i.e. information seeking, pattern recognition, monitoring, planning, and action) that are performed by an operator in complex work environments (Cacciabue et al., 1992). However, as cognitive models become increasingly complex, there is a growing need to develop new approaches to truly depict the nature of human performance.

2.3 Human Performance Assessment

Human performance modeling approaches are accomplished through simulation, one of the most effective means for assessing performance (Hale, 2004). Simulation technology has been one of the most effective means for implementing the prior approaches and assessing human performance. Since the 1960's, it has been used by industrial engineers to focus on the underlying principles of modeling, accurately represent systems, and evaluate designs in complex settings. Over this period, simulation has also been a cost effective way to demonstrate cost efficient alternatives. However, rising costs and competitiveness have led to increased awareness of the value of simulation in evaluating such alternatives (Drury & Laughery, 1994).

2.3.1 Simulation

The appeal of simulating human performance in complex systems has also increased because it extends representations of the human-machine system, allowing for the prediction of system dynamics (Laughery, 1999). Advantages of simulating human performance include: the ability to evaluate designs before prototype development, to test multiple designs with a reduction in time and experimentation, and to predict system performance under extreme conditions that are undesirable for human subjects (Campbell & Bowers 2000; Wu & Liu, 2007). This is typically achieved since simulation models embed both human characteristics in the form of statistical distributions derived from collected real world data, which allow for predictions regarding performance to be made based on emergent behavior (Gore, 2002). Each of these aspects allows simulation models to imitate human performance by analyzing interactions among the human, the system, and the environment (Feyen, 2007).

2.3.2 Tools

A variety of simulation tools can be used to accurately model performance. Such tools have proven much value in accurately modeling human performance. Early modeling tools were developed for the purpose of predicting human operator performance efficiently (Laughery, 1998). Over the years, however, tools for modeling human performance have tremendously evolved and can now be effectively integrated into the systems engineering process to support early analysis and design (Laughery, 1999). With these tools, simulation can be applied to a wide variety of problems to decrease costs and increase efficiency, yielding in better decision making, savings, and productivity.

2.3.2.1 Micro saint. A modeling tool introduced in 1985, Micro Saint allows many types of complex systems to be modeled via the task network approach. In this software, task network models are represented by nodes and arrows which depict a sequence of activities. Models created in the software have the potential to vary from simple to complex (Drury & Laughery, 1994). Its key principle, however, is the task network model which extends task analyses into predictive models of human activity. Micro Saint can be used to illustrate, predict, evaluate, and describe humans, equipment, and environment interactions of the system. In the software, a library of micro models calculate various times for general classes of cognitive, perceptual, and psychomotor activities. These models have been derived from sources such as human factors literature, established data sources, and other models. Furthermore, the software has been used to address issues such as manning, performance prediction, and the probability of system failures (Laughery, 1998).

When developing models in Micro Saint, two steps are involved, defining the structure of the task network and defining the objects within that network according to human and system activities. To create a model, a network diagram must be constructed. These networks are composed of tasks which have connotations of human activity performed by humans, processes, or machines. In the network, tasks represent the lowest level and hold modeling elements such as timing information, conditions for execution, and task properties. To reflect complex task behavior and interrelationships, information to describe the behavior of the task must also be provided (Laughery, 1999). Task times are represented by statistical distributions and the task time taken for execution. Task sequencing is controlled through multiple paths and decision types. Probabilistic decision types execute tasks based on the likelihood of the task, multiple decision types execute non-zero task values, and tactical decision types execute according to the highest task value. Variables are based upon the information that the user desires to obtain from the model. More importantly, variables hold the potential to dynamically change various aspects of the simulation. Completed simulation models can be viewed via the network diagram or the animator when executed. In the network diagram view, the model shows as a flow chart; whereas, in animator view, the model shows a visual representation of the process.

With new software improvements, the scope of the problems applied to Micro Saint has increased and is now being used in industries such as manufacturing, healthcare, retail, government, and human factors. In these sectors it is used to evaluate and improve efficiency in terms of task definition, quality control, process redesign, workload, safety, and productivity. This efficient and cost effective tool for simulating the complexities of systems has proven itself to be effective in addressing problems and providing solutions on queuing, resource utilization, and complex human decision making (Bloechle & Schunk, 2003).

2.3.2.2 Jack. Jack software is a physical human performance modeling tool which builds models that improve ergonomic design and work tasks. Using this software allows designers to evaluate the physical aspects of behavior and to improve human performance while overcoming constraints such as time, capital, and safety (Kaufthal, 1996). Within the software, specific capabilities of Jack allow users to build and place a biomechanically accurate digital human in a virtual environment where tasks are assigned. In the environment, the digital human can mimic physical motions and operations with real world accuracy, and users can evaluate simulated human performance (Demirel & Duffy, 2007). Application of this software has the potential to yield in increased efficiency and profitability through better design, improved safety, and ergonomics (Burnette, 1998).

2.3.2.3 iGEN, MIDAS, and CSEES. In addition to Micro Saint and Jack, several other modeling tools have been developed: iGEN, Man-Machine Integrated Design and Analysis System (MIDAS), and Cognitive Systems Engineering Educational Software (CSEES). Each tool has specific features which can be used to address human performance. A modeling tool based on cognitive task analysis, iGEN concentrates on analyzing operational effectiveness. It is also useful in evaluating the effectiveness of interfaces in decision making. A prime example of its application is in military or battle space domains where human operators make critical decisions based on the use of system interfaces. MIDAS, another tool, offers an architecture of physical component agents and human operator agents. This software focuses on modeling and predicting human error. It is particularly effective in the aviation domain. CSEES is an integrated modeling tool that models and evaluates programs related to human judgment and decision making. It has been proven to be useful in modeling judgment tasks, decision making, signal detection, and rule-based navigation (Wu & Liu, 2007).

2.4 Shortcomings of HPMs

Human performance models that predict interaction in complex systems have shortcomings in their development and application (Corker, 1999). "Many models have been found to lack flexibility, realism, and struggle to model human behavior" (Wellbrink, Zyda, & Hiles, 2004, p.29). In particular, there have been problems with modeling performance with construction machinery such as the hydraulic excavator. Simulating these systems present a challenge for researchers due to the dynamic behavior of their hydraulic, electronic, and mechanical subsystems. Review of literature indicated three shortcomings of past research models: limited research with regard to human performance in fluid power systems such as hydraulic excavator, emphasis on system performance rather than on human performance, and a lack of knowledge on the interaction between cognitive and physical factors contributing to human performance.

For instance in 2004, Park and Lim noted that "knowledge of coupled dynamics is crucial in the design of hydraulic systems and that simulation of excavators can allow the researcher to gain insight on the effects of design on operator comfort (p.1)." In this study, a simulation model was created for the combined mechanical and hydraulic dynamics of an excavator. Two tools, Advanced Dynamic Analysis of Mechanical Systems (ADAMS) and Matlab-Simulink software, were chosen to model the mechanical and hydraulic dynamics respectively. Experiments were performed under two conditions: moving the boom slowly and moving the boom quickly with a sudden stop. Results indicated that the simulation environment had reasonable accuracy and was a highly applicable technique to solve dynamics-related real world problems such as hydraulic system design, structural design, and ride quality.

In 2002, Zhang and Prasetiawan investigated the application of control techniques to a earthmoving vehicle's powertrain. The main objective of the study was to design a speed tracking controller for the system with a robust power source to loading condition disturbances. A dynamic model was developed for the earthmover's powertrain, built from a subsystem of component models which were assigned nominal operating conditions. Models were validated by quantitative and qualitative comparisons made between the model and the excavator vehicle's powertrain system, which was designed to have a structure similar to the real world system. Results of the study indicated that the speed tracking controller had better nominal performance and robust performance than the original controller in terms of quicker response, wider tracking range, and better disturbance rejection.

Filla, Ericsson, and Palmberg (2005) focused on the development of an operator model and a description of the working task, to draw conclusions about a machine's total performance, efficiency, and operability. This research was accomplished through a simulation model of a human operator which describes the machine's working cycle. The working task described how the simulated machine operated in its environment; whereas; the operator model described machine control to accomplish the working task. Although this research seemingly incorporates the human operator, its underlying purpose was to evaluate the potential fuel efficiency of virtual prototypes with regard to bucket filling. Results for the simulation indicated that operator inputs for engine throttle, lift, and tilt functions as well as the power distribution to hydraulics, drive train, and the engine load affected both performance and fuel efficiency. In closing, the author noted that it could be beneficial to utilize the results of existing research into mental workload of the operator's control efforts.

Simulation has also been used to make projections based on adaptive control to approximate the nonlinear gain coefficient of the valve. Objectives aimed to address system dynamics, parameters, uncertainties, and external disturbance. Boom motion control experiments were also performed to demonstrate feasibility. System controllers were modeled to analyze controller designs and to experimentally validate new control schemes. The research resulted in new control design methodologies applicable to hydraulic systems requiring high control performance (He et al., 2006).

In another study, Bundy, Chlosta, and Gutkowski (2002) concentrated on optimum excavator bucket positioning. This study was motivated by processing times, operator effort, and automation. The objective related to the minimum time needed for the bucket to travel from an initial position. Studies consisted of modeling arm torque, bucket trajectories, and travel time. Results, showed a relationship between torque and time as well as significant differences between torque time relations for various trajectories.

Such models often overlook human representations of the system despite the fact that system performance is determined by the performance of the human operator. By many researchers, this is believed to be caused by the difficulty in creating models with the same level of fidelity and predictability as in the real world (Laughery, 1999).

Although the literature pertains to hydraulic excavator systems, they clearly emphasize technical performance such as mechanics, drive train, hydraulics, and control of the system, rather than human performance. As a result, researchers often produce superficial assessments of performance that only reflect the surface of the entire system. Such assessments strongly limit human performance models because system performance can not accurately be gauged without proper consideration of the human operator.

Beyond the overwhelming number of models which concentrate on technical performance, there has been some research performed on fluid power systems such as the hydraulic excavator that do concentrate on operator performance. For example in 1999, Laughery described the use of task network modeling in simulation to reflect complex task behavior and interrelationships of task information in human behavior. Two case studies were used to address various applications on human performance. The first study concentrated on operator responses. Modeled tasks were dependent on comparative readings which determined subsequent tasks performed by the operator. In the second study, the authors concentrated on determining the number of operators for systems to effectively operate. However, this model evaluated the number of necessary operators by the summation the attentional demands across simultaneous tasks.

Another study investigated autonomous control fluid power systems based on operator skill. The primary objective was to analyze the difference of the operational skills between skillful operators and non-skillful operators by comparing their bucket trajectories in the same working environment. In the experiment, both skillful and non-skillful operators operated a backhoe in the same working environment to illustrate the difference in operation. Results indicated that the form of both operators improved simultaneously. Differences were found between operator skill in the time, length, depth, and width, showing that skillful operators work more efficiently (Sakaida, Chugo, Kawabata, Kaetsu, & Asama, 2006).

Interestingly, though these studies concentrate on the human operator, they fail to recognize the factors contributing to human performance. For example, past models typically focus on physiological aspects of the human operator rather than on higher level mental processes. Performance can be impacted by internal factors (e.g. intelligence, expertise, personality, emotion, or attitudes) and by external factors (e.g. fatigue, time, and stress). Neglecting either of these factors can have a significant impact on performance predictions, given physical actions are triggered by cognitive processes (Gore & Jarvis, 2005). Therefore, it is important that human performance models accurately account for the impact of relevant human conditions on human-system performance. Consequences of accepting the data from human performance models that do not account for such factors increase the risk of selecting inappropriate technologies or developing unrealistic procedures. Thus, in order to accurately predict human performance, both system characteristics and human cognitive functioning must be modeled (Corker, 1999).

Hence, another shortcoming of past human performance models is that they fail to recognize the interaction of these factors to produce performance. In 2001, Park and Chaffin aimed to address the lack of standards in models evaluating human motion. The study aimed to investigate performance in two areas and to detail a standard for their role in human performance. With regard to representations of human motion, the authors believed that in order to properly describe motion patterns, multiple attributes are necessary to represent its various features. The authors furthermore believed that with quantitative representations of motion patterns, similarity measures, and statistical techniques can be used to compare simulated motions with actual samples to simulate motion. Therefore, a study was designed to investigate methods of representing human motion patterns. To determine attributes describing these motion patterns, human lifting and reach motion data were collected experimentally and recorded. Reach and lifting tasks were modeled and compared to sets of recorded human motions, distorted motions, and randomly generated motions by using different similarity measures and statistical tests. Results demonstrated the strengths and limitations of the similarity measures and statistical tests.

In 2003, the Department of Defense also acknowledged that human factors issues are necessary for consideration when developing a system or assessing performance. In terms of the environment, research indicated that it is characterized by three subsystems: physical, functional, and social. However, more importantly, it was found that human issues were interwoven within almost every aspect of operations. Significant factors were defined as stress, fatigue, psychological operations, the physical environment, and equipment.

From this literature it is demonstrated that there is an array of human behaviors that have yet to be incorporated into existing performance models (Ritter, Shadbolt, Elliman, Young, Gobet, & Baxter, 2001). This issue is significant because tasks which were traditionally manual and physical in nature are now being replaced with tasks that are more cognitive in nature. This is exemplified in many industries where automation is being adopted to increase efficiency and safety (Gore, 2002). Since performance has multiple dimensions, models should not only consider the task or the system, but also the influence of various factors relating to the human (Nickols, 2006). With the limited amount of research in this area, most research models concentrate on either physical or cognitive behavior, dividing human performance into neck up and neck down. Consequently, both of these areas interact to produce behaviors. Therefore, such techniques neglect the relationship between cognitive and physical functioning on human performance. “Current human models have less cognitive ability than an infant and still have difficulty perceiving much of the environment as well as responses to the environment” (Feyen, 2007, p. 382). Thus, to improve human performance models, better understanding is needed on how various factors influence the human decision making, strategies, and responses. Another example as noted by Gore et al. (2008) is that models are often subjective and overly rely on physical factors; when in fact, many physical behaviors require cognitive triggering. Specifically, cognitive factors such as memory, memory loads, and communication are often overlooked. Incorrectly modeling or omitting any of these performance factors can lead to incorrect predictions. Therefore, by considering cognitive and physical aspects, future performance models can be useful for identifying system vulnerabilities, proposing system redesigns, and alternate methods for reaching the desired performance.

2.5 Overcoming Limitations of HPMs

To improve human performance models it is necessary to: obtain detailed data about human behavior, have a clear understanding of human performance, improved architectures for building models, validation of model characteristics, and the inclusion of individual differences to ensure that models simulate a range of human responses (Wellbrink et al., 2004). However, to evaluate system performance, efficiency, and operability, the simulation must not be limited to the machine itself. It must also include the operator, environment, and working task (Filla et al., 2005). Increasing interest and momentum in this area has driven researchers to expand and build better models of human performance. Therefore, researchers have begun to combine approaches to modeling performance that simulate human responses and predict how humans interact with advanced technologies (Gore, Hooey, Foyle, & Scott-Nash, 2008; Gore & Smith, 2006).

2.5.1 General Frameworks

Over the years researchers have used various approaches to improve human performance models. Such approaches have been realized through improved software, more accurate data, and better knowledge of human capabilities. The framework approach, specifically, has given researchers the ability to build better performance models by establishing the foundation upon which they are developed. "A framework is described as a general structure which contains the elements and parameters common to the scenario being modeled" (Feyen, 2007, p. 384). With the framework approach, the task, environment, and human information to be modeled in the system are identified. In particular, frameworks yield in better logic in simulation models that parallel human reasoning and facilitate interactions with the user (Campbell & Bowers, 2000).

A variety of frameworks have been developed to provide a standard for the assessment of human performance. In particular, one of the most widely recognized frameworks was by Lewin (1935) who defined human behavior in terms of the interaction between individual and environmental factors. The significance of this work provided knowledge of human behavior through a schema of factors and types which should be described. In later years, researchers narrowed the scope frameworks by concentrating on factors which shape human performance. For example, Miller and Swain (1987) identified relevant environmental, organizational, and individual factors contributing to human error in performance. Another example is Furnham (1992) whose model identified five categories of individual factors affecting occupational behavior. The identified factors consisted of personality, intelligence, demographics, motivation, and ability. Similarly, in 1996, Stone and Eddy developed a framework to model factors impacting performance in terms of the individual and the organization.

In more recent years, frameworks have been developed which concentrate specifically on human performance for the improvement of work design and the development of systems. One such framework was based on human performance in computer simulation. This framework aimed to represent human performance in complex environments with discrete event simulation models using real world data and research literature. This approach has been often used in military and industrial applications to model the contribution of humans to system performance (Dahn & Laughery, 1997; Bunting & Belyavin, 1999). Another approach was used by Schmidt (2000) who created a modeling framework of physical, emotional, cognitive, and social effects of performance by representing human processes and performance in social systems. In 2001, Parker et al. integrated more specific psychosocial and physical factors into these frameworks by relating the human and the organization into the design of work. This was later improved upon by Toriizuka (2001) who designed a framework to improve work style, efficiency, and comfort for better workload and human reliability.

The most recent studies in this area combine many of these multi-disciplinary frameworks into a comprehensive framework to include the physical and psychosocial factors of human performance. For example, Carliner (2003) attempted to form relationships between various factors relating to human performance to enable human performance modeling as an aid in manufacturing system design. In 2005, Baines et al. also developed a theoretical framework from an array of past framework which summarized the principal factors and relationships to incorporate when modeling a system. This approach was intended to improve upon the awareness of the impact that human factors have on design, enable assessments of significant human behavioral factors, and to induce further consideration of these factors during the design process. Influencing factors were related directly with worker performance by measuring variations of human performance, identifying the human factors which are most likely to have an impact on those metrics, and compiling performance measures were brought together to form the framework.

2.5.1.1 Limitations of general frameworks. Like performance models, frameworks are not without limitation. Many of the earlier frameworks examined are broad in nature and fail to define specific factors associated with human performance; whereas, other frameworks are very context specific and based on technicalities of a specific application or work domain. On the other hand, more recent models lack consideration of the broad range of factors that affect performance. Of those models which identify relevant factors, many are indefinable or intangible which would lead to difficultly in quantification and modeling. More importantly, all prior cases ignore the interaction of many other variables and neglect to fully consider aspects contributing to human performance. As noted by Gore (2003), both cognitive and physical elements of a job interact to create performance. Although a variety of theoretical frameworks currently exist which attempt to address issues in human performance, their limitations illustrate a fundamental lack of knowledge about human interaction and performance.

This lack of knowledge is implied by Glenn, Neville, Stokes, and Ryder (2004) who found few research studies applying multiple modeling frameworks to complex systems as well as Baines, Asch, Hadfield, Mason, Fletcher, and Kay (2005) who noted that the factors which affect performance are less understood. Limited appreciation of the wide range of factors that influence performance has led to designs not performing as expected due to overestimation of both human and system efficiency. These frameworks emphasize the current research problem and the need for an integrative framework which accounts for the multitude of human factors that should be considered when modeling human performance (Baines et al., 2005). This notion is later reaffirmed by Feyen (2007) who established that “published research on the interactions between various models is scarce, if not nonexistent (p.386).”

2.5.2 Integrative Frameworks

Despite the limited knowledge of these factors and the limited amount of research available, researchers have begun to produce frameworks that pay attention to the many factors contributing to human performance. Integrative frameworks have become the tool in which researchers have laid the foundation. They attempt to help identify various aspects contributing to the system to be modeled. These frameworks are set apart from the general frameworks in that they model multiple dimensions of system elements and parameters. Using integrative frameworks in human performance modeling allows researchers to: describe cognitive or physical constraints, identify relationships between independent and dependent variables, better understand operator responses, strategic decisions that guide behavior, and avoid underlying theoretical assumptions. The application of integrative frameworks in simulation models allow users to combine various components, environments, operator profiles, task sequences, and external simulations into a single system model (Dahn & Laughery, 1997).

Baines et al. (2005) believes that creating better human performance models begins with the development of a framework that relates performance with the key factors that influence the performance. Key factors are human factors that are most likely to have an impact on performance in the real world. Hence, these frameworks will help to build models that offer a more realistic representation of the variations in human performance and the human factors which influence such variations. Using simulation as a vehicle to better consider human factors during the process of system design and development will enable the creation of more valid models which allow for better decisions to be made with greater confidence.

In 1997, Dahn and Laughery revealed that integrative frameworks can provide more realistic representations of humans in complex environments through the interoperability of model components. For instance, an integrated modeling framework can be used with human performance simulation tools to integrate models and help human factors practitioners analyze human-system performance. Such models include: a model of the environment, the operator, a task network, the workspace, and performance shaping functions. These components can be combined in various combinations to realign simulations of different environments, operator profiles, task sequences, and external simulations into a single system model.

In the study, researchers used performance environments to create an integrated model, representing extreme climatic conditions. The model incorporated relationships for temperature dependent on environment model stressors such as time-of-day, illumination, and weather conditions. Performance shaping functions and equations were also added within the models in order to dynamically impact operator performance in terms of the task time and failure rate. From the study, the authors found that the ability to distinguish differences between operators and environments improves realism of the simulation models and helps the practitioners to address problems when many stressors are involved.

Later in 2001, Hancock et al. proposed descriptive framework for the evaluation of stress on operator performance. The approach of the paper concentrated on assessing stress on psychological and physiological functioning, while paying attention to the influence of both physical and cognitive forms of stressors on response efficiency. Therefore, it allows for specific insights regarding the effects of specific types of influences of both forms of stress. In the study, participants performed sustained attention tasks in a dynamic environment and were asked to make critical decisions. Compensatory action was then measured from the experimental findings of cognitive performance under physical demand.

In 2006, Ward, Line, and James created a computational framework for integrative modeling by layering information and discrete-event simulation due to the need of modeling environments to integrate, compute, and visualize components. The authors detailed the development of computational environments for improving the integration of the various components for digital human computational environments. Specifically described were potential concepts to facilitate full integration of data acquisition, model computation, display of results, and predictions. The primary objective to be addressed was integrating modeling approaches based on discrete information and continuous or time dependent simulation. Hence, two concepts were suggested as potential ways to bridge various modeling approaches.

One concept was layering information. Layering of information was recommended to enable knowledge discovery in support of modeling and simulations and to extract relevant anatomic, metabolic, or physiological information affecting simulations. The second approach, discrete-event simulation, was recommended to incorporate discrete reaction kinetics. Furthermore, discrete event simulation acted as a bridge between approaches to support data and user interface layers for characteristics in the virtual human-machine system. This framework approach was later applied to humans wounded in military operations. During this phase of the study, two computational modeling approaches were used: High-Level Integrative Physiological (HIP) models and three-dimensional Finite Element (FE) models for electrophysiology and mechanical motion. HIP models were optimized and results were transferred to FE models. A visualization environment was also developed to display information that captured three-dimensional anatomy and physiology of the human body. Authors conclusively state that future studies using the framework approach should be done to better integrate environments for multi-scale human modeling and simulation.

One of the most important studies was described by Feyen (2007) who provided a foundation for integrative frameworks by identifying internal and external factors as well as their interaction that is necessary to accurately predict human performance. In the external environment these factors consist of the activity, equipment, and the environment. Activities pertain to the task attempted by the human, equipment refers to the mechanisms available for the human to carry out the activities, and the environment refers to the location in which these entities exist. These factors are important in the development of performance models because past models often fail to capture the broad range of activities undertaken by the human. Such activities have the potential to produce distractions or interruptions, and the ability to hinder or facilitate activities.

Beyond these factors, the author also discusses the interaction physical and cognitive factors in performance models. Two factors impacting physical performance is the need of the cognitive system to acquire information to support activities and the impact of errors. Another area of interaction was found to be the effect of physiological influences which produce variations in body positions and activity sequences that impact overall task performance. Specifically, emotion can significantly impact performance causing the human to perform too quickly, select the incorrect strategy, quit the task before completion, or even perform actions unrelated to the task. Overall, each of these aspects must be used to properly model human performance and the context of the interactions involved (Feyen, 2007).

2.5.3 Workload

An effective way to assess cognitive and physical human performance is through workload assessment. Workload refers to the demand placed upon a human when performing some task. High workload occurs when excessive demands are placed on the human performing work (Keller, 2002). Workload can also intensify when tasks are performed simultaneously, resulting in excess workload. Both high workload and excess workload have been found to result in various problems or compensating behaviors (i.e. errors, slowing execution, poor scheduling, decomposition, or switching). Workload also plays an important role, in the design of emergent systems. For instance, many systems are designed to enhance human productivity and reduce the workload of the operators. In some cases, the tasks required to operate these systems increase the associated workload, resulting in reduced performance and productivity. Such results can result in costly design changes that must be implemented following system development. Therefore, models that predict workload can be extremely useful and effective when applied during the design stage of system development.

Workload has also been proven to be effective in overcoming obstacles in human performance. Workload has been applied in many work domains to assess human performance. For example, in 1997, Hockey described workload as the "effort which coordinates processes by adjusting inputs and outputs from response outcomes to provide the basis of computational control for central decision processes" (p.74). From studies of past research the author found that many performance models do not adequately account for the variability of human performance under stress, fatigue, emotion, and other conditions that affect the human. Therefore, computational models should incorporate such factors that trigger adaptive responses. In the study, a set of fatigue experiments were conducted and conclusions were drawn on the impact of workload on human behavior. Tasks were considered as externally imposed goals which direct behavior towards a goal over a period of time.

Findings revealed that in circumstances where processes were carried out less effectively, tasks yielded in a reduced level of performance. Furthermore, cognitive tasks can be taken at the expense of behavior since mentally demanding tasks can conflict with other goals. Management of effort, however, can allow for improved task behavior in relation to competing or concurrent goals, changing demands, and available resources. For example, effort can be managed by adopting a passive coping mode such as reducing accuracy, speed, or control strategies that adjusts performance. More importantly, it was determined that a compensatory tradeoff existed between cognitive goals and effort under stress and high workload. This tradeoff was demonstrated by subjects in the fatigue experiments when the level of effort was increased for brief periods in order to respond to test challenges. Prolonged work tasks indicated that subjects compensated for the effects of fatigue by choosing methods requiring low effort despite a higher risk of error.

Keller (2002) used the application of multiple resource theory to assess human performance. The aim of the study was to describe the process of assessing human performance through discrete event simulation as a quantitative predictor of workload during system development. Tasks were broken down into four components: visual, auditory, cognitive, and psychomotor. For each component, scales were also developed to provide a rating of the degree to which each component was used. Higher scale values denoted the greater usage and effort required for the resource component.

In 2005, Fowles-Winkler used a modeling framework, a single task network, and workload assessment in order to analyze human performance and stressors. The goal of this study was to simplify the task network model and reduce workload calculations. Significant findings consisted of determining that the factors which impact cognitive workload can be reduced in their effect on the amount of information processed (i.e. an operator's cognitive limits), and the amount of time available before the task must be completed (i.e. an operator's time pressure). It was also found that human operators change their processing strategy to reduce the amount of information to be processed or increase the time available. For instance, structural interference between tasks appear when: an operator is required to operate isolated controls with a single limb, visual focus is required for images great distances, or an operator is required to simultaneously verbalize information. Hence, it can be assumed that workload is invaluable in the assessment of human performance.

2.6 Future of HPM with Fluid Power Systems

Models of human performance in complex systems serve to predict system performance by identifying performance deficiencies in the human-machine system under various scenarios, aiding systems to augment human performance, and establishing functional assumptions about the underlying process of human behavior (Corker, 1999). As long as humans remain a critical component of many systems, they must be considered during the system design and engineering process. Furthermore, researchers should provide well supported inputs regarding the human and system, their interaction, and resulting performance (Laughery, 1999).

Review of past research literature reflects the significance of human performance models in the development, design, and implementation of these complex systems. This is even more so evident in fluid power industry where there have been significant overhauls to hydraulic excavator systems. Beyond the many capabilities and tools that allow researchers to address performance, there have been significant oversights in human performance models. These limitations have led to difficulties in predicting the variability of human behavior. Such limitations are beginning to become more apparent to researchers and are beginning to be addressed. However, with fluid power systems such as the hydraulic excavator, little has been done. As these systems become increasingly complex, there is a growing need to develop integrated approaches to human performance modeling which produce comprehensive performance models that fully represent the human as well as the system. To facilitate such integration, the models require a common descriptive language to interact and communicate. One such method is to develop human performance models using an integrative human performance modeling framework (Salvucci & Lee, 2003).

Integrative frameworks and modeling human performance provide a timely and cost effective means to fill this research void. Utilizing these approaches will yield in human performance models that concentrate on the human operator and recognize the various factors contributing to human performance in emergent fluid power systems. Using the framework will provide a foundation on which simulation tools and models can be integrated. Completion of research endeavors in this area will yield in a better understanding of the factors to be considered when modeling human performance, identification of the human factors which influence performance, and examination of the factors that cause or amplify variance in human performance models. Ultimately, this research will examine each of these areas to conclusively provide the basis for more realistic representations of human performance in simulation models.

CHAPTER 3

METHODOLOGY (INTEGRATIVE FRAMEWORK)

3.1 Framework Requirements

A variety of methods and applications are available to create models of human performance; however, in order to fill the voids in past research, a theoretical framework was developed to facilitate the integration of human performance models. In the development of a performance modeling framework, procedures were followed to support the integration of both cognitive and physical factors as well as various simulation tools to create better models of human performance. Requirements for the framework consisted of establishing the levels at which performance should be assessed, defining states of human performance, differentiating cognitive and physical functions, extracting performance measures, selecting modeling tools, linking performance measures, and integrating representations which will act as a blueprint in model development. The following sections describe those requirements in further detail.

3.1.1 Levels of Performance Assessment

Human performance is multi-dimensional, being subject to the effects of many factors that are often considered separately in traditional research models. Since this quality holds the potential to positively or negatively affect performance, it was appropriate to consider at various levels. The appropriate levels at which to assess human performance were determined in order to set the proper boundaries which constrain human performance, to convey human-machine interaction regarding abilities and limitations, as well as the combination of individual differences that add complexity to human behavior and cause performance to vary extremely. Hence, they were especially necessary when modeling human performance in complex systems.

3.1.2 Definition of Performance States

Performance states (Figure 3.1) were defined during conception of the framework to form an environmental representation in which human performance can occur. Initial performance consisted of the internal state which represents intangible processes existing or situated within the limits of organized structures such as the mind or body. In contrast, the subsequent external performance state represents tangible processes existing independently from the human mind but with respect to the body. Both of these finite primary states have a linear relationship which is interrupted by the transformation state which served to bridge the internal and external processes, to facilitate action, and to create a full representation of the performance environment.

Within each performance state, the task, human, system, and environmental information was specified through a methodical approach indicating the required elements and parameters to be altered when modeling. Furthermore, each of the described performance states served to set boundaries or limits on allowable human performance during the execution of integrated simulation models.

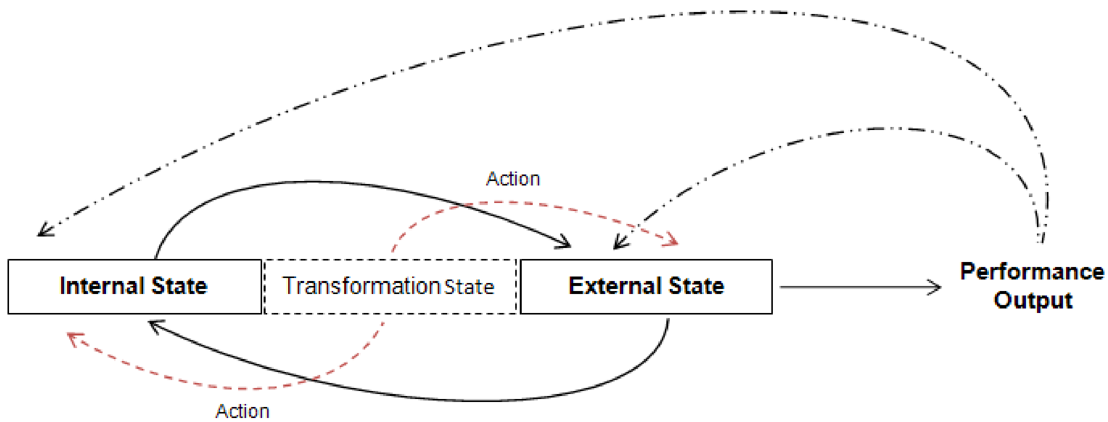

Figure 3.1. Definition and Relationship of Performance States.

3.1.3 Classification of Cognitive and Physical Functions

Another requirement for creating the framework was to establish the key system factors and human factors of performance. With regard to complex human-machine systems, performance functions consist of both cognitive and physical elements. These functions were necessary to consider when developing the framework because they influence and constrain the human operator.

3.1.3.1 Cognitive factors. Cognitive factors were also a critical component of the framework due to their complexity and the interactions that influence human behavior. Such factors have the ability to constrain the system and human performance. These factors convey human mental processes as well as determine task difficulty.

3.1.3.2 Physical factors. From an alternative perspective, cognitive factors also dictate system and human responses to performance limitations, equipment capabilities, and environmental constraints. Therefore, physical factors were used as the second component of human performance to convey the interaction between physical structures and the motor responses of the body during task performance. The definition and inclusion of each factor as functional components was fundamental in understanding human performance since many operational processes require physical responses that are triggered by cognition.

3.1.4 Selection of Modeling Tools

Simulation provided an efficient method to model and to analyze human performance with regard to the interaction between the human, system, and environment. The technology allowed for computer-based models to be constructed that emulate the behavior of the proposed system. To avoid loss of accuracy, assumptions regarding behavior, and validate models, multiple simulation tools were selected in order to support the framework's structure. Both tools expanded beyond the capabilities of past simulation models and acted as a tool to better consider both the cognitive and physical components of human performance. Each tool was later integrated in the framework to create more valid simulation models as described in Section 3.2.

3.1.5 Categorization of Metrics

Upon differentiating cognitive and physical functions and selecting the appropriate software to model those functions, research literature was used to aid in the identification of possible metrics with regard to the functions of performance. Categorization principles were based on field theory which regards individual behavior as the outcome of a dynamic system where factors relating to the individual interact with elements of the environment (Lewin, 1935). Based on this theory, metrics were screened according to their relevance in the domain of fluid power, measurability, and the extent to which they are likely to affect human performance. The most relevant metrics were used as categories from which individual performance variables can be later extracted and modeled. Following, the metrics and performance variables were brought together to form the integrative framework.

3.1.6 Linking Performance Variables

Based on the categorized metrics, performance variables were linked to form explicit relationships linking both cognitive and physical performance factors. This relationship was formed through linking such variables in cognitive and physical human performance models (Figure 3.2). By linking performance variables, models of performance were integrated by compensating for portions of performance model representations lost due to lack of dimension from the other variables (i.e. cognitive variables compensate for what is lacking in physical performance variables, and physical variables compensate for what is lacking in cognitive performance variables). This compensatory relationship was also used as a predictor of subsequent performance to encompass the entire realm of human performance within the real world, resulting in a comprehensive performance model representation.

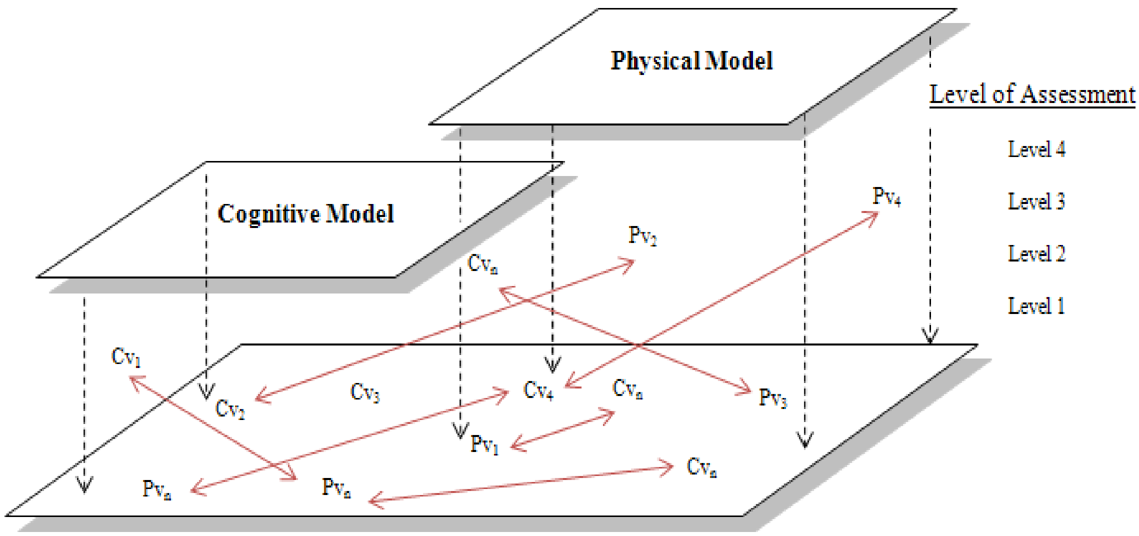

Figure 3.2. Linking of Performance Variables and Layered Metrics.

3.2 Framework Integration

Integration of models was facilitated through the prior methods to enable an accurate representation of human performance as it occurs in the real world. By using the acquired knowledge from performance assessment, techniques were used to create models that account for both cognitive and physical facets of human performance in a comprehensive performance model.

3.2.1 Integration Schema

Based on the requirements found in Section 3.1, two performance modeling tools were selected to simulate the cognitive and physical aspects of performance. In order to integrate these tools and to form a comprehensive human performance model, a comparison of requirements was developed. Inputs required for the cognitive tool were identified and compared with the required inputs of the physical modeling tool.

Differences among features of these modeling tools were then bridged by identifying common characteristics between modeling capabilities and parameters.

3.2.1.1 Integrating tools. Tools were combined to model the system in a virtual environment, along with both the physical and cognitive tasks of the human to return output regarding expected performance and limitations. Integration of these modeling tools mimicked performance in various tasks scenarios with better accuracy and understanding than previous models. By modeling with the framework, all mental and physical tasks of the operator were taken into account. This yielded in a better understanding of human interaction, alternate methods to accomplish task goals, and knowledge of the limitations of human performance.

3.2.1.2 Integrating variables. In human performance, a bi-directional relationship exists between physical and cognitive components to create interaction. This relationship was recognized and included to better model human interaction and behavior. Therefore, each factor was integrated to produce human performance models that simulate human responses and predict how humans interact with complex systems.

In the environment where interaction occurs, cognitive and physical components profoundly affect the human and the system by contributing to behavior and modifying performance. Cognitive components in the framework represented conscious and unconscious internal processes that form the human ability to understand and reason; whereas, the physical components represented measures of external human movement. Performance is generally initiated by cognitive tasks such as attention, memory, and perception of stimuli. Transformation of internal and external processes enabled the linking of performance variables to create action and trigger physical tasks. Such processes iterate until performance goals have been met.

3.3 Framework Implementation

Implementation of the framework's modeling approach was necessary to demonstrate the benefits of accounting for various factors that impact performance. With the framework's defined structure, a comprehensive representation of human performance was achieved.

3.3.1 Performance Model Representation

Upon completing each of the components involved in the development of the integrative framework, a comprehensive performance model representation was obtained. The integrated representation served to gain valuable insight on the correlation between cognitive and physical factors of human performance, to acknowledge the interactions that produce operator behaviors during excavation processes, and to better replicate and predict human performance to aid in the design of fluid power systems.

3.3.2 Model Structure

Structures of the integrated model representation (Figure 3.3) were used to depict human performance and to facilitate interaction from the flow of logic that parallels human reasoning and physical action. The integrated performance representation consisted of four primary areas: human centered factors which serve as the basis for human performance assessment, a functional relationship which connects cognitive and physical performance, discrete-event simulation tools to facilitate the integration process, and model output to provide a comprehensive representation of performance. The representation initiated with the key human centered factors from which performance metrics were used as a subset to classify performance variables. From each performance metric, variables were linked through a functional relationship integrating cognitive and physical performance. Both the cognitive and physical aspects of performance were assessed in human performance modeling tools. Simulation with both tools resulted in output capable of creating an integrated performance representation. With the use of both tools, the human, system, and environment were represented.

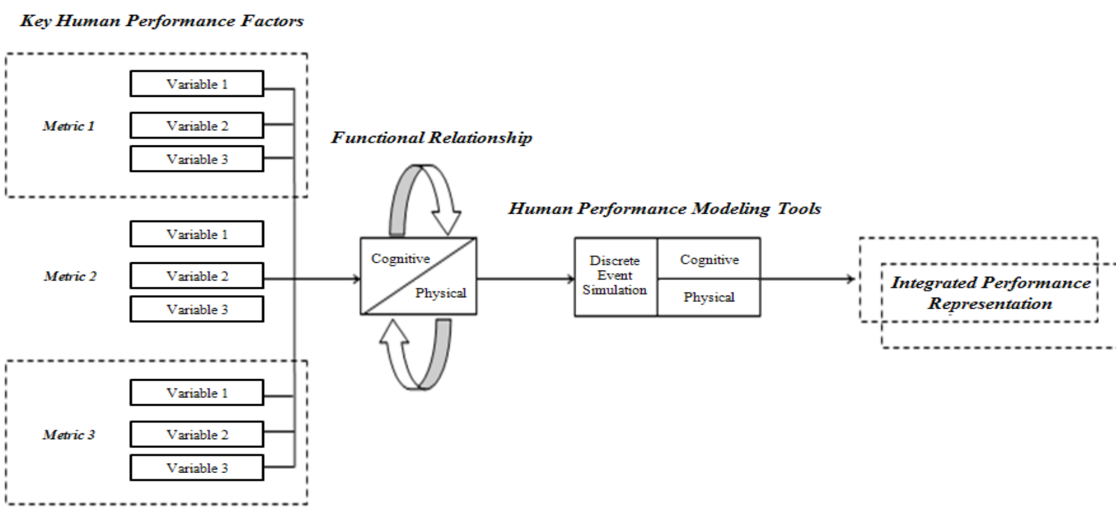

Figure 3.3. Integrated Human Performance Model Representation.

3.3.3 Application of Integrated Model

The framework's primary advantage was that it allowed for the simultaneous examination of the influences and effects of physical and cognitive factors both individually and combined on human performance. Benefits of integrating internal models of cognitive function and external models of physical function resulted in insight being gained on human performance in terms of operator responses and the cognitive constraints that guide behavior. More importantly, an understanding of the interaction between physical and cognitive components as well as the influences of tasks, strategies, and responses in human behavior were gained. With proper application, the framework led to more accurate simulation models. Integrative models that are both predictive and computational to simulate cognitive and physical functioning yielded in more realistic representations and accurate predictions of human performance. Moreover, the framework was used to overcome the past challenges of modeling human behavior, identify system vulnerabilities, aid in the proposal of system redesigns, and foster alternate methods for reaching desired performance.

CHAPTER 4

METHODOLOGY (EMPIRICAL STUDY)

For the development of the integrated framework, procedures were followed to ensure that human performance models derived from the framework offer the same degree of validity as real world fluid power applications involving a hydraulic excavator. Procedures consisted of data collection, tool selection, and variable identification to act as components in model development. The following sections describe each of these procedures in greater detail.

4.1 Data Collection

Real world data for the models was collected on the work tasks, control operations, and system functions of a hydraulic excavator in its natural work environment. Information was obtained through three primary resources: interviews of expert operators to provide a thorough understanding of the operations such as work experiences, operator difficulties, and skill requirements; system manufacturers to provide details on newly implemented design changes, model specifications, and tooling for work applications; and video recordings to gain insight on time variations in dynamic work settings as well as to investigate the interaction between the system and the operator. Research literature and case studies were also used to supplement general data.

4.1.1 Task Analysis

Collected data was used to construct task analyses from 40 video recordings based on excavator control type (e.g. hydraulic and electronic) and environmental terrain (e.g. soil and gravel). Each analysis outlined and described the sequence of steps involved in the excavation process, as well as assessed task requirements in terms of the operator's actions and cognitive and physical processes to achieve goals. Based on the observations from the analysis, key tasks were identified. Acquired knowledge from the tasks acted as a reference for which human functioning and system features were tested.

4.1.2 Time Studies

To complement the task analysis, time studies were performed to determine operator efficiency in reaching work goals, identify inefficient work methods, and quantify changes in performance. Timing data was captured from each of the categorized video recordings of excavator operators in real world work environments. Mission critical tasks were timed, recorded, and organized by the sequence of tasks determined during the task analysis. From this data simple statistics such as mean and standard deviation were calculated, and distributions were fit to tasks for accurate modeling of work processes.

4.2 Modeling Tools and Software

For this study, two simulation tools, cognitive and physical, were chosen based on the requirements of the framework to create valid simulation models of operator performance with hydraulic excavator systems. This technology was used to model and analyze human performance through the interaction between the human, system, and environment, allowing for quick and economical evaluation of design options and safe testing of system performance under extreme conditions (Baines et al., 2005). As described in Chapter 3, cognitive and physical modeling tools were selected to support the framework. In this study, Micro Saint was used to model cognitive human performance and Jack was used to model physical human performance. Each tool provided the opportunity to expand beyond the capabilities of past modeling approaches to evaluate and conclusively predict human performance. A description and purpose of each tool used for the study is provided below.

4.2.1 Micro Saint Software

Micro Saint modeling software was used to model cognitive components of performance such as human cognition and decision making. The tool allowed for various processes and complex systems to be modeled by means of a task network model. In the software, models were denoted by nodes and arrows; depicting sequences of human activities. This tool was used with regard to fluid power systems to evaluate and improve performance efficiency in areas such as process definition and design, operator workload, safety, and productivity.

4.2.2 Jack Software

For the physical performance representation, Jack software was used to model physical human capabilities and limitations with regard to the system and the environment. The tool offered visualization models of a digital human, known as Jack, who carries out scheduled tasks and procedures within a virtual environment. Applications with human performance modeling included the analysis of anthropometric dimensions or biomechanical constraints and verification of programmed task behaviors in terms of sequence, execution, and time.

4.3 Model Development

As stated in the previous chapter, the theoretical framework was used as the blueprint for model development. Based on the states of human performance and cognitive and physical functioning, two human performance modeling tools (e.g. Micro Saint and Jack) were chosen. Software was used to build complementary models of human performance to simulate cognitive and physical human performance.

4.3.1 Cognitive Human Performance Model

In Micro Saint simulation software, findings from the task analysis were used to create task network models, extending each task analysis into predictive models of cognitive and physical functioning. With the task network models, it was intended to determine the range of performance expected with regard to the length of time required to perform a task as well as human error rates (Laughery, 1998; Verra, 2001). Each task network model was organized by the task sequences executed by hydraulic excavator operators to accomplish the desired goal. Task network model hierarchies included the movement task (i.e. operator's physical action), operator task (i.e. operator's cognitive task), and the system task (i.e. system's response to the operator action), which served as the basis for the task network model and sub-model of the human-machine system.

Micro Saint simulation models were built based on excavator control type and environmental terrain: Hydraulic Control-Soil Terrain (HS), Hydraulic Control-Gravel Terrain (HG), Electronic Control-Soil Terrain (ES), and Electronic Control-Gravel Terrain (EG). Development of the models involved defining the structure of the task network models and objects within those models based on the findings from the task analyses. Network structures were composed of tasks performed by humans, processes, or machines, and were organized by the task sequences that the operator executes to accomplish work goals. Activities within the task network models were represented by a diagram of nodes and arrows, representing the sequence of tasks performed.

The task hierarchies included the movement task, operator task, and the system task. Tasks represented the lowest level of the network and held modeling elements such as timing information, conditions for execution, and beginning or ending effects. Real world data recorded from the time studies and the appropriate statistical distribution were also embedded within the task networks to accurately model operator tasks and excavation process. Timing information for each task, in terms of mean time, standard deviation, and the appropriate distribution, allowed the model to simulate process variance and to provide a high level of validity for workload estimates or modeling results (Drury & Laughery, 1994). Each model was also coded and debugged to create simulation models that replicate typical excavation processes.

4.3.2 Physical Human Performance Model

In Jack simulation software, manufacturer specifications and human anthropometric data was used to model the excavator system and physical functioning of the human operator. Like Micro Saint simulation models, Jack models were built based on excavator control type and environmental terrain. Development of the models involved building a representation of the system and defining procedures to be performed by the human operator based on manufacturer specifications and the tasks analysis. A digital human was used to simulate excavation procedures in a virtual environment generated in the software. Tasks followed by the digital human were governed by the sequence of activities outlined in the task analyses and Micro Saint network models. Real world timing and frequency data recorded from the time studies was used to accurately simulate operator tasks and excavation process as well as to validate model results. Such models replicated the human operator's physical actions, capabilities, and limitations in response to various system interface designs, creating predictive models of the human-machine system.

Within each software, simulation models were programmed and coded according to the requirements and components defined in the theoretical framework. Variables were extracted and modeled, conveying the functional relationship between cognitive and physical performance and linking cognitive models to physical models. Output obtained from these models was used in an empirical study.

4.4 Empirical Study

An empirical study on human performance was conducted using the integrative framework to assess the impact of cognitive and physical factors on human performance. The following sections describe the empirical study in further detail.

4.4.1 Stimulus Material

The empirical study on the human performance models was conducted using the cognitive and physical simulation models as described in Section 4.3.

4.4.2 Simulation Tasks

Key tasks involved in excavation processes were selected for modeling in simulation software to provide insight on the interaction between the human operator and the excavator system. Tasks were based on their relevance in the integrative framework, significance in excavation processes, and value in assessing human performance. Simulation tasks that were used in the study consist of the following.

4.4.2.1 Initialization. Initialization tasks were used to simulate operations involving activation of the system (i.e. monitoring and positioning). Such tasks are relevant to consider when assessing performance given that they are dependent on human cognition that is known to impose high mental demands on the human operator.

4.4.2.2 Active work. Active work tasks (Figure 4.1) were used to convey the operator's actual work procedures involved in the excavation of materials (i.e. digging, scooping, and releasing). Such tasks are critical to performance because they hold the potential to vary extensively based on the environmental conditions, system design, or human abilities.

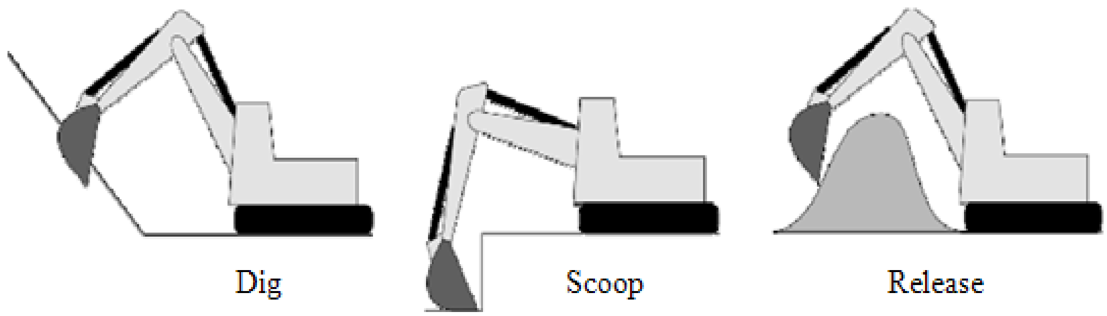

Figure 4.1. Tasks Simulated in Human Performance Models (Sakaida et al., 2006).

4.4.2.3 Finalization. Finalization tasks were used to simulate the tasks and operations following the completion of work goals during hydraulic excavation processes. The inclusion of these work tasks aided in determining the effects of various processes on human operator performance.

4.4.3 Equipment

Simulation models were run in Micro Saint and Jack simulation software. The software was installed on a laboratory PC with a Microsoft XP operating system.

4.4.4 Experimental Design

Two experiments were conducted to examine the relationships between independent and dependent variables with regard to their effect on human performance. The following experimental designs were chosen to ensure validity, make inferences, and draw conclusions from performance model data.

4.4.4.1 2x2 factorial design. A 2x2 factorial design was used in this study to analyze human performance in the non-integrated models. The two independent variables consisted of excavator control type at two levels (hydraulic and electronic) and environmental terrain at two levels (soil and gravel). The dependent variables were task completion time and workload.

4.4.4.2 2x2x2 factorial design. Similarly, a 2x2x2 factorial design was used to analyze human performance in the integrated models. Three independent variables consisted of excavator control type at two levels (hydraulic and electronic), environmental terrain at two levels (soil and gravel), and integration at two levels (non-integrated and integrated). The dependent variables were task completion time and workload.

4.4.5 Procedure

Micro Saint and Jack performance models were completed in compliance with the integrated framework as described in Section 4.3. Initial models were created using Micro Saint, defining the cognitive functioning of the human operator as well as the sequence of tasks involved in hydraulic excavation processes. Jack software was then used to expand beyond the predictive capabilities of the cognitive models through physical models, which were linked to convey a functional relationship between internal and external human functioning. Models created in Micro Saint and Jack software were not treated as separate entities. Each simulated the same scenario and key tasks identified in Section 4.4.2. Models were randomly executed one hundred trials and simulation output was simultaneously documented and recorded based on framework requirements.

4.4.6 Data Collection

As the simulation models were executed, performance was monitored, documented, and recorded. Output for the models was displayed visually in the form of numerical and graphical data. For both cognitive and physical models, descriptive statistics and empirical results were obtained from simulation output. Model output comprised the dependent variables in both cognitive models (e.g. completion time and workload) and physical models (e.g. energy expenditure, fatigue, and recovery time).

CHAPTER 5

INTEGRATIVE HPM FRAMEWORK

Human performance is comprised of an array of elements forming the human-machine system. When representing such performance, great detail is necessary to fully capture the complexity and variability of human behavior. As described in the previous chapters, many human performance models fail to fully capture the essence of human performance due to a neglect of contributing factors as well as a variety of other critical aspects, leading to errors and overestimations of efficiency. The following portions of this chapter describe an integrated human performance modeling framework which combines cognitive and physical performance in an integrated model to create more accurate models of human performance. Its purpose is to provide common structure for the development of human performance models with complex human-machine systems.

Furthermore, the framework can be used as a blueprint to identify the necessary parameters and elements to be considered when modeling human performance in complex systems and to improve predictions with existing and emergent systems. Although it is not possible to develop a framework that is applicable to all systems; it is possible to develop a new method of modeling which considers the contribution of cognitive and physical behaviors in producing human performance. Development of the framework involves applying several types of knowledge such as human factors, domain information, simulation, and human performance modeling. Increased understanding of these types of knowledge along with the integrated framework allows for the improvement of human performance models. The framework was constructed by: examining the levels at which human performance can be assessed, the factors which affect human performance, quantification of those factors, methods for representing such factors in an integrated model, and a case study to demonstrate the framework's application. The following sections of this chapter describe those elements and parameters to be modeled with regard to the developed framework.

5.1 Human Performance Assessment

A variety of factors exist when modeling human performance. The term human performance refers to "the effectiveness or skill to accomplish goals through operations associated with human behavior" (Hockey, 1997, p.77). Being a multi-dimensional construct, human performance is subject to the effects of many factors that are often considered separately in traditional research models. This quality holds the potential to positively or negatively impact performance. Therefore, human performance must be studied comprehensively at multiple levels of abstraction to develop a deeper understanding for integrated models of human performance.

5.1.1 Levels of Performance

When modeling performance with complex systems, performance should be represented at four hierarchical levels (Figure 5.1) with regard to the environment, system, human, and the task. Within each level, various elements exist, significantly altering human performance. Such abstraction conveys the relationship that performance at higher levels has an effect on performance at lower levels (e.g. solid line) and that performance is directly affected by performance at the level immediately superior (e.g. dashed line). Modeling human performance in such a manner allows researchers to more accurately capture and predict complex human-system interaction and behavior through integrated human performance models.

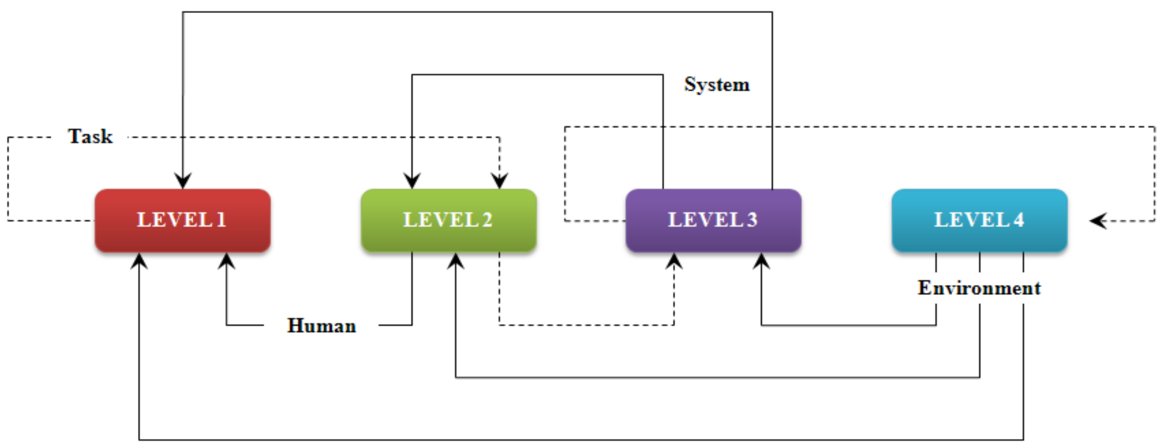

Figure 5.1. Levels of Assessment for Integrated Human Performance Models.

5.1.1.1 Task. The first and lowest level at which human performance should be assessed is at the task level (Table 5.1). With regard to human performance, tasks are low-level detailed descriptors or action rules that describe how work is performed. Tasks provide the foundation for human performance models because they are the means through which performance is achieved. Other qualities such as the ability to represent performance at various states or levels, the ability to describe the system and the human, as well as the ability to change the context of work, makes the task a highly important aspect to consider when assessing human performance (Diaper & Stanton, 2004). For instance, tasks contribute to work methods (e.g. series or parallel execution), the amount of workload experienced (e.g. physical or cognitive), job difficulty (e.g. simple or complex), as well as the length of time (e.g. short or long duration). Furthermore, tasks are highly relevant when modeling complex systems due to their ability to convey the composition of work. Therefore, to fully model the range of tasks that a human performs, models should begin with high level goals (i.e. processing tasks) then breakdown into actions (i.e. operational tasks) associated with the goal. Models should also accommodate dynamic uncertain characteristics which dictate the manner in which performance is modified in response to abnormalities (Wickens & Hollands, 2000).

Table 5.1. Human Performance Model Elements at the Task Level.

Element	**Description**	**Performance Effect**
Processes	Preparation Activation Finalization	Varies the amount of time taken and the job's degree of complexity.
Operations	Series Parallel	Impacts work methods, workload, and the amount of time taken to complete goals.
Anomalies	Malfunctions Failures	Affects vigilance, error, and recovery rates for performance efficiency.

When undertaking work with complex systems, humans perform a variety of tasks to complete work goals. Both process and operation tasks are coupled together to create performance. During initialization processes which engage the system, operational tasks occur; whereas, during active work processes which convey the human's actual work procedures, tasks occur to facilitate work. The inclusion of these tasks helps determine the effects of work processes on human performance.

5.1.1.2 Human. More importantly, the human being who undertakes these tasks must be considered. Humans are the most important contributors when assessing performance due to behavioral complexity. At the human or second level of performance assessment, there are countless numbers and combinations of individual differences which can cause performance to vary tremendously (Table 5.2). Such factors can consist of age which affects the speed of performance; training or experience which affects knowledge; and gender which affects performance capabilities or limitations.

Table 5.2. Human Performance Model Elements at the Human Level.

Element	Description	Performance Effect
Individual Features	Age Experience Gender	Influences the speed of performance, capabilities, or human limitations.
Cognitive Factors	Memory Attention Recognition	Impacts workload and the mental processing of task information.
Physical Factors	Biomechanics Anthropometry	Changes the human's physical speed, accuracy, and degree of control.

Furthermore, human behavior is a result of cognitive processing and physical functioning. When performing any task, a human typically does three things: receives information, makes decisions, and takes action. Information from perceived stimuli and prior knowledge form the basis from which decisions are made. These decisions are then translated into actions. Such actions are not only physical, but also involve cognitive processing (Al-Masalha, 2004).

The human mind acts as a central processing unit to manage data for performance. In complex systems, humans control and supply much if not all of the information processing capability necessary for performance. For instance, humans execute tasks by utilizing the system's interface (e.g. controls, affordances, etc.). With this task, the human operator controls all informational components such as monitoring the system, identifying critical tasks, and determining when to begin or end work processes. Such factors contribute to workload impacting performance which can lead to human error or misunderstandings.

In addition to cognitive or informational processing, the human also contributes to physical performance. In terms of physical performance, the capacity of humans varies from one to another due to the aforementioned differences (e.g. age, sex, health, and physical fitness). For example, younger individuals may react more quickly to changes, exert greater force, or possess more endurance than older individuals when performing repetitive tasks. Physical processes involved with complex systems are likely to involve various physical activities such as manipulating controls. Such activity over extended periods, however, has the ability to affect performance in terms of high workload or stress, resulting in fatigue and slowing work processes.

5.1.1.3 System. Human-machine interaction occurs when humans utilize systems to undertake a set of defined tasks. Interaction with the system plays a critical role in human performance not only based on its design, but also its mechanics which affects human capabilities and limitations. Systems are designed with the intent to augment rather than to hinder human capabilities. Thus, systems are often responsible for providing a vast majority of the physical work capability, while humans provide much of the information processing capability (Al-Masalha, 2004). The system level also consists of a number of well-defined elements (Table 5.3). In terms of interface design of the system, performance can be affected by a number of factors. It is important to consider the intuitiveness of the system given that improperly designed interfaces can lead to errors and misunderstandings which hinder work processes if the human fails to recognize critical information.

Table 5.3. Human Performance Model Elements at the System Level.

Element	Description	Performance Effect
Interface Design & Layout	Monitors Controls Displays	Leads to errors and misunderstandings from unintuitive system designs.
Affordances	Buttons Levers Switches	Provides the mechanisms to facilitate performance functions and task execution.
Automation	Manual Semi-automated Automated	Impacts the speed at which work is performed and the amount of workload experienced.

With complex systems where a human must utilize controls, it is important to model elements of the system's design or layout. For instance, depending upon the size of the human and the system's specifications, performance can be affected in terms of infeasible reach constraints or bodily discomfort (e.g. stress, strain, or fatigue). System interfaces enable the integration of controls to structure performance. Moreover, the system's level of automation determines the effort needed to accomplish work. Affordances, in particular, guide how easily work can be accomplished and facilitate work that a human being can or cannot perform.

5.1.1.4 Environment. The last and highest level at which human performance should be considered is with regard to the environment. Performance at the environmental level is dynamic due to the interaction of entities such as humans, systems, objects, or resources which shape human performance (Table 5.4). Therefore, this level establishes the point at which boundaries are set, constraining feasible performance.

Table 5.4. Human Performance Model Elements at the Environment Level.

Element	Description	Performance Effect
Space	Area Obstacles	Constrains performance boundaries and sets the allocated work area.
Weather	Light Temperature	Increases pressure and stress on various interacting entities.
Time	Hours Minutes	Alters normal decision making strategies.
Resources	Personnel Tools Equipment	Modifies task methods and processes.

The environmental level also consists of a number of well-defined elements. Environments where work is performed have the potential to vary extensively, affecting overall performance at all levels. Environmental elements such as space and resources bound the range of work and the methods by which to complete such work affecting task performance. More importantly, this performance is subject to dynamic elements such as obstacles, weather, and time. These and many other elements increase complexity, affecting human performance.

5.1.2 Relationships among Performance Levels

As previously described, performance should be assessed at four levels: the task level to define the composition of work, the human level to depict the complexity of behavior, the system level to convey human-machine interaction, and the environmental level to constrain and modify performance. Since each level holds various elements which significantly affect human performance, they also share direct (i.e. effect on) and indirect (i.e. affect by) relationships conveying their impact on human performance with respect to one another. Considering this structure, elements at a superior level have an effect on performance at a subordinate level (i.e. high level performance affects low level performance and low level performance is affected by high level performance).

For example, at the lowest level of assessment, the task has no direct effect on performance given that it is inferior to all other levels. Yet, in contrast, task performance is affected by the human, system, and the environment. The environment exemplifies this relationship because it has the potential to increase the difficulty of the task; whereas, the system in terms of its interface design modifies methods by which tasks are performed. This performance is also affected by elements at the human level of assessment, directly impacting the task itself based on cognitive processing which triggers physical actions. Other individual factors (e.g. skills, training, or experience) are also likely to determine task efficiency at that level. However, the human level is affected by the environment as well as the system. Like the task, the human can be affected by the environment by imposing additional demands (e.g. terrain or weather). Furthermore, the system level has an impact on performance at both the human and the task level in terms of how quickly (e.g. engine dynamics), efficiently (e.g. task execution), and effectively (e.g. intuitive design) work can be performed. In contrast, the only level of performance that affects the system is the environment.

At the highest level of human performance, the environment has a direct effect on human performance at the subordinate system, human, and task levels. From this perspective, the environment has the ability to affect system capabilities, alter work methods employed by humans, as well as build upon the complexity of the task itself. Such relationships help establish links between performance at multiple levels which define complexity and the level of detail necessary for the development of integrated human performance models with complex systems. These relationships support an integrated strategy by reflecting complex human-machine operations at the macro- and the micro-level. Together by representing performance at each level, models can accurately simulate the environment and the system in conjunction with the human performing the assigned task.

5.2 States of Human Performance

Human performance is not only multi-dimensional in the sense that it occurs at various levels, but it is also dynamic in nature. Therefore, performance can be defined in terms of states to describe the conditions under which it occurs as well as the human's ability to execute a defined set of tasks, interact with the system, and cope with a variety of other factors. The following performance states serve to validate models by constraining and setting boundaries on allowable performance as well as by describing natural human functioning to convey performance (Figure 5.2).

5.*2.1 Internal State*

Performance initiates internally through conscious or unconscious processes situated within the limits of organized structures in the human mind or body. Because the internal state of performance is intangible and not directly observable, it is often overlooked or ignored by researchers due to its difficultly in modeling. However, it is critical to consider given that it has the ability to vary extensively based on complexity, uncertainty, and duration throughout work processes (Wickens & Hollands, 2000; Wickens, 1984). Such performance is achieved through cognitive functioning which enables the human to perceive and interpret the world, form goals or intentions, as well as to evaluate outcomes of actions which describe mental processes. Cognitive functioning provides the foundation to internal performance due to the fact that it forms the human's ability to interpret sensory inputs and initiate action. Such processes begin with perception which gives the human awareness or understanding of stimuli from the environment. Attention is then used to selectively concentrate on a particular aspect of the environment by allocating cognitive resources such as memory for storage, retention, and recall to manipulate the perceived information. The most complex of all cognitive functioning is problem solving which follows the prior processes to move human intentions from a given state to a desired goal state. Decision mechanisms are subsequently activated resulting in the selection of courses of action or responses among several alternatives associated with the presented stimulus. Cognition then continues with the interpretation of feedback to assess the outcome of those decision processes.

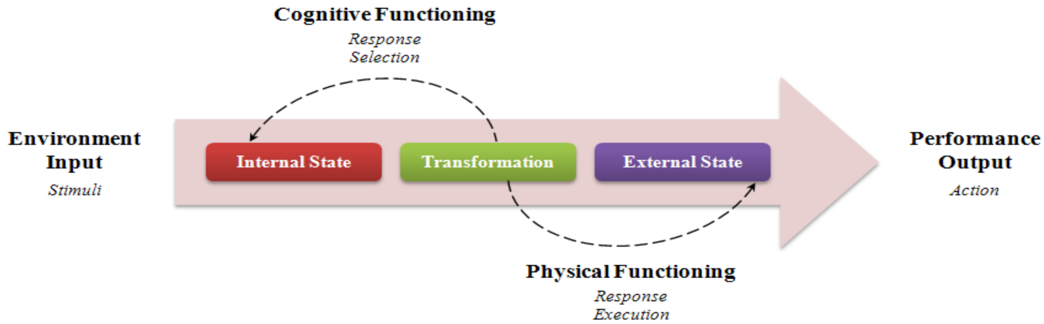

Figure 5.2. Relationships among States of Human Performance.

5.2.2 Transformation State

From the point at which decision responses are selected, internal performance is interrupted by a state of transformation which serves to bridge internal and external processes, facilitate action, and fulfill performance goals. This transition emerges from internal processes to move human intentions from a given state to a desired goal state by signaling responses that trigger action.

5.2.3 External State

Extending from the point at which internal performance transforms, external performance occurs through tangible processes that are independent from the human mind. Such performance emerges as a byproduct of internal cognitive functions which triggers action. External physical performance is essential since it measures autonomous activity and reflects the variability of performance through human functioning.

Unlike cognitive functioning which dictates human responses to performance limitations, equipment capabilities, and environmental constraints, physical functioning conveys the interaction between physical structures and the motor responses of the body during task performance. Such responses consist of dexterity, flexibility, range of motion, as well as endurance over extended work periods. More importantly, this functioning conveys the operational processes requiring physical responses that are triggered by cognition from which human performance can be assessed and evaluated.

5.2.4 Contribution of Human Performance States

The states of human performance are reflected in numerous applications, in particular those involving human interaction with complex systems. With complex human-machine systems, activities used to achieve performance require varying degrees cognitive and physical functioning on behalf of the human operator.

5.2.4.1 Structure of human functioning. For instance, with complex systems, internal performance is initiated from cognitive demands imposed by the environment, the system, as well as the task. Humans are also subject to constant interaction of these entities and constraints. When humans receive information from the environment, they must use cognitive functioning to perceive and interpret what is occurring, to form goals, and to signal the correct responses or actions for work to be completed. During the internal state of performance, cognitive tasks of humans involve perception of the work environment, memory to recall training skills, and recognition while paying attention to dynamic conditions in the environment such as other workers, machines, and the communication of information.

Furthermore, humans must also monitor gauges to assess the system's status and use decision making to determine the proper work procedures to follow. While in a state of transition, humans use stimulus received (e.g. system feedback, environment changes, or work commands) from the environment to develop strategies or intentions for goals preceding action. Humans use these transforming cognitive processes to execute physical action in response to external stimuli (e.g. execution of responses resulting in performance).

Upon response selection, action is executed primarily through the operator's physical use of affordances (e.g. buttons, levels, pedals, and joysticks) which carry out work functions with the system. For example, human operators of complex systems maneuver systems through the environment by using physical tasks which often require use of the upper and lower extremities (e.g. turning, reaching, pushing, or pulling) to engage controls. Since every physical action executed by the human has a corresponding machine reaction from the system, physical functioning correlates not only to the human but to the system and the environment as well. Such qualities make physical performance subject to the effect of factors such as vigilance, fatigue, and workload which can tremendously impact outcomes.

5.2.4.2 Distribution of human functioning. Furthermore, since humans interact with complex machinery, both internal and external performance occurs. Internal performance involves cognitive functions to capture, manipulate, and execute the information to perform work processes; whereas, external performance involves physical functioning to perform such operations. Each component, cognitive and physical, contributes at varying degrees to that interaction when performing tasks (Figure 5.3).

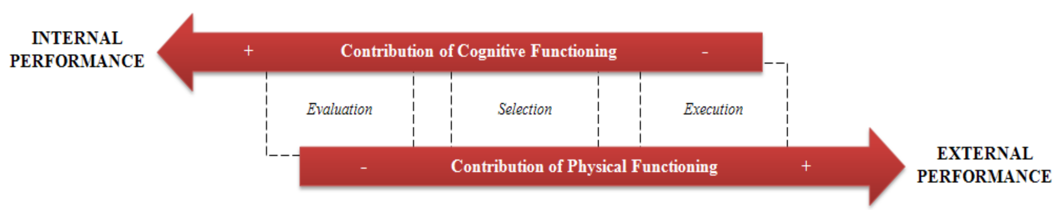

Figure 5.3. Contribution of Cognitive and Physical Functioning.

Human beings supply most of the information processing capabilities when interacting with complex systems. For instance, when evaluating a job, cognition is the single most important function utilized by the human through internal processes such as attention, perception, and decision making. Since the human is the only source of input for such tasks, cognitive functioning accounts for 95% of the steps required to perform a task (Al-Masalha, 2004).

In contrast, with selection, the contribution of performance begins to shift from a total state of cognitive functioning to that of physical functioning (i.e. execution) which the human performs to carry out tasks physically through external movements. Physical functioning occurs in conjunction with cognitive function during execution because it involves the selection of methods and tools to perform the task. Therefore, when tasks are abstract and goals are implicit, there is a higher level of contribution from cognitive functioning; whereas, when tasks are concrete and goals are explicit, there is a higher level of contribution from physical functioning.

Both internal and external states describe the conditions under which performance occurs as well as the cognitive and physical mechanisms from which performance is composed. Within each state, the interaction between the human and the system with regard to the environment and the task is specified. These states also describe how humans shift from intentions to actions and reflect the level of effort required for performance with regard to mental and physical demands (Wickens et al., 2004). Benefits of integrating internal models of cognitive function and external models of physical function applied to complex systems can result in insight being gained on human performance in terms of human responses and the cognitive constraints that guide behavior. Hence, models depict human performance with a flow of logic that parallels human reasoning and physical action, leading to increased accuracy and viability.

5.3 Integration of Human Performance Models

The integration of human performance models requires the identification of the relationships between experimentation, performance criteria, integration strategies, and methods to implement those strategies (Rasmussen et al., 1994). A variety of domain applications involve human-machine systems in complex and dynamic environments. These qualities make such processes in the real world difficult to evaluate due to increased expenses, prolonged time, as well as a limited degree of visualization. A viable tool to model work operations is through simulation (Al-Masalha, 2004). Simulation provides an efficient method to model and analyze human performance with regard to the interaction between the human, system, and environment. Such technology allows for computer-based models to be constructed that emulate the behavior of the proposed system and to evaluate work processes performed by the human. The dynamic and complex nature of work processes, however, is very difficult to describe and model using the traditional modeling techniques.

Existing modeling techniques represent human performance but fail to consider the role of a variety of performance shaping factors such as those earlier described (e.g. environment, system, or task) as well as the contribution of cognitive and physical functioning. Internal and external human functioning are important factors that influence the modeling of work processes. For instance, humans make decisions regarding complex work processes including the appropriate methods, the selection of tooling, as well as the planning and execution of operations. Such operations involve both cognitive and physical performance. Thus, to overcome the prior mentioned limitations and improve human performance, integrated models are necessary in order to capture, model, evaluate, and improve human performance.

5.3.1 Modeling Tools

As described in Chapter 4, multiple simulation tools should be selected in order to avoid loss of accuracy, assumptions regarding behavior, and validate human performance models. The modeling tools should also expand beyond the limitations of past simulation models by modeling cognitive and physical performance; thus, creating the foundation for the integration of human performance models.

5.3.1.1 Cognitive tool. When using the integrative framework, a cognitive performance modeling tool should be used to represent the internal functioning of the human (e.g. perception, decision making, etc.). Such a tool allows for the assessment of mental processes (e.g. how the human perceives stimuli from the environment, forms goals, and evaluates action alternatives) in relation to the affects of those processes on performance outcomes.

A variety of these tools are available with capabilities of modeling these processes. Benefits include evaluation in terms of work processes, quality control, process redesign, workload, safety, and productivity. However, since each tool has its own capabilities in modeling a specific aspect of cognitive performance, caution must be taken prior to tool selection based on the available data as well as the goals of the researcher in order for proper assessment to occur. Table 5.5 identifies examples of possible modeling tools appropriate but not limited to representing cognitive performance using the integrative framework.

Table 5.5. Cognitive Performance Modeling Tools.

Tool	Description
Apex	Models human performance in complex and dynamic environments by using the GOMS approach to describe perceptual actions (Cooper et al., 1998).
Cognitive Objects within a Graphical Environment (COGENT)	Describes cognitive processes by depicting high-level processes using memory buffers, rules, etc. Applications include reasoning and decisions (Freed et al., 2000).
Cognition as a Network of Tasks (COGNET)	Builds models of human performance in real time using Cognitive Task Analysis (CTA). Applications include tactical decision making tasks (Zachary et al., 2000).
Cognitive Systems Engineering Educational Software (CSEES)	Models programs related to judgment and decision making. Useful in applications for judgment, signal detection, and navigation (Wu & Liu, 2007; Bolton & Bass, 2005).
Executive-Process Interactive Control (EPIC)	Emphasizes perceptual processes by accounting for timing of cognition. Suited for analysis in design, training, and selection (Kieras, et al., 1997; Kieras & Meyer, 2000).
iGen	Models performance based on cognitive task analysis. Applications include domains of human decision making based on the use of system interfaces (Wu & Liu, 2007).
Operator Model Architecture (OMAR)	Models human operators in complex systems by assuming behavior is goal-directed. Applications include evaluation of operator procedures for system design (Deutsch et al., 1999).

5.3.1.2 Physical tool. In addition to the cognitive tool, a physical tool must also be used to represent the external functioning of the human. Physical software allows for the assessment of motor responses (e.g. physical actions or bodily movements) and their resultant effect on performance outcomes. Such tools typically involve modeling with a digital human in a virtual environment where tasks are assigned. With regard to physical modeling, a variety of tools are also available to model various aspects of physical performance. Using such software can be advantageous in the improvement of human performance while overcoming constraints such as time, capital, and safety. Like the prior tool, care must be exercised when selecting a tool that is suitable for research goals. Table 5.6 names a few examples of physical modeling tools.

Table 5.6. Physical Performance Modeling Tools.

Tool	Description
Computerized Biomechanical Man-Model (COMBIMAN)	Represents physical properties of an operator for operability analyses and to correct designs. Evaluates both existing and conceptual stations (Mattila, 1996).
Human CAD	Creates digital 3D humans using ergonomics and kinematics. Provides data on injury, comfort, reach, or fit (UsErgo, 2010).
Jack	Models performance with a biomechanical human. Such abilties make it suitable for many applications (Blanchonette, 2010).
Man Machine Integrated Design and Analysis System (MIDAS)	Consists of an agent-based operator model, with modules for perceptual, cognitive, and motor processing. Applications include the modeling and prediction of error (NASA, 2010).
Santos Human Engine	Uses an avatar in a virtual environment based on biomechanics and kinematics to simulate motion and posture. Applications include equipment and task design (SantosHuman, 2010).

5.3.2 Comparison of Model Requirements

As described in the prior section, a variety of modeling tools are capable of simulating performance in complex systems. Together, these as well as other tools have the capability to model the system in a virtual environment, along with both the physical and cognitive tasks of the human operator to return output regarding expected performance. Hence, all mental and physical tasks of the human should be taken into account yielding in a better understanding of human interaction, alternate methods to accomplish task goals, and an understanding of the limitations of human performance. To integrate models, however, a comparison of requirements must be developed to identify key similarities and differences between features of the selected tools so that models can be bridged together, creating a comprehensive human performance model.

5.3.2.1 Theoretical fidelity. Foremost, performance software should be considered with regard to its theoretical fidelity (i.e. the degree to which the selected tool complies with major components of the integrative framework). It defines the purpose of the chosen tool to be used exclusively for cognitive or physical performance modeling. By initiating the comparison of the selected modeling tools in this respect, it will ensure that the tools are appropriately chosen for use with the integrated framework. Furthermore, it also reflects the degree to which the tools comply and adhere to the details identified in the theoretical structure of the framework, yielding in better knowledge and acceptance of the theories on which it is based.

5.3.2.2 Input parameters. Having identified which aspect of human performance that the chosen tools are suitable for modeling with the integrative framework, it is necessary to also determine the inputs required. Input parameters convey the key pieces of information specific to the system to be modeled (e.g. task analysis, time studies, statistical distributions, etc.) enabling the quantification of human performance. Collecting such information affects the difficulty or complexity of model development which can alter the feasibility of the chosen modeling tools, making it highly important in determining how closely those parameters match the theoretical concepts identified in the framework.

5.3.2.3 Modeling capability. Another important aspect which should be compared is the modeling capabilities of the selected tools. Such capabilities relate to the levels at which human performance can be affected in the integrative framework. Since the selected tools are capable of modeling cognitive and physical performance, it should also be determined whether the chosen tool is capable of accounting for the factors that significantly alter performance. Considering modeling capabilities are vital for the validation of integrated performance models. Thus, by ensuring that both of the chosen tools account for performance at each level as specified in the framework, the current modeling techniques can be enhanced to a degree which reflects human performance as it occurs in real world settings.

5.3.3 Categorization of Performance Metrics

Performance metrics serve as a precursor for the measurement of human activities and performance in the integrative human performance modeling framework. Specifically, they are quantifiable measures based on expected outputs in relationship to the human-machine system being analyzed. Such measures provide a baseline for improvement and characterize the type of performance to be assessed.

The purpose of choosing performance metrics in the integrative framework is to identify a category from which variables can be extracted to quantify human performance. Therefore, when integrating models, it is necessary to select and categorize measures to determine a method by which to assess such performance. Since field studies regard human behavior as the outcome of a dynamic system where factors relating to the individual interact with elements of the environment, measures of human performance can be categorized with respect to both the states and levels of human performance. Considering performance in such a manner allows for assessment in terms of efficiency, cost, resources, quality, and action. Furthermore, it establishes a target for the comparison of results. However, care must be taken when choosing performance metrics since their value will be determined using mathematical methods. Thus, if inappropriate metrics are chosen, they will yield output or findings of little value upon model integration.

Foremost, when developing performance metrics, it is pertinent to gather knowledge regarding the human-machine system being assessed (e.g. from literature, manufacturers, subject matter experts, etc.). Once obtained, it is then necessary to identify key work processes, performance requirements, and desired outcomes followed by developing measures for critical work processes (e.g. time studies, manning, etc.) or viable results (e.g. completion). Good performance metrics should hold true to three attributes: specificity, measurability, and feasibility. Metrics should be specific to ensure clarity and focus within a given research area so that results obtained from integrated performance models can be easily interpreted. Secondly, metrics should be measurable so that variables can be extracted to quantify performance for the comparison of data and meaningful statistical analysis. They should also be feasible to determine likelihood at which it can be achieved; meaning that the metric must be reasonable, credible, and not subject to software modeling constraints. Selection of metrics by such terms ensures that the chosen metrics encourage improvement, effectiveness, and the appropriate levels of control for a better of understanding human performance.

Since human performance within the integrated framework must be modeled using two tools, cognitive and physical, the chosen metrics should also relate to those measures in order to represent the internal and external functioning of the human. These measures which are represented in the integrated model are subject to the effects of the task, system, human, and the environment which compose the four levels of human performance. Figure 5.4 illustrates this concept by depicting the relationships between the performance measures with respect to the levels of human performance that have an effect on those measures once performance is assessed.

The human silhouette represents the bodily entity by which performance is accomplished. Dashed lines extending from each metric illustrate how both metrics work together to create performance. These lines also illustrate how cognitive and physical metrics are subject to the effects of a variety of independent factors such as the dynamics of the environment, design of the system, individual characteristics of the human, or the task being performed.

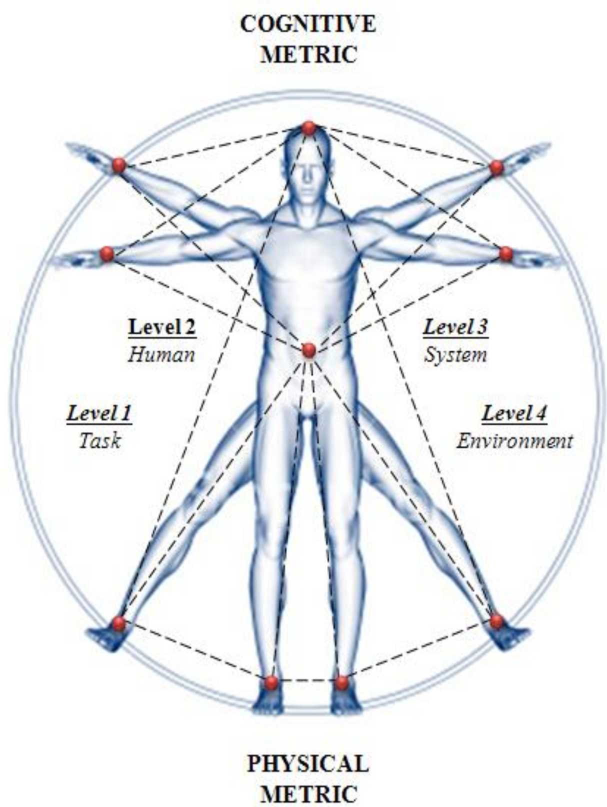

Figure 5.4. Relationship of Framework Metrics (Marchal, 2008).

5.3.4 Extraction of Performance Variables

More importantly, metrics serve as categories from which performance variables can be extracted and modeled. The extraction of performance variables is essential for the integration of performance models given that they must match the capabilities of the selected modeling tools to implement the framework's modeling approach. Since the framework's structure requires that one of the selected tools be capable of modeling human cognition, a corresponding set of cognitive performance variables should be used in order to model the internal functioning of the human.

Cognitive variables are those which are internal to the human performing the task and cannot be observed. Such variables enable models to quantify performance in terms of the output obtained from simulation as well as to facilitate model integration by providing a basis from which independent models can be linked. The variables selected for modeling, however, can vary tremendously depending upon the capabilities of the chosen tool as earlier described. Table 5.7 provides a sample of potential variables that may be used to quantify performance using a cognitive modeling tool.

Table 5.7. Cognitive Performance Modeling Variables.

Sample HPM Variables			
Alertness	Error Rate	Perception	Role
Attention	Evaluation	Personality	Selection
Boredom	Experience	Priority	Situation Awareness
Communication	Failure Probability	Problem Solving	Spatial Cognition
Complexity	Fatigue	Procedures	Stress
Cooperation	Info Availability	Reasoning	Supervision
Cycle Time	Intelligence	Recall	Time
Decision Making	Judgment	Recognition	Training
Demand	Memory	Reliability	Vigilance
Difficulty	Morale	Response Time	Workload

Performance variables must also be selected with respect to the physical tool to model external motor functioning. Such variables are quantifiable, observable, and act on the human externally. Yet, like cognitive variables, physical variables also vary based on the capability of the researcher's selected human performance tool. Examples of these variables are provided in Table 5.8.

Table 5.8. Physical Performance Modeling Variables.

Sample HPM Variables			
Agility	Energy	Location	Response Time
Anthropometry	Fatigue	Manipulation	Speed
Clothing	Fit	Manual Response	Strength
Complexity	Force	Mobility	Target
Cycle Time	Gender	Motion	Temperature
Demand	Humidity	Motor Control	Terrain
Dexterity	Idle Time	Noise	Time of Day
Difficulty	Illumination	Power	Visibility
Duration	Interference	Recovery	Weather
Efficiency	Kinesthetics	Reach	Workload

Both sets of variables are highly critical for the integration performance models due to their bi-directional relationship impacting one another. For instance, a cognitive variable such as vigilance may have an effect on a physical variable such as manual response in the event that attention is not sustained over a prolonged period; thus, slowing performance. Likewise, manual response can in turn impact vigilance if tasks are too demanding, interrupting cognitive processes.

Though the tables present a number of options when selecting performance variables, they must not be considered as an exhaustive list limited to the bounds of the framework. Such variables represent only a subset of the possibilities for modeling performance within a particular tool and may change based upon the capabilities or limitations of the researcher's chosen tool as discussed in the previous section. Hence with proper consideration, it must be known that there are infinite numbers of possibilities for variable selection.

5.3.5 Linking Factors of Cognitive and Physical Performance

Since a bi-directional relationship exists between physical and cognitive variables, both must be integrated to model human interaction and behavior that can simulate human responses and predict how humans interact with complex systems. Such variables can be brought together through linking factors which define the relationship between cognitive and physical performance to integrate simulation models. Linking factors in the model are affected at various levels (e.g. task, human, system, and environment) either enhancing or constraining human performance. By linking performance variables, simulation models can compensate for portions of performance lost due to lack of dimension in independent models. Cognitive variables account for internal performance that is absent in the physical performance model, and physical variables can account for external performance that is absent in the cognitive model. This relationship more accurately predicts human performance by accounting for the factors that create and contribute to naturalistic interaction in the real world, resulting in a comprehensive representation of human performance.

Figure 5.5 describes the bi-directional relationship between the cognitive and physical factors that produce human performance. For instance, cognitive psychometric factors (e.g. knowledge, abilities, attitudes, and personality traits) can have an effect on physical anthropometric (e.g. functional reach), biomechanical (e.g. exerted force), and kinesthetic (e.g. movement) factors. In addition, the latter physical factors can also have an effect in turn on psychometric factors.

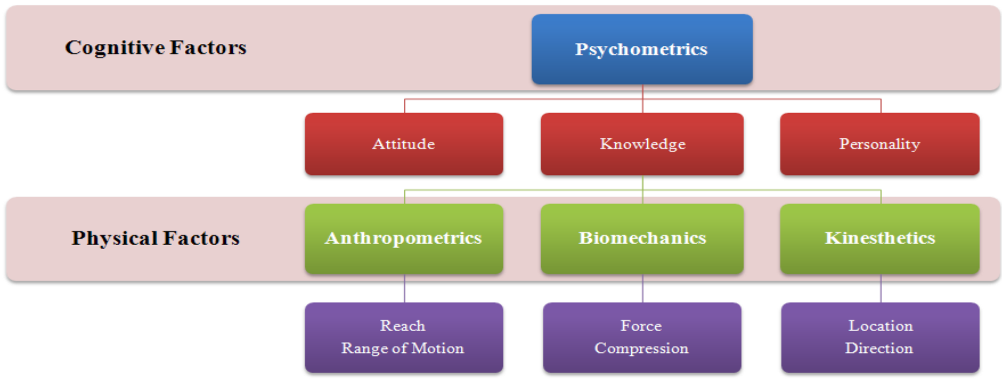

Figure 5.5. Linking Factors of Cognitive and Physical Performance.

5.3.5.1 Intra-variable relationships. Further defining this concept are intra-variable relationships which convey the relationship within variables of the same performance model. For instance, a cognitive variable such as decision making can be impacted by other internal variables such as stress, training, or experience when performing a given job or task. Such variables are likely to have a significant effect on the human's ability to properly assess the task, select the correct alternative, and execute work processes. With respect to the physical model, a variable such as strength may be impacted by relative variables such as gender, age, or dexterity which affect performance in a similar manner.

5.3.5.2 Inter-variable relationships. Although intra-variable relationships convey the relationships within variables of the same model, inter-variable relationships extend beyond the limits of models independently to bridge the gaps between cognitive and physical models. Inter-variable relationships convey the reciprocal relationship occurring between performance variables derived in the physical and cognitive model. For instance, cognitive variables such as demand or complexity can be affected by physical variables such as anthropometry or kinesthetics of the human body. Such relationships between the limits of both models constrain human performance in the same nature as human performance in the real world. Moreover, both inter- and intra- relationships serve to convey the manner in which cognitive processes and physical processes work together to create human performance.

5.4 Implementation of Integrated Human Performance Models

The integrative framework offers a variety of options for creating integrated human performance models. However, specific tools as well as variables corresponding to the capabilities of those tools must be selected to develop integrated performance models. The following sections provide an example of how the framework can be implemented using two human performance modeling tools which comply with the prior defined requirements for integration.

5.4.1 Simulation Software

As earlier described, two simulation tools should be selected to capture the true essence of human performance as it occurs in the real world. Hence, both cognitive and physical human performance software should be selected and used. Micro Saint and Jack software are examples of two modeling tools that are appropriate to use with the integrative framework.

5.4.1.1 Micro saint. Micro Saint, a cognitive simulation software, allows for the human functioning that initiates performance to be modeled. Its modeling approach decomposes the processes used to achieve performance through task network models which depict sequences of human activities. Having this capability, the tool can be used to simulate internal performance of the human in terms of cognitive functioning with regard to the work task, system design, and the work environment. Furthermore, in applications with complex systems, Micro Saint can be beneficial for the evaluation of performance efficiency in terms of the definition and design of work processes implemented by the human, workload imposed by the environment, as well as safety or productivity of the system.

5.4.1.2 Jack. In contrast, physical performance describes the motion undergone by various body parts during normal activity with regard to the interaction between the human and the system. A tool capable of modeling physical performance is Jack software. Jack software models performance through a biomechanically accurate digital human who carries out scheduled tasks within a virtual environment by describing static dimensions of the body in standard postures. This physical human performance modeling tool can be used to model external performance of the human in terms of physical functioning with regard to the work task and the design of the system. A variety of applications can prove beneficial from analysis with this tool because it models anthropometric dimensions and biomechanical constraints such as forces, strain, and pressure.

5.4.2 Software Modeling Capabilities

Since Micro Saint and Jack are capable of simulating cognitive and physical performance, both tools should be compared based on their requirements to define their capabilities and limitations as well as to bridge the tools together to create an integrative human performance model. Table 5.9 describes the utility, parameters, and capabilities of the selected modeling software.

Table 5.9. Comparison of Human Performance Modeling Software.

Model Requirements	**Modeling Software**	
	Micro Saint	**Jack**
Theoretical Fidelity		
Cognitive	x	
Physical		x
Input Parameters		
Task Analysis	x	x
Time Study	x	x
Statistical Distributions	x	
Model Capabilities		
Task	x	x
Human	x	x
System	x	x
Environment	x	

For instance, Micro Saint simulation software models performance with regard to cognitive human functioning. Such models are enabled by the input of task analyses (i.e. network models) which decompose processes into series of tasks. Tasks are then quantified by timing data used in conjunction with statistical distributions to add variability and validity to the model. With these requirements, the software has the capability to model the task in terms of the processes undertaken to accomplish work goals, the human's cognitive functioning, as well as the effects of the system design or the environmental conditions on human performance.

In contrast, Jack simulation software models performance with regard to physical human functioning. Like the cognitive tool, Jack requires inputs such as task analysis and timing data. However, rather than using statistical distributions to account for the variability of human behavior, Jack uses human biomechanical and anthropometric representations to model physical human functioning. With these requirements, this tool has the capability to model the task in terms of processes executed to complete work, the human's functional capabilities with regard to the system's design, as well as environmental conditions. Therefore, together each tool represents both internal and external performance as well as each level of performance as defined by the framework.

5.4.3 Performance Measures and Variables

Cognitive and physical metrics should be used to provide a basis for quantifying human performance. With such measures defined, performance variables can be chosen to enable the integration of performance models.

5.4.3.1 Cognitive measure. In Micro Saint, cognitive measures should be used to correspond with the modeling capabilities of the software. Considering an application with complex systems in a real world environment, humans use cognition to initiate task performance. During the initial phases of work, humans rely on cognitive functioning to carry out goals. For instance, humans must simultaneously monitor gauges and controls to assess the status of the system as well as to make decisions on which controls and strategies will safely and quickly get the job done. Such decision processes vary extensively depending upon the training and experience of the human operator. In addition, the human must also cope with a variety of dynamic elements such as job conditions, available tools, as well as other workers.

The relationship between these demands and the human's ability to manage the amount of work done with a given load is referred to as workload (Wickens, 1984). Such a measure has the capability to be modeled as a performance variable in Micro Saint software, making it appropriate to assess performance. By evaluating the cognitive workload experienced by a human operator interacting with a complex system, issues such as bottlenecks and overload can be identified. Furthermore, since the human operator is critical to performance, workload assessment is necessary for the identification of design problems for safe, efficient, and effective systems. Within the framework, workload represents cognitive processing of the human operator by modeling how tasks are performed, work interference, as well as relative difficultly (Wickens, 1984). Hence, workload in the cognitive model can be quantified in terms of the effort exerted (i.e. total energy output) by the human versus that of the system (i.e. amount of time taken to complete work processes) for a given task over an extended period.

Furthermore, temporal characteristics of performance are also important to consider for the examination of the impact of time on human performance. Since workload is a function of temporal characteristics, human effort, and the range of tasks, cycle time can also be modeled as a variable in Micro Saint to denote the total duration of a process based on the period required to complete a recurring series of operations, functions, jobs, or tasks. Consequently, cycles do not stand alone; instead, they are composed of tasks which decompose into smaller elements of an entire process. Tasks are entities which account for the steps that decompose a cycle and denote the time taken to complete individual pieces of a given process. By using Micro Saint as a modeling tool with the integrative framework, both task and cycle time can be used to determine statistics for proper modeling parameters which produce accurate estimates of human performance (e.g. average output per work period, operating time for the work task, and the length of time required to complete the work process).

5.4.3.2 Physical measure. With respect to physical operations, human operators execute series of tasks to complete work. These tasks are often repeated until work goals are reached. Such processes with a complex system involve human-machine interaction wherein the operator directly manipulates system affordances through physical contact with interface controls. Physical actions require the use of energy which has the capability to be modeled as a variable in Jack software. Energy expenditure refers to the amount of energy used for physical action (Wise, Orr, Wisneski, & Hongu, 2008). Such a variable is essential in the physical performance model due to the fact that humans work over extended periods of time. Energy expenditure can simulate the amount of activity necessary to complete work processes by accounting for the internal stimulus that produces external performance. Therefore, it can be modeled to simulate the external work as a measure of the human's physical activity level. However, to truly capture the impact of the variable energy, its consequences on the human should also be assessed to determine the manner in which physical exertion affects performance.

Fatigue can be used as a variable to measure the loss of strength or energy as a result of recurring tasks. Fatigue, by definition, is a physiological reaction to exertion or stress (Hawley, 1997). More importantly, it has both physical and mental characteristics. Physical fatigue is the inability to continue functioning at a level of normal ability (i.e. the inability to exert muscle force to the degree that would be expected given a general degree of fitness); whereas, mental fatigue affects the state of awareness in terms of a decreased level of attention or consciousness. Physical fatigue is typically work-induced as a byproduct of overuse, strain, or stress from work exertion. In either case (e.g. physical or cognitive), fatigue can be dangerous when performing tasks that require concentration. When interacting with complex systems, fatigue is a precursor to hazards when performing tasks because it negatively affects the human's internal state (e.g. cognitive functioning), slowing performance. Therefore, fatigue can be used as a performance variable in Jack software to assess human reliability in comparison to that of the system to gauge possible consequences of human error.

To better understand how these physical measures affect subsequent performance, recovery rates can also be modeled as a variable in Jack software to determine whether a given period is sufficient to restore energy and continue work. Recovery refers to the act or process of energy renewal that was lost from physical exertion or energy expenditure. In the integrated model, it accounts for the time taken for a human operator to return to normal performance or former physical functioning. Each of these variables were selected as examples of how to extract variables from a chosen performance software according to their relevance in various domains with complex systems, feasibility with regard to the selected software, their degree of measurability, and the extent to which they are likely to affect human performance.

5.4.4 Connecting Performance Models

Having selected variables to simulate performance, models have a basis from which they can be bridged given the bi-directional relationship that exists between physical and cognitive performance. A collective comparison of Micro Saint and Jack software based on their respective modeling capabilities reveal shared requirements of using tasks analyses and time study data as model inputs. Figure 5.6 illustrates the relationships among model variables, denoting that cognitive performance affects physical performance no less than physical performance affects cognitive performance.

5.4.4.1 Intra-variable relationships. In the figure, intra-variable relationships are denoted by the dashed lines which show the relationship of variables within the same performance model. For instance, the variable workload that is experienced by a human, shares a relationship with the variable task time, given that it is a result of the task performance over a given period of time. These tasks also compose cycles of work; thus, describing the time taken by the human to fully execute work processes. With respect to the physical model, a human must expend energy to accomplish work. Since fatigue is a byproduct of energy, which occurs when there is an insufficient amount of time to recover, these variables also share an intra-variable relationship.

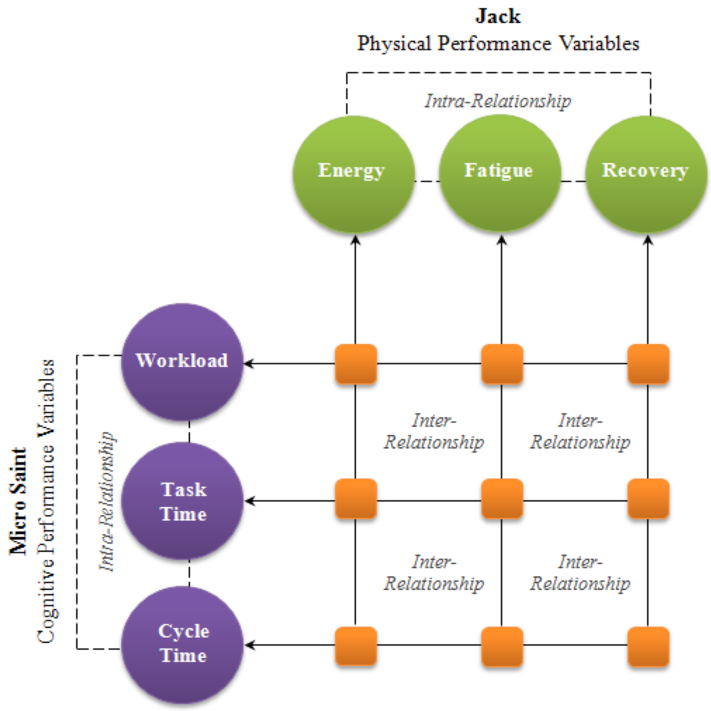

Figure 5.6. Variable Linking of HPM Tools.

5.4.4.2 *Inter-variable relationships.* In addition to intra-variable relationships which convey the relationships within variables of the same model, inter-variable relationships extend beyond the limits of independent assessments to bridge the gaps between cognitive and physical models. These relationships convey the reciprocal connections occurring between performance variables derived to simulate the interaction between internal and external human functioning. Such relationships are denoted by the intersections between cognitive and physical performance model variables. For instance, cognitive variables from the Micro Saint models (e.g. workload, task, and cycle time) are affected by physical variables in the Jack model (e.g. energy expenditure, fatigue, and insufficient recovery time). Specifically, conditions under which a human uses a considerable amount of energy, experiences fatigue, or has a limited period to recover can result in an increased amount of workload. It can also lead to longer task times and cause higher energy expenditures resulting in longer cycle times. Furthermore, these conditions can result in a higher amount of workload, leading to increased fatigue, high energy levels, and limited recovery time. These bi-directional (i.e. cause-effect) relationships between the limits of both models constrain human performance in the same nature as human performance that occurs in the real world; thus, integrating performance models.

Moreover, both inter- and intra-variable relationships convey the manner in which cognitive processes and physical processes work together to create human performance. By linking performance variables and modeling performance in this manner, Micro Saint and Jack models compensate for portions of performance lost due to lack of dimension (i.e. inability to model both cognitive and physical performance) in the models independently. Hence, cognitive variables account for internal performance that is absent in the physical performance model, and physical variables account for external performance that is absent in the cognitive model. This relationship more accurately predicts human performance by accounting for the factors that create and contribute to naturalistic interaction in the real world, resulting in a comprehensive representation of human performance in the simulation models.

5.4.5 Modeling Quantification

In addition to the development and integration of cognitive and physical performance models, they must also be quantified to identify, depict, and verify human performance. The following sections describe in detail how performance can be assessed using Micro Saint and Jack software as well as provide a mathematical quantification to facilitate integration of the performance models.

5.4.5.1 Non-integrated performance models. In the past, it has been customarily assumed that cognitive processes are too difficult to analyze in a practical context. Therefore, many researchers have bypassed their analysis by representing cognitive processes with dummy variables or placeholder operators. Such practices are only permissible when cognitive processes are irrelevant to performance which rarely occurs in the real world. Such misconceptions result in documentation of the presence of human cognition, but fail to yield in assessment of its effects. More importantly, it is likely to produce misleading results (Diaper & Stanton, 2004).

As described in the prior section, human performance in the cognitive Micro Saint model can be measured in terms of the variables time and workload. However, in order to quantify performance, the tasks must first be understood. One such method is by modeling mental workload of the human to convey the relationship between cognitive resources and task demands. By considering internal cognition in human performance models, human processing can be examined at a procedural level by making explicit the capacity of the human mind, decision functions, goal evaluation, planning, and execution of planned tasks. Task analyses define the sequence of tasks performed by the human;

whereas, time studies define the timing information associated with each task and background scenario. Furthermore, each task must be defined to a sufficient level to allow for realistic physical and mental workload values to be estimated and to determine which resources or combinations of resources are required to assess performance.

Workload can be obtained by quantifying the internal and external factors that contribute to performance. Such measures correlate to the system and to the operator while concentrating on the effort exerted during physical and cognitive tasks. In Micro Saint, task times are reflected for movement tasks (e.g. physical) and operational tasks (e.g. cognitive). Since workload is driven by these demands, it is appropriate to measure the level of effort required to achieve the goal. Consequently, tasks times from trace data within simulation output can be used as a direct measure of workload to indicate the amount of time taken for the human to reach the desired goal. Given that tasks within the Micro Saint network model are represented as a hierarchy consisting of the operational task (e.g. cognitive), the motor task (e.g. physical), and the system task (e.g. goal), model formulation can be described in terms of the total cognitive and physical effort exerted by the human. This effort can be considered in terms of task time versus the task time taken to reach the work goal as described by the following equations.

$$\sum (O_T + M_T) = E_H \tag{5.1}$$

$$\sum S_T = E_S \tag{5.2}$$

$$\frac{E_H}{E_S} = W_K \tag{5.3}$$

The prior equations depict that internal human performance (e.g. task time, cycle time and workload) can be described as a measure of the total cognitive and physical effort exerted which is given by the time taken to perform a task versus the time taken by the system to reach a desired outcome or goal. Effort of the human (E_H) is measured by the summation of the time of the physical movement task (M_T) and operational task (O_T) preceding the system task or work goal; whereas, effort of the system (E_S) is measured by the execution time of system work functions as provided by the human. A numerical value is assigned to each task of the human which is modeled against each type of resource of the system (e.g. time taken to execute a process). Workload can then be expressed as a ratio of effort exerted by the human versus that of the system obtained by the contribution of effort across work tasks; thus, resulting in the percentage of human operator workload (W_K).

Similar to Micro Saint, Jack software can quantify external performance using physical variables of energy expenditures, fatigue, and recovery rate. To obtain such output, a virtual environment along with the proposed system can be composed using imported CAD data and system specifications. In this environment, a biomechanically accurate human model can be used to model human performance. Since Jack software requires the definition of work procedures, task analyses can be used to specify or control the virtual human's behavior; whereas, time studies can be used to define time constraints and to add parameters so that tasks can occur simultaneously over a specified interval. Simulation algorithms use these commands to instruct the human model. Once a particular task sequence has been defined for the human model, performance can be quantified in terms of the energy, fatigue, and the necessary recovery period.

As earlier demonstrated, the physical human performance model can be used to assess performance in terms of the prior stated performance variables. Jack software models human performance via a digital human who performs scheduled tasks in a virtual environment. In the model, the digital human is scaled and proportion by software algorithms and statistical measures from which behaviors are defined to condition how the model reacts when performing tasks. Based on inputs from task analysis and time studies, the human model can simulate performance in the virtual environment, enhancing realism and visualization as denoted in equations 5.4 and 5.5.

$$T_N - T_A = r \tag{5.4}$$

$$e \times r = f \tag{5.5}$$

The equations show that performance can be quantified in terms of physical exertion and motion of the human model in a given posture and environment (Godin, 2009). Such capabilities enable comparisons of physical performance necessary to accomplish various tasks. Algorithms in the Jack model automatically gauge physical performance and produce estimates of energy (*e*) and recovery rate (*r*) for each task given by the difference in the time needed to recover (T_N) versus the time available to recover (T_A). Furthermore, energy and recovery, yield in fatigue (*f*) derived as a byproduct of both estimates for a given task. In this way, Jack can model external physical performance as well as the relative impact of these performance variables on one another.

5.4.5.2 Integrated performance models. Although Micro Saint and Jack have individual strengths in modeling cognitive and physical performance, neither accounts for the performance modeled by its counterpart. Therefore, cognitive and physical factors must be integrated to compensate for portions of performance lacking in independent models. Software can be easily integrated by enabling models and performance data to "speak" to one another; thus, illustrating the bidirectional relationship between cognitive and physical human performance. This is achieved through bi-directional linking factors wherein psychometric cognitive factors (e.g. knowledge, individual abilities, etc.) have an impact on physical factors (e.g. anthropometry, biomechanics, and kinematics) and vice versa.

Modeling human performance in Micro Saint requires the use of timing and task data to form the structure of the task network model. Models in this software yield output in the form of trace data, conveying dynamic descriptions of work process in terms of the executed tasks and workload estimates. Since this software has decision making (i.e. cognitive) capabilities, task and timing data from the cognitive Micro Saint model can be directly input into the physical Jack model to assess human performance. Such data can be used to develop the sequence of activities undertaken by the digital human in the physical model. For instance, beginning with the trace data (i.e. simulated tasks and time data) derived from the Micro Saint model, output can be directly input into Jack software, which requires both task analysis and timing data to model the processes performed by the digital human. Portions of the task network model can then be reflected in the Jack software to model physical performance for key work processes within a given domain. With such inputs from the cognitive model, the physical model will define and constrain the range of tasks in the simulated process. These parameters enable the Jack model to accurately simulate the physical motor processes subject to the effects of human cognition in terms of energy, fatigue, and recovery; thus, compensating for the limitations of the cognitive model independently.

Unlike the Micro Saint model, Jack software has no capability to model the effects of cognitive performance (i.e. decision processes). Hence, output obtained from the Jack model enhanced with cognitive inputs can be integrated back into the original Micro Saint model to obtain a comprehensive representation of human performance. For key performance tasks and work processes, fatigue estimates from the Jack model can be used as a direct input back into the Micro Saint model as a performance variable to assess the impact of physical stressors on cognitive performance. In this case, limited recovery can be used as an indicator for tasks and work processes where physical fatigue may occur. Fatigue can be used as a variable in Micro Saint to gauge physical performance and its impact on workload due to the fact that both models are developed according to the same task analysis. Being that fatigue is a byproduct of energy expenditure and recovery, its integration with workload should lead to insight being gained on the effects and relationship between cognitive and physical model variables. Adding fatigue as a performance variable extracted from Jack and placed into the Micro Saint, will slow performance as if it were occurring in the real world. However, to model these affects, Micro Saint mathematical quantifications for performance estimates must be reformulated. The modified quantification for workload in the integrated model can be described in terms of the following equations.

$$f\sum(O_T + M_T) = fE_H \tag{5.6}$$

$$\sum S_T = E_S \tag{5.7}$$

$$\frac{fE_H}{E_S} = iW_K \tag{5.8}$$

As in the original Micro Saint model, performance in the integrated model is represented by task time, cycle time, and workload to measure cognitive and physical functioning of the human. In order to account for physical performance in the cognitive model, performance estimates for energy expenditure (e) and recovery (r) for each task can be used to obtain a variable for integration into the original model formulation wherein the effort of the human is measured by the summation of the human's physical movements (M_T) and the cognitive task time (O_T) preceding the system task goal. Since fatigue (f) is a byproduct of energy and recovery, both physical estimates should be derived according to the task and be modeled as a coefficient to convey its effect on human effort. An integrated workload (iW_k) estimate can then be expressed as a comparison ratio of human effort exerted subject to the effects of cognition as well as physical fatigue (fE_H) versus the system (E_S) which is measured by the time taken by the system to execute work functions provided by the human. With such inputs from the physical model, the cognitive model will validate human performance models. Furthermore, it enables Micro Saint to more closely simulate cognitive processes subject to the effects of motor responses in terms of time and workload to compensate for the limitations of the physical model alone.

5.5 Integrated Human Performance Representation

Having the critical elements, accounted, and integrated into a comprehensive model, performance can be accurately assessed. The integrated framework representation depicts states of performance at both a micro-level (e.g. cognitive internal functioning) and macro-level (e.g. external motor functioning). Not only does its concurrent integrated structure describe the human, but it also comprises the potential contribution of entities at various levels of performance that are subject to the environment, system, as well as the task.

The integrated performance structure creates a hierarchical level of interactivity between the functional components of human performance and the levels by which performance can be affected. Considering the environment, system, human, and task levels of the integrated framework, it creates a common ground and foundation from which human performance models can mirror that which occurs in the real world. Such organization also makes the integration between the software based on the framework feasible and enables the enhancement of models making simulations more accurate. From these levels within the integrated structure, functional human performance can be represented, distinguishing both facets, cognitive internal functioning and physical external functioning. Cognitive internal functioning includes aspects such as individual differences as well as the planning of strategies to accomplish goals; whereas, physical external functioning includes the capability and the means by which to execute such goals. Representing both facets of performance serves to bridge the gap between past modeling approaches.

Hierarchies within the levels of performance are depicted by the components of cognitive and physical functioning at the human level. Models are linked through each of these component levels by the variables which were extracted to link human performance via the exchange of model inputs and outputs. Hence, the established links between cognitive and physical performance at various levels defines the complexity and the degree of detail for integrated performance models with regard to complex human-machine systems. Furthermore, the integrative framework was derived given that an integrated approach to modeling human performance does not exist and has not been used for representing human performance with complex human-machine systems. However, it is essential to enhance models so that they fully represent and capture the essence of human performance. With both states and all levels represented in the integrated framework, human performance can be assessed and compared through the integrated structure that depicts the measures to be considered when modeling. The framework integrates multiple theories to produce a modeling schema that not only predicts human performance from the "neck-up" or the "neck-down," but also provides a foundation for modeling performance subject to various factors.

It provides the required guidelines for developing human performance models that account for cognitive functioning and physical behaviors in relation to a variety of factors that shape human performance. A major contribution of the integrative framework is that it closes the gap between independent performance models to enhance the knowledge of how human performance occurs. It also improves modeling techniques by developing a new approach to modeling human processes with complex systems. The framework provides a structured blueprint that can be usefully utilized to model, analyze, record, and potentially improve human performance.

Also, this framework identifies major types of knowledge that is required to increase the understanding of human performance and model integration. Such knowledge includes: an understanding of performance at various levels, knowledge of the states and functional components of human performance, acknowledgement of the interactions that produce operator behaviors, and the correlation between cognitive and physical factors of human performance. Further understanding of these types of knowledge provide a major opportunity for using the developed framework to analyze human performance as well as work tasks and operations to improve, evaluate, and select more efficient processes and systems. The following chapter describes a case study to be used for application with the integrated human performance modeling framework in a given work domain.

CHAPTER 6

A CASE STUDY IN FLUID POWER

To illustrate how the proposed integrative framework can be utilized to accurately model human performance in complex systems, a case study is described to demonstrate its viability in an applied domain with respect to its described structure and modeling parameters. Thus, high fidelity models can be achieved that capture performance at a general level (e.g. tasks and work processes) as well as at a more detailed level (e.g. human functioning) to make clear the contribution of cognitive and physical aspects.

6.1 Fluid Power Domain

Fluid power is characterized as control mechanism which is used to generate, transmit, and control power (Figure 6.1). In both forms (e.g. hydraulics and pneumatics), fluids are pressurized and exploited, enabling many of today's technological systems to operate with an enhanced degree of capabilities which minimize costs and increase productivity. Specifically, hydraulics enable liquids to produce movements between pistons and cylinders to create a force or movement and to lead to action (Ritchie, 2009). Such technology is commonly used in complex systems and large machinery making it a suitable domain to consider for the application of the integrated human performance modeling framework.

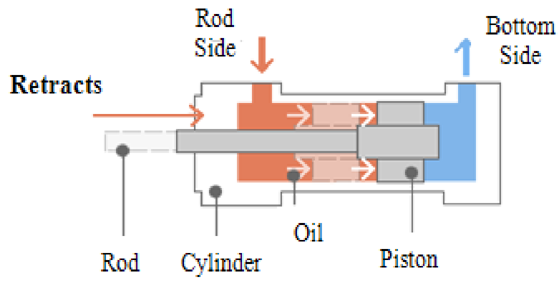

Figure 6.1. Fluid Power Hydraulics (Hitachi, 2010).

6.1.1 Hydraulic Excavator

An example of this technology that complies with the structure of the integrated framework is the hydraulic excavator which utilizes fluid power technology to perform work processes (Figure 6.2). In this system, a human operator manages work operations by controlling its mechanical and hydraulic components (e.g. boom, cylinders, swing, and tracks). Hence, the contribution of both the operator and the technology conveys how complex human-machine systems function together to produce performance.

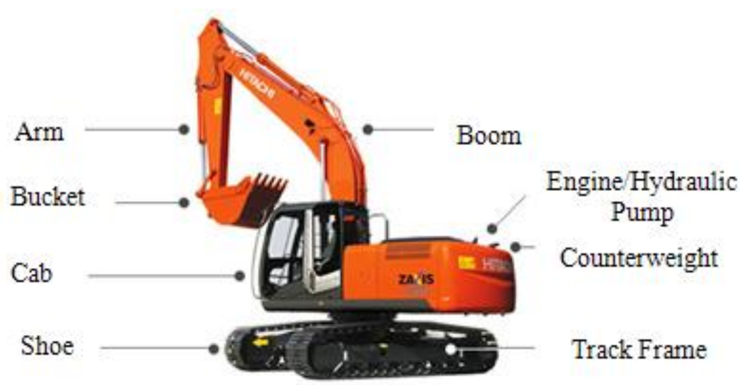

Figure 6.2. Parts of a Hydraulic Excavator (Hitachi, 2010).

Hydraulic excavators are used for a variety of purposes due to specialized tooling (Figure 6.3) which enables their use in a multiple applications such as material handling, demolition, and heavy lifting (Boyanovsky, 2005; Miller, 2010). Its principle application, however, remains material removal; therefore, it is most appropriate to analyze such systems in the construction industry where it is able to be demonstrated their full range of performance capabilities.

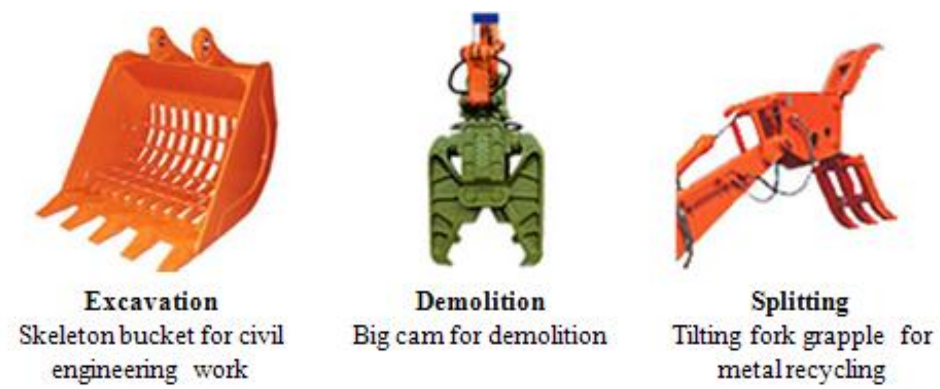

Figure 6.3. Excavator Tooling Attachments (Hitachi, 2010).

6.1.1.1 Excavation. The most common application undertaken when using this type of machinery is excavation, the method by which hydraulic excavators remove matter such as dirt, soil, rocks, or other materials for some purpose (Ritchie, 2009). Performing such processes requires tremendous effort on behalf of the human operator making the application further suitable for consideration.

6.2 Human Performance in Fluid Power Applications

The integrated framework supports modeling fluid power systems such as the hydraulic excavator since its structure allows for the modeling of excavation processes at various levels of detail with regard to the human's cognitive and physical functioning. In addition, it also allows for a variety of other performance shaping factors such as the task, human, system, and the environment to be considered.

6.2.1 Environmental Considerations

The highest level at which human performance can be assessed as defined by the integrative framework is at the environmental level. With regard to hydraulic excavator systems, the environment has the potential to significantly affect performance in a number of ways, making the area appropriate for application.

6.2.1.1 People, machines, and obstacles. In the environment where hydraulic excavation processes are performed, operators encounter many dynamic variables. Excavator operators receive information by sensing the elements within the environment (e.g. people, machines, obstacles, etc.). For instance, obstacles may present apparent (e.g. visible structures) or hidden hazards (e.g. underground lines) while working. Therefore, such obstacles must be perceived, assessed, and managed to ensure safety and efficient work. In many work operations, it is also common for hydraulic excavators to work in unison with other machines or construction equipment. An example is the digging process wherein excavated materials are piled onto a wheeled loader (e.g. bedded truck) and moved to an alternate worksite location. Caution, however, must be exercised when using information regarding the position of machines to align work processes. Consequently, the primary source of this information comes from other workers. Excavator operators communicate with other workers through hand motions to signal execution of desired work processes as seen in Figure 6.4. Excavator operators perceive and interpret this information, leading to decision making based on the data extracted from the environment in connection with their prior knowledge. Decisions are then translated into cognitive or physical actions. Such characteristics are often difficult to model due to their uncontrollable and unpredictable nature, increasing complexity and the potential or severity of error.

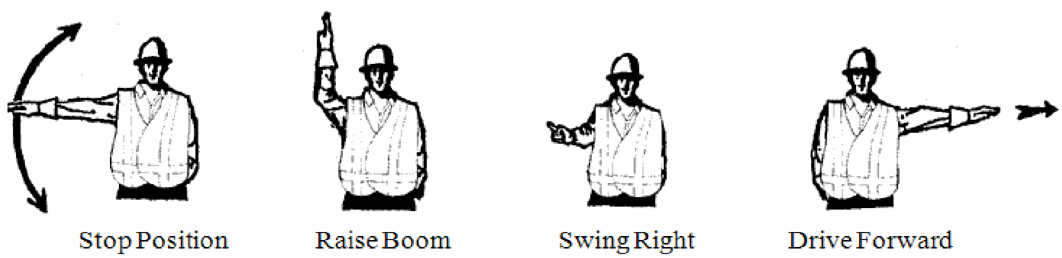

Figure 6.4. Standard Hand Signals for Equipment Movement (WorkSafeBC, 2011).

6.2.1.2 Terrain conditions. More importantly the terrain at work sites can vary tremendously. Excavation jobs have the potential to involve materials such as sand, soil, gravel, rock, concrete, or even asphalt. Such materials vary extensively in terms of condition (e.g. wet or dry) as well as composition; however, excavator operators must have the ability to effectively utilize the system to penetrate the surface and remove any unwanted materials.

Soils are generally classified based on their geological formation (e.g. grain size, shape, and arrangement of mineral particles). For instance, grain types can either be fine or coarse. Figure 6.5 illustrates major soil textures and their percentage of composition grouped according to their class. These classifications have hydraulic properties, meaning that they can be either wet or dry. Since these characteristics have an effect on their permeability, it can make excavation processes considerably more difficult and increase work complexity.

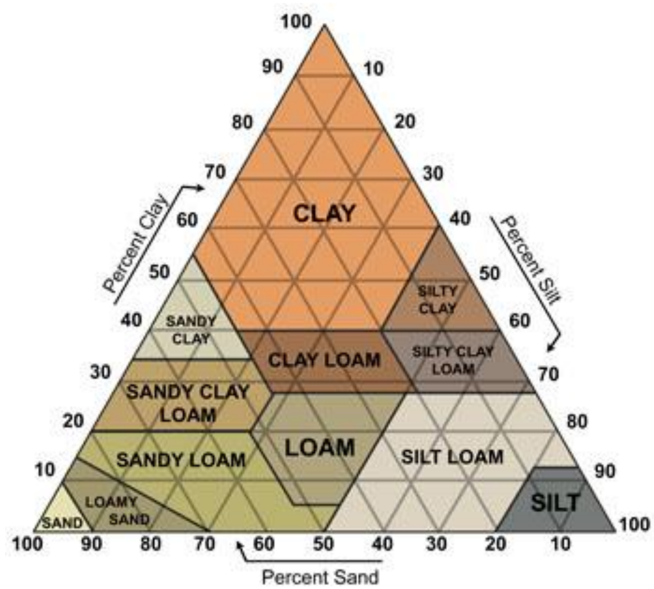

Figure 6.5. Texture Triangle of Soil Types and Compositions (Krumbein, 2010).

Such classifications also have a significant influence on the physical engineering properties of soil. For instance, silt and clay soils are predominantly fine grained; whereas, sand and gravel are predominantly coarse grained (Stead, 2006). Predominant soil types also have distinct consistencies (i.e. the texture and firmness) which are often directly related to its strength. Soils such as sands and gravels can be loose, dense, or cemented; silts can be soft or loose, firm or dense; whereas, clays can be soft, firm, stiff, or very stiff. This characteristic has a significant impact on the ease at which materials can be excavated, affecting overall performance. Therefore it is important to consider this property as it relates to human performance in the integrated framework. Table 6.1 identifies terms used for the classification of soil consistency and permeability.

Table 6.1. Classification of Soils by Permeability (Stead, 2006).

Class	Permeability
Very Loose	Easily excavated with spade.
Loose	Easily penetrated with 13 mm (0.5 in.) reinforcing rod pushed by hand. Alternatively, shows some resistance to spade or penetration with a hard bar.
Compact	Easily penetrated with 13 mm (0.5 in.) reinforcing rod driven with a 2.25 kg (5 lb) hammer. Alternatively, shows considerable resistance to spade or penetration with hard bar.
Dense	Penetrated 0.3 m (1 ft) with 13 mm (0.5 in.) reinforcing rod driven with a 2.25 kg (5 lb) hammer. Alternatively, shows no penetration with hard bar or requires pick for excavation.
Very Dense	Penetrated only a few centimeters with 13 mm (0.5 in.) reinforcing rod driven with 2.2 kg (5 lb) hammer. Alternatively, shows high resistance to pick.

6.2.2 Utilizing the Excavator System

Hydraulic excavators come in a variety of sizes ranging from small or compact to mid-size and large-scale to tackle a number of construction applications. They are also configurable with various tooling attachments for adaptability in multiple work tasks and operations. The versatility in these systems requires the operator to have excessive amounts of energy, intense task concentration, and high skill level. Such requirements can result in complex human-machine interactions.

Furthermore, the greater factor with regard to these systems is that they have evolved in design in order to facilitate efficient work processes.   In most systems, hydraulic control is the standard operating mechanism; however, in newer systems, electronic control allows operators to switch between a traditional control and an alternate control pattern.

6.2.2.1 Hydraulic control. In traditional hydraulic control systems, the excavator is controlled by a human operator using series of buttons, monitors, gauges, and controls to carry out work tasks. Most important of these controls, however, are the system's two manual joysticks. These controls, which are located within the interior of the cab, are responsible for carrying out the primary functions that the operator uses to accomplish work processes.

Hydraulic joysticks offer six degrees of freedom in a quadrant design known as the H-pattern as shown in Figure 6.6. This pattern allows operators to control the system through horizontal motion (i.e. left and right) to employ swing and tilt functions; vertical motion (i.e. forward and backward) to employ the arm and dipper, as well as diagonal motion to produce simultaneous movements. Hydraulic control patterns not only offer simplicity, but also provide a high level of feedback to the operator.

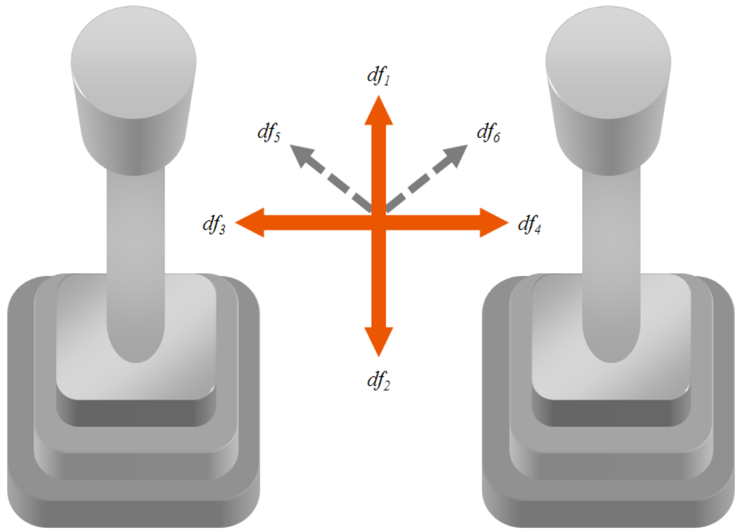

Figure 6.6. Hydraulic Joystick Control Mechanism.

6.2.2.2 Electronic control. Electronic control excavators systems retain many of the basic functions of hydraulic systems, but instead give operators the option of utilizing dual control patterns. The primary difference is that operators can switch between the traditional H-pattern of control and a sub-control pattern of functional joystick buttons as denoted in Figure 6.7.

Like hydraulic systems, when the traditional control pattern is selected, the system is controlled by horizontal, vertical, and diagonal joystick movements; whereas, when the electronic control pattern is selected, joystick buttons control system movements as well as engine dynamics such as horsepower and speed. This control pattern has been thought to be more comfortable and less fatiguing to the operator over long periods of time (Berndtson, 2007).

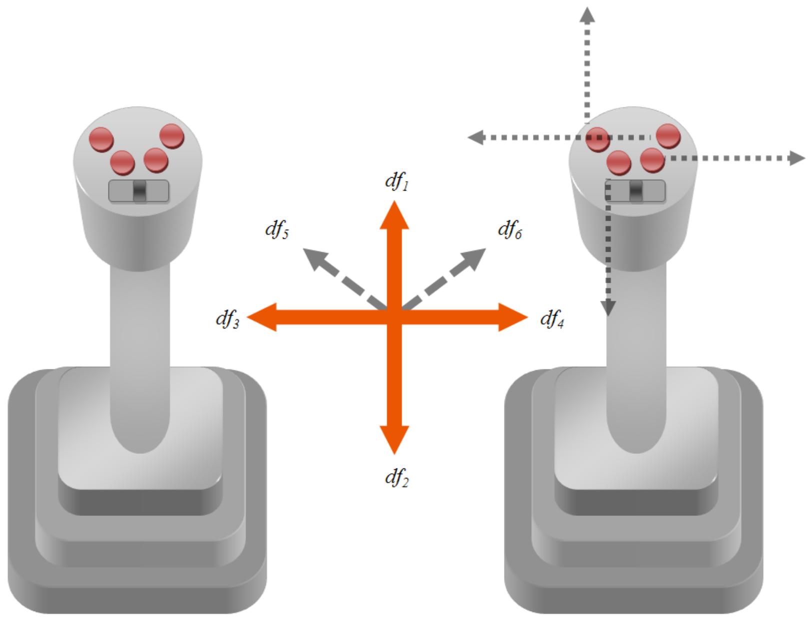

Figure 6.7. Electronic Joystick Control Mechanism.

Consequently, the degree of performance achieved by the human operator can be impacted by the design of the system. Considering new control mechanisms, emergent hydraulic excavators are becoming more advanced and complex than ever before. Though both hydraulic and electronic controls offer distinct advantages when performing excavation processes, it is also appropriate to investigate their affects in terms of performance tradeoffs using the integrated human performance modeling framework. Hence, with the integrated framework, it will be possible to quantitatively assess the effects of design on performance.

6.2.3 Role of the Human Operator

Beyond the scope of the system, the operator is the most critical component when modeling human performance. Performance can be affected drastically by a range of factors with respect to the operator's abilities. These abilities vary among operators due to a host of individual differences. Such differences (e.g. training, experience, age, etc.) can cause operators to be more or less suited for performing particular tasks according to their cognitive and physical skill; thus, making such characteristics essential to consider when modeling performance.

6.2.3.1 Cognitive activity. Human operators provide majority of the information processing capabilities during hydraulic excavation processes. Cognition is critical when evaluating human performance in fluid power systems because it initiates performance, enabling the human operator to perceive stimuli, form goals, and evaluate outcomes. Demands such as perception, attention, and memory are necessary for operators to receive information, make decisions, and the control actions which can be imposed by factors including the environment, system, and the task.

In hydraulic excavation processes, work begins with monitoring (i.e. assessing the job with regard to the system's capability) which involves perception of the work environment to give the operator awareness of surrounding conditions or understanding of the tasks to be performed. Having understood the environment and the task through cognitive processing, actions must be carried out to fulfill work goals. The next step of the excavation process is positioning the system at the desired worksite. With this task, operators rely on cognitive resources such as attention and memory to aid in selecting a course of action (e.g. the location to position the system or proper work procedures).

Both monitoring and positioning tasks are cognitive in nature and impose additional demands which have the potential to affect workload. Therefore, by considering cognitive activity with the hydraulic excavator, human performance models will have the ability to reflect the operator's development of strategies and intentions which precede action to achieve work goals.

6.2.3.2 Physical activity. In conjunction with cognitive activities, physical tasks also take place to complete work processes. Such processing is triggered upon selection of methods and tools and causes the contribution of performance to shift from the state of cognitive functioning to that of physical functioning. Humans use these transforming cognitive processes to execute physical actions (e.g. external movements) in response to stimuli to carry out tasks.

For example, upon response selection, hydraulic excavator operators perform work tasks through physical manipulation (e.g. reaching, pushing, pulling, or turning) of interface affordances (e.g. buttons, joysticks, pedals, or levers). The physical tasks of the human operator execute corresponding functions that are carried out by the system to produce the intended work goal. Such an example exists in fluid power digging operations, the most common task of a hydraulic excavator. In order for this process to occur, the human operator must determine an appropriate location to excavate and pile materials, followed by manipulating the system's manual joystick controllers whose range of motion executes specific functions. These operations impose demands on the human operator, holding the potential to affect a variety of performance factors (e.g. workload, fatigue, or time) because they can occur in series or parallel and are often repetitive in nature. Hence, it is also appropriate to investigate the role of physical activity on human operators using complex systems.

Both cognitive and physical activities reflect mechanics of human performance. With respect to each, the interaction between internal and external human functioning can be specified by describing the mechanisms through which operators shift from intention to action as well as the level of effort required with regard to various demands (Wickens et al., 2004). More importantly, integrating internal cognitive functioning and external physical functioning enables models to consider the factors that guide human behavior and to parallel the human responses that are necessary for performance.

6.2.4 Decomposition of Excavation Tasks

Furthermore, with regard to hydraulic excavations, a variety of tasks occur in order to complete work processes. These processes also require various levels of cognitive and physical activity on behalf of the human, comprising the degree to which performance is attained. Therefore, to reflect these processes, the excavation task must first be understood. Task analyses provide the methods to effectively assess excavation processes at a sufficient level of detail.

Task analysis describes the means through which work is fulfilled with regard to both cognitive and physical activities of the human being to yield in a better understanding of human behavior. As identified by the framework, the system as well as the task must be defined for the integration of human performance models. The following sections describe in detail the task of a typical hydraulic excavation process through which performance can be examined.

6.2.4.1 Hydraulic control. Excavation processes generally occur in distinct phases comprised of key work tasks. Beginning with initialization, key tasks occur to engage the system and prepare for anticipated work in terms of job type, work conditions, and location. In this phase, tasks include starting the system, monitoring gauges, determining the appropriate system settings, as well as the location to position the system at the worksite. For instance, hydraulic excavator operators initiate work processes by engaging the system which is accomplished by physical extension of the arm to reach and turn the engine's starter switch. Cognitive processes ensue when the operator checks the system's monitor panel to obtain critical information from various gauges and indicators. The key task of monitoring involves perception and recognition of information which enables the operator to select the appropriate configuration for the system according to the type of job (e.g. material or tooling required), size of the job (e.g. small, medium, or large), as well as environmental conditions (e.g. terrain, workers, or obstacles).

Once the type of excavation process has been determined, the operator will proceed to adjust the engine speed through physical tasks such as reaching the arm and manipulating the appropriate control. Upon completion of these tasks, physical work continues when the operator moves the excavator to the desired work location which is achieved by manually reaching the arm, extending the leg or foot, and pushing or pulling the system's travel levers. Like other physical tasks, positioning is also preceded by cognition to determine where to position the excavator. Positioning can be achieved by one of two methods. Based on the operator's experience level, the system can be positioned by sequential or simultaneous movements. For instance, an inexperienced or novice operator is likely to sequentially position the excavator by extending the leg or foot to push or pull the travel levers; followed by reaching the arm and tilting the hand to adjust the swing arm control lever. In contrast, an experienced or expert operator is more likely to simultaneously position the excavator by reaching the arm, tilting the hand, and adjusting the swing arm control lever to the position excavator. Since these tasks are performed concurrently, the latter procedure requires fewer steps to accomplish the work goal, making process more efficient. As can be recognized, many tasks during the initialization process rely on cognition which plays an important role in the foundation of human performance.

In the active work phase of excavation processes, tasks become less cognitive and more physical in nature. During this phase, the operator completes excavation tasks via the hydraulic system using manual joystick controls used to dig, scoop, and pile excavated materials. To begin the key task of digging or excavating materials, the operator must lower the large extendable arm of the excavator, known as the boom, by tilting the hand and pushing the bucket control lever. Following, the dipperstick (i.e. the small extendable arm), must also be lowered to the ground by tilting the hand and adjusting the swing arm control lever. Subsequently, the excavator will use its bucket attachment to scoop materials upon the operator titling the hand and pushing or pulling the bucket control lever. To move the dirt to the desired location, the operator will repeat a similar process of tilting the hand and pulling the bucket control lever in the opposite direction (e.g. backward) to raise the boom which has been loaded with the excavated materials. The excavator will then rotate forward when the operator tilts the hand and moves the swing arm control lever to place the load. Lastly, the operator will tilt the hand and press the bucket open control to release excavated materials. Once the load has been released from the bucket, the operator will tilt the hand and move the swing arm control lever right to rotate the excavator back to its initial work position. Depending on the experience level of the human operator, digging processes may also be performed more efficiently by simultaneously executing work tasks.

At this point in the excavation process, there are three possible actions that the operator can undertake. The operator has the alternatives of: repeating the digging task until the work is complete, repositioning the system at an alternate location, or completing the initial excavation process. In the event that the operator decides to continue the excavation process, the prior stated tasks iterate until work goals have been met. However, if work is complete, the operator will proceed to the finalization phase. The finalization phase of the excavation process mirrors that of the initial phase involving tasks of shutting down the system at a designated location. For this operation, the operator must reach the arm and turn the starter switch to end work. This series denotes that all work tasks in the excavation process have been completed. Each of these tasks in some aspect reflects the range of performance that occurs for work to be completed as well as the parameters necessary to accurately model human performance when modeling hydraulic excavation processes. A summary of these tasks can be found in Figure 6.8.

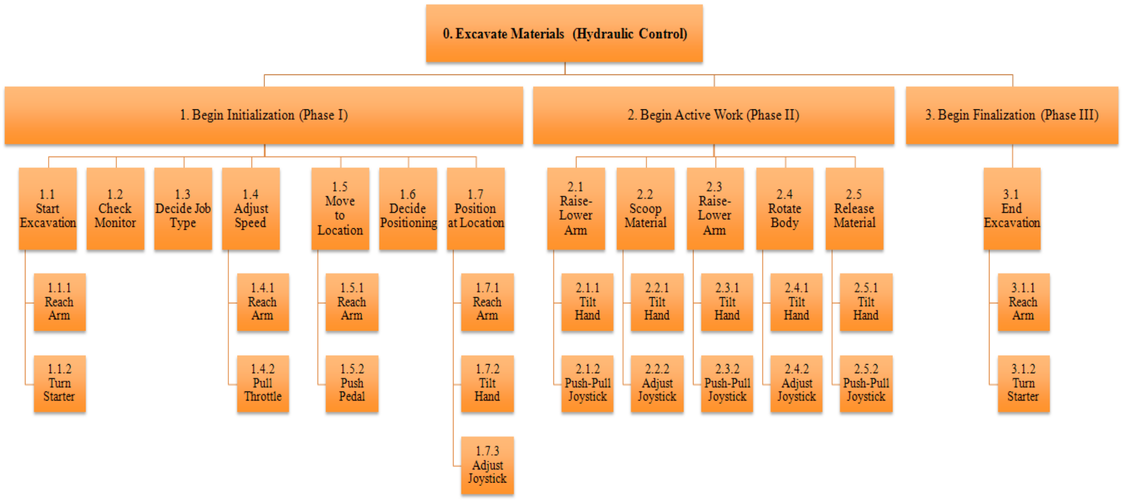

Figure 6.8. Task Analysis of Excavation Processes Using Hydraulic Control.

6.2.4.2 Electronic control. As described in Section 6.2.2, hydraulic excavators have undergone changes in their design, transitioning from hydraulic to electronic control mechanisms that are intended to be more comfortable and less fatiguing to the human operator. With these controls, the operator has the option of using the traditional H-pattern or an alternate sub-pattern of control by using functional joystick buttons that control rotation, travel, and movement of system attachments. Such changes not only alter the physical design of the system's primary controls, but it also modifies the manner in which the operator performs tasks to facilitate work processes.

Like hydraulic control systems, the phases of typical hydraulic excavation processes with electronic control systems also consist of initialization, active work, and finalization. Key tasks also include that of monitoring, positioning, and digging to excavate materials. The sequence of steps used by the human operator to complete these tasks within each work phase also remains the same with the exception of the active work process. In the initialization phase, monitoring and positioning tasks occur and involve human cognition; whereas, in the finalization process, tasks consist of the operator shutting down the system. The primary difference is that the operator uses the finger to press joystick buttons instead of tilting the hand or wrist to move joysticks.

For example, with excavators using electronic control mechanisms, the operator begins the active work process by lowering the boom. Instead of tilting the hand and pushing the bucket control lever, the operator presses the inner-left joystick control button by moving the finger. Following, the dipperstick is lowered to the ground in the same manner, but using the outer-left button on the joystick controller. Next, the bucket, which is used to excavate material, is moved by pressing the corresponding bucket control button. To move the dirt to the desired location, the operator will repeat a similar process of pressing inner-left joystick button to raise boom which has been loaded with the excavated materials. Following, the excavator will rotate forward when the operator presses the functional button on the outer-right side of the joystick control. Lastly, the operator will press bucket open control to release excavated materials and rotate the excavator back to its starting position.

In the finalization phase, the operator concludes work processes and shuts down the system. Like the task analysis for the hydraulic system, tasks become less cognitive and more physical in nature. A task summary can be found in Figure 6.9.

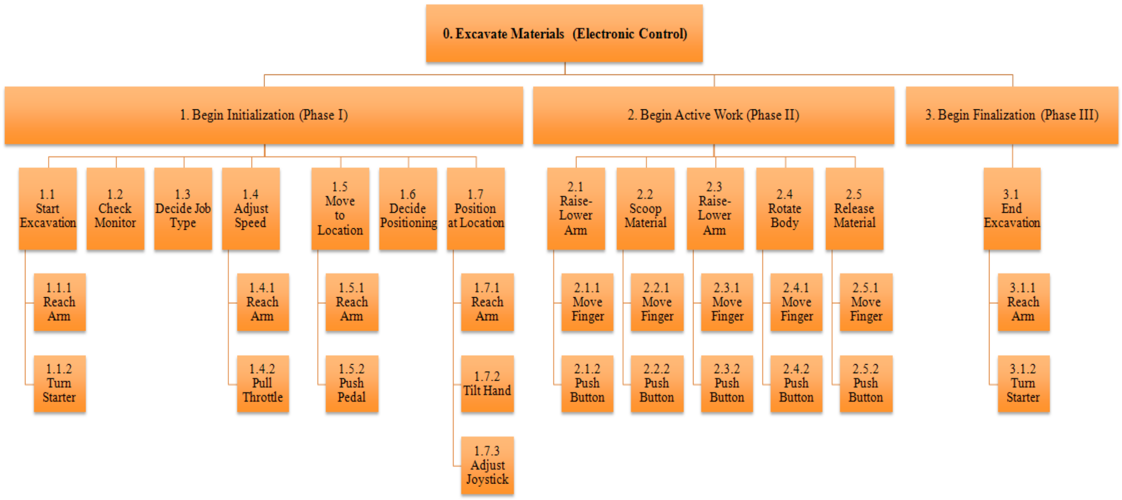

Figure 6.9. Task Analysis of Excavation Processes Using Electronic Control.

With regard to both task analyses, it can be noted the contribution of both cognitive and physical functioning in task performance. Task analyses which are decomposed in a hierarchy allows for representation of steps or procedures necessary to accomplish a task preceding the goal.

Furthermore, task analyses provide benefits of qualitative information regarding excavation processes by considering the factors that affect performance. To model performance, tasks analyses can be complemented by time studies to convey element durations, task frequency, task allocation, and task complexity required for the human operator to perform a given job; thus, extending the collected real world data into predictive human performance models.

6.3 Integrating Human Performance in Excavation Applications

Fluid power systems such as the hydraulic excavator provide a suitable domain for application with the integrated human performance modeling framework. Characteristics of excavation processes enable the framework to capture performance at various levels of detail as well as to account for the variety of factors that impact performance.

6.3.1 Case Description

The integrated human performance modeling framework is applied to the previously described fluid power case study involving a hydraulic excavator controlled by a human operator performing routine excavation processes to remove earthen materials within a typical construction environment. Tasks are studied with regard to the system's design and function as well as the cognitive and physical tasks employed by the human operator to attain work goals; thus, reflecting the degree of detail necessary to comply with the framework's structure.

6.3.2 Domain Relevance

There has been substantial advancement to hydraulic excavator systems in recent years with the introduction of new technologies that accommodate a variety of tasks, make work processes more efficient, protect the environment, and make work easier for the human operator. Though such changes have increased the appeal of this technology, it has caused these systems to become more complex; altering the role of the human operator. The role of the human has thus transitioned from monitoring and control in traditional systems to more supervisory in modern automated systems, resulting in tradeoff with system complexity and its impact on the human operator.

Many research, design, engineering, and user initiatives recognize the importance and need to consider the influences on the human operator as the critical component to performance by using modeling approaches that simulate human-system interaction. However, human performance often presents challenges, making it difficult to capture its shaping factors (e.g. characteristics specific to the individual or unpredictable dynamics of the environment). In addition to these contributing factors, many human performance modeling approaches rely on superficial “neck-up” or “neck-down” analysis, when both cognitive and physical processes interact to produce human behavior. Such errors lead to research gaps and inaccurate performance models which result in unanticipated performance outcomes with regard to the system and the human operator. This is particularly true in the development of fluid power systems such as the hydraulic excavator where there is an absence of research aimed at addressing and improving upon such matters.

The integrated framework presents a more sophisticated human performance modeling technique to capture such complexities and accurately model human performance to enhance the quality of predictive human performance models. Using the integrated framework provides realistic models of the human operator by capturing work processes, effects of the environment, as well as providing a means to assess system components that are highly unpredictable and traditionally difficult to model.

By concentrating on fluid power systems such as the hydraulic excavator, there is the potential to gain insight on interaction, investigate the limitations of human performance, and better support the needs of operators (Laughery, 1998). Since the modeling technique can be used to simulate performance under various conditions, performance models can accurately account for the system as well as the operator by evaluating their effects in complex settings. Insight can be gained in terms of work processes, system design, cognitive and physical workload, and operational safety; ultimately, yielding in better decisions during the design process.

The case study described herein only presents one applicable domain to apply the integrated human performance modeling framework; however, there are also many opportunities for its application in a variety of other areas to address new varieties of problems concerning human performance with complex human-machine systems.

CHAPTER 7

RESULTS

Human performance models were developed using Micro Saint and Jack software to assess cognitive and physical human performance based on the fluid power case study involving a hydraulic excavator as described in Chapter 6. An empirical study on human performance was run following the framework in Chapter 5 to examine the effects of hydraulic and electronic control mechanisms as well as the effects of soil and gravel terrain environments; common conditions under which excavation processes are performed. By considering the cognitive and physical factors that impact performance as identified in the framework, independent simulation models were linked for the purpose of integration and to develop a comprehensive representation of human performance. The following sections describe task and statistical analyses from the results of the case study.

7.1 Micro Saint Human Performance Models

Four simulation models were built in Micro Saint based on excavator control type (e.g. hydraulic and electronic) and environmental terrain (e.g. soil and gravel). Real world data for the models was collected on the excavation tasks, control operations, and system functions of a hydraulic excavator in traditional work environments through video recordings. Recordings were categorized with regard to control and the environment, and task analyses were conducted for each of the four systems: Hydraulic Control-Soil

Terrain (HS), Hydraulic Control-Gravel Terrain (HG), Electronic Control-Soil Terrain (ES), and Electronic Control-Gravel Terrain (EG). Analyses were used to create task network models (Appendix A). Model development involved defining its structure based on a subset of the elements and parameters as identified by the integrated framework; thus, reflecting tasks performed by humans, processes, and the machine. Task descriptions, timing information, and statistical distributions were then embedded within the models to simulate variance across hydraulic excavation tasks as well as to provide a higher level of validity for performance estimates and modeling results. Each of the simulation models was coded, debugged, and randomly run for 100 iterations. The following sections provide results from task analysis and the empirical study for cognitive, physical, and integrated human performance models.

7.1.1 Task Analysis

Tasks analysis provided a means to decompose work processes for a better understanding of human performance. The following sections provide details from the results of those analyses.

7.1.1.1 Hydraulic control-soil terrain. Results of the task analysis for the operators using a hydraulic control excavator to excavate soil revealed the processes involved during typical excavation tasks. Tasks were classified in three work phases: initialization, active work, and finalization. Primary work tasks were monitoring, positioning, and digging. Cognitive tasks consisted of monitoring the system and the work environment as well as decision making procedures to execute functions. Physical tasks consisted of manipulation of system controls to complete work. With regard to the controllers, operators utilized manual joysticks with six degrees of freedom. Joysticks were used to control rotation, travel, and movement of the system. In this environment, operators performed work tasks fluidly. These instances were observed with positioning and digging processes during the movement of the system's mechanical components. Task analysis and timing data for these tasks can be seen in Table 7.1.

Table 7.1. Task Analysis and Time Study (sec) for Hydraulic-Soil Model.

#	Task	Time	#	Task	Time
	Phase I - Initialization		23.	Tilt Hand	4.20
1.	Start Excavator	3.00	24.	Adjust Joystick	4.20
2.	Reach Arm	2.29	25.	Scoop Material	4.48
3.	Turn Starter	2.00	26.	Tilt Hand	1.08
4.	Check Monitor	5.00	27.	Adjust Joystick	4.20
5.	Turn Head	1.50	28.	Rotate Body Forward	3.92
6.	Decide Job Type	0.00	29.	Tilt Hand	1.08
7.	Adjust Speed	2.86	30.	Adjust Joystick	4.20
8.	Reach Arm	2.29	31.	Release Material	3.55
9.	Pull Throttle	2.30	32.	Tilt Hand	1.08
10.	Move to Location	13.64	33.	Pull Joystick	4.20
11.	Reach Arm	2.29	34.	Lower Boom	3.14
12.	Extend Leg	2.20	35.	Tilt Hand	1.08
13.	Push Pedal	2.13	36.	Pull Joystick	4.20
14.	Decide Positioning	0.00	37.	Lower Dipperstick	3.35
15.	Position at Location	12.85	38.	Tilt Hand	4.20
16.	Reach Arm	2.29	39.	Adjust Joystick	4.20
17.	Tilt Hand	1.08	40.	Rotate Body Backward	3.88
18.	Adjust Joystick	4.20	41.	Tilt Hand	1.08
	Phase II - Active Work		42.	Adjust Joystick	4.20
19.	Lower Boom	3.14		*Phase III – Finalization*	
20.	Tilt Hand	1.08	43.	End Excavation	3.00
21.	Push Joystick	4.20	44.	Reach Arm	2.29
22.	Lower Dipperstick	3.35	45.	Turn Starter	2.00

With regard to the operator's physical movements, tasks consisted of extending the leg or foot, reaching the arm, tilting the hand, and turning the head. Figure 7.1 presents the graphical results associated with hydraulic control excavator systems in soil terrain in terms of task time and the variation throughout the excavation process. Monitoring and positioning tasks such as turning the head and extending the leg took operators an average of 1.0 seconds and 2.9 seconds. These tasks yielded in the lowest variation between 0% and 1%; whereas, tilting the hand resulted in the least amount of variation at 20% within the model, taking an average of 1.1 seconds to execute. Overall, both reaching the arm and extending the leg were the longest tasks, taking an average of 2.9 seconds each.

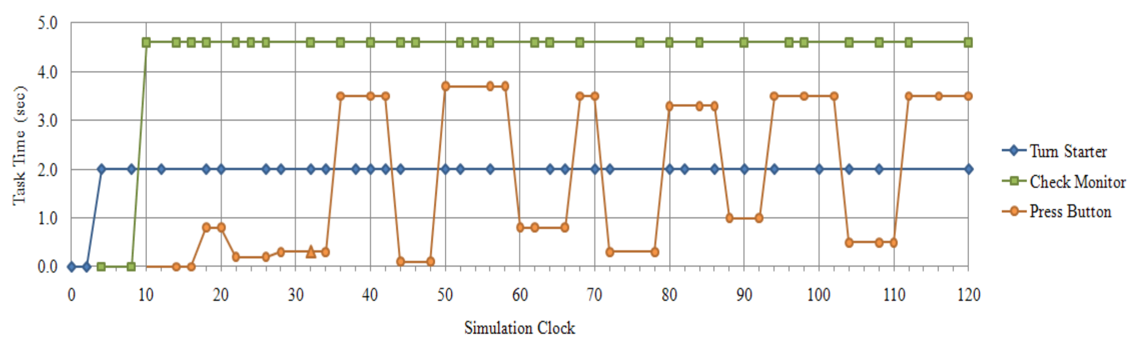

Figure 7.1. Movement Tasks for Hydraulic-Soil Model.

For work operations, performance tasks consisted of turning the starter, checking the monitor, pushing or pulling levers, as well as adjusting or pulling the joystick controls. As seen in Figure 7.2, monitoring yielded the longest task time of 5.8 seconds and was carried through the entire excavation process. Both pushing and pulling levers as well as turning the starter switch took operators an average of 2.2 seconds and 2.0 seconds; whereas, the shortest tasks were adjusting and pushing or pulling the joystick controllers, yielding average values of 0.62 seconds and 0.70 seconds.   However, the latter tasks also yielded in a higher amount of variation at 16% and 37% as compared to longer tasks such as checking the monitor and pulling the lever at 0% each. Pulling the lever yielded in variation at 19%.

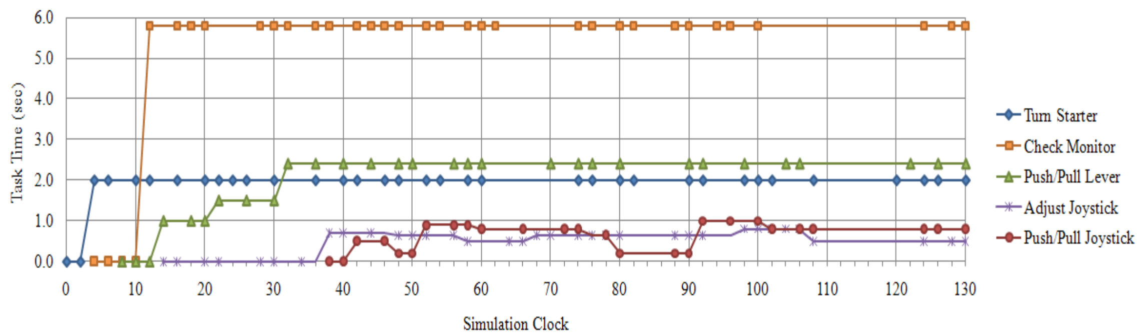

Figure 7.2. Operation Tasks for Hydraulic-Soil Model.

7.1.1.2 Hydraulic control-gravel terrain. Operators using hydraulic control systems to excavate gravel revealed work tasks consistent with monitoring, positioning, and digging. Cognitive and physical tasks performed by the operators likewise consisted of monitoring and movements to manipulate the joystick controls. In this case, the primary difference observed was that operators encountered a greater degree of difficulty when attempting to accomplish work goals. These conditions (e.g. gravel terrain) increased work requirements and difficulty for operators. Task analysis and timing data for are summarized in Table 7.2.

Table 7.2. Task Analysis and Time Study (sec) for Hydraulic-Gravel Model.

#	Task	Time	#	Task	Time
	Phase I - Initialization		22.	Lower Dipperstick	5.08
1.	Reach Arm	2.40	23.	Tilt Hand	1.61
2.	Turn Starter	2.00	24.	Adjust Joystick	8.00
3.	Begin Excavation	8.00	25.	Scoop Material	4.88
4.	Turn Head	3.50	26.	Tilt Hand	1.61
5.	Check Monitor	11.33	27.	Adjust Joystick	8.00
6.	Reach Arm	2.40	28.	Rotate Body Forward	5.63
7.	Pull Throttle	4.17	29.	Tilt Hand	1.61
8.	Adjust Speed	8.00	30.	Pull Joystick	8.00
9.	Reach Arm	2.40	31.	Release Material	4.16
10.	Extend Leg	2.20	32.	Tilt Hand	1.61
11.	Push Pedal	3.22	33.	Pull Joystick	8.00
12.	Move to Location	36.00	34.	Raise Boom	3.97
13.	Reach Arm	2.40	35.	Tilt Hand	1.61
14.	Tilt Hand	1.61	36.	Adjust Joystick	8.00
15.	Adjust Joystick	8.00	37.	Raise Dipperstick	5.08
16.	Position at Location	9.60	38.	Tilt Hand	1.61
	Phase II - Active Work		39.	Adjust Joystick	8.00
17.	Tilt Hand	1.61	40.	Rotate Body Backward	5.40
18.	Push Joystick	8.00		*Phase III – Finalization*	
19.	Lower Boom	3.97	41.	Reach Arm	2.40
20.	Tilt Hand	1.61	42.	Turn Starter	2.00
21.	Adjust Joystick	8.00	43.	End Excavation	8.00

Figure 7.3 illustrates that the shortest movement tasks for operators of hydraulic excavators excavating gravel terrain was tilting the hand, taking an average time of 1.4 seconds, followed by extending the leg with an average time of 2.0 seconds. Although tilting the hand is one of the fastest tasks, it also yielded in the most extreme variation and the least consistency during the simulation with variation at 40%.

The graphical output also revealed that turning the head and reaching movements engaged the operator longer with average task times of 2.9 seconds and 2.3 seconds. Graph series with the most consistent trends throughout the excavation process were turning the head and extending the leg with 0% variation each.

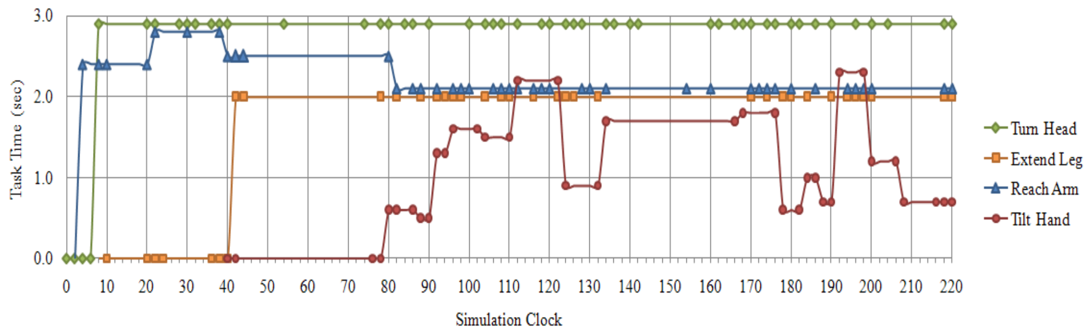

Figure 7.3. Movement Tasks for Hydraulic-Gravel Model.

Results for the hydraulic control system in gravel terrain (Figure 7.4) revealed that the longest operational task was checking the system's monitor, yielding an average value of 14.0 seconds. Other operational tasks yielded in significantly lower values such as pushing or pulling levers, taking an average of 4.6 seconds as well as turning the starter switch, taking an average of 2.0 seconds to complete. The lowest operational task times were associated with the manipulation of the joystick, yielding in an average time of 1.4 seconds for pushing or pulling and 1.1 seconds for adjusting. Trends in the data revealed that longer tasks (e.g. checking the monitor panel) generally yielded in the least variation at 0% whereas; shorter tasks (e.g. adjusting or pushing the joystick) yielded in greater variation with coefficients at 35% and 12%.

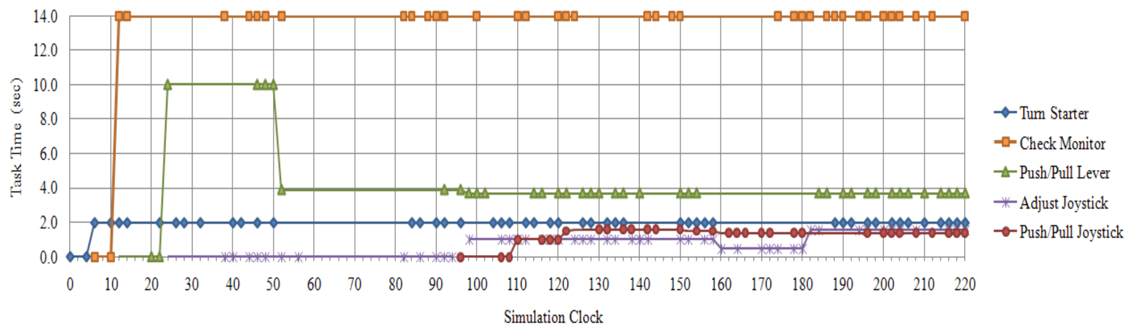

Figure 7.4. Operation Tasks for Hydraulic-Gravel Model.

7.1.1.3 Electronic control-soil terrain. Task analysis for electronic excavators excavating soil indicated that processes involved work phases of initialization, active work, and finalization. Key work tasks of these operators again involved monitoring, positioning, and digging. Although tasks were consistent with this analysis in comparison to the analyses for hydraulic control excavator systems, operators using electronic control systems utilized different work methods due to the design of the system's controllers. Like the hydraulic control systems, electronic control excavators have joystick controllers. The primary difference is that these controllers are equipped with functional buttons that are embedded in the joystick which control system movement (i.e. rotation, positioning, and tooling attachments). Therefore, rather than using the joystick controller's range of motion, operators used buttons to execute work tasks. Such changes altered the methods utilized by operators to achieve work tasks during the excavation process. With these changes, the physical task of the human operator was pressing the button rather than titling the hand. Table 7.3 describes task analysis and time study data for those excavation tasks.

Table 7.3. Task Analysis and Time Study (sec) for Electronic-Soil Model.

#	Task	Time	#	Task	Time
	Phase I - Initialization		21.	Move Finger	1.00
1.	Reach Arm	2.29	22.	Press Joystick Button	1.55
2.	Turn Starter	2.00	23.	Scoop Material	4.76
3.	Begin Excavation	3.33	24.	Move Finger	1.00
4.	Turn Head	2.00	25.	Press Joystick Button	1.55
5.	Check Monitor	2.67	26.	Rotate Body Forward	3.47
6.	Move Finger	1.00	27.	Move Finger	1.00
7.	Press Joystick Button	1.55	28.	Press Joystick Button	1.55
8.	Adjust Speed	5.00	29.	Release Material	3.49
9.	Move Finger	1.00	30.	Move Finger	1.00
10.	Press Joystick Button	1.55	31.	Press Joystick Button	1.55
11.	Move to Location	6.50	32.	Raise Boom	3.32
12.	Move Finger	1.00	33.	Move Finger	1.00
13.	Press Joystick Button	1.55	34.	Press Joystick Button	1.55
14.	Position at Location	6.44	35.	Raise Dipperstick	2.50
	Phase II - Active Work		36.	Move Finger	1.00
15.	Move Finger	1.00	37.	Press Joystick Button	1.55
16.	Press Joystick Button	1.55	38.	Rotate Body Backward	3.47
17.	Lower Boom	3.32		*Phase III - Finalization*	
18.	Move Finger	1.00	39.	Reach Arm	2.29
19.	Press Joystick Button	1.55	40.	Turn Starter	2.00
20.	Lower Dipperstick	2.50	41.	End Excavation	3.33

Movement tasks for operators of electronic control systems excavating soil are illustrated in Figure 7.5. Under these conditions, tasks consisted of reaching the arm, turning the head, and moving the finger. The shortest movement time for operators of electronic excavators in soil terrain environments was moving the finger to press the joystick button with an average time of 1.0 seconds. Moving the finger was closely followed by the task of turning the head to check the monitor, yielding in an average task time of 1.6 seconds.

Consequently, turning the head presented no variation in the model results; whereas, moving the finger presented the highest variation with a coefficient of variation at 37%. Reaching the arm presented a low amount of variation at 10%, taking an average time of 1.9 seconds to complete during the excavation process.

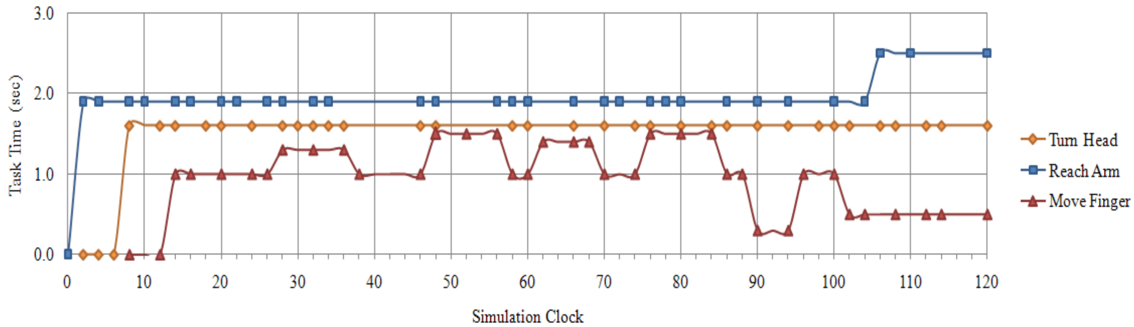

Figure 7.5. Movement Tasks for Electronic-Soil Model.

Operational tasks for electronic control systems consisted of turning the starter, checking the monitor, and pressing buttons embedded in the joystick controllers. Similar to hydraulic control systems, the longest task was associated with checking the system's monitor panel, yielding in an average value of 3.8 seconds and turning the starter switch with 2.0 seconds. The shortest task was revealed to be that of pressing the joystick buttons with an average time of approximately 1.9 seconds. However, as can be seen in Figure 7.6, this task yielded in the greatest amount of variation at 95%; whereas, both of the longer tasks (e.g. checking the monitor and turning the starter) yielded no variation with values at 0% each.

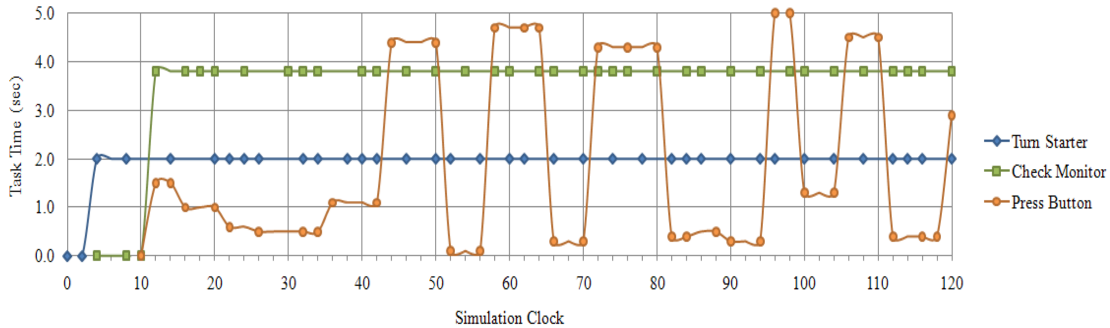

Figure 7.6. Operation Tasks for Electronic-Soil Model.

<u>*7.1.1.4 Electronic control-gravel terrain*</u>. Operators using an electronic control excavator to excavate gravel performed three key work tasks consisting of monitoring, positioning, and digging processes. Similar to these systems when excavating in soil terrain environments, operators used the joystick buttons rather than employing the controller's range of motion (e.g. degrees of freedom) to complete the excavation process.

Work tasks consisted of rotation, traveling, and movement of the system's hydraulic tooling attachments. However, like operators of the hydraulic control systems, these operators encountered difficultly when performing work tasks in gravel terrain. Thus, operators performed work tasks slower, due to an increase in environmental complexity and job difficulty. A summary of the task analysis and time study data for operator of electronic control systems in gravel terrain can be found in Table 7.4.

Table 7.4. Task Analysis and Time Study (sec) for Electronic-Gravel Model.

#	Task	Time	#	Task	Time
	Phase I - Initialization		21.	Move Finger	1.07
1.	Reach Arm	2.00	22.	Press Joystick Button	1.22
2.	Turn Starter	2.00	23.	Scoop Material	4.50
3.	Begin Excavation	3.33	24.	Move Finger	1.07
4.	Turn Head	2.00	25.	Press Joystick Button	1.22
5.	Check Monitor	2.67	26.	Rotate Body Forward	3.47
6.	Move Finger	1.07	27.	Move Finger	1.07
7.	Press Joystick Button	1.22	28.	Press Joystick Button	1.22
8.	Adjust Speed	5.00	29.	Release Material	3.10
9.	Move Finger	1.07	30.	Move Finger	1.07
10.	Press Joystick Button	1.22	31.	Press Joystick Button	1.22
11.	Move to Location	10.33	32.	Raise Boom	2.82
12.	Move Finger	1.07	33.	Move Finger	1.07
13.	Press Joystick Button	1.22	34.	Press Joystick Button	1.22
14.	Position at Location	4.33	35.	Raise Dipperstick	3.47
	Phase II - Active Work		36.	Move Finger	1.07
15.	Move Finger	1.07	37.	Press Joystick Button	1.22
16.	Press Joystick Button	1.22	38.	Rotate Body Backward	3.47
17.	Lower Boom	2.82		*Phase III - Finalization*	
18.	Move Finger	1.07	39.	Reach Arm	2.00
19.	Press Joystick Button	1.22	40.	Turn Starter	2.00
20.	Lower Dipperstick	3.47	41.	End Excavation	3.33

As seen in Figure 7.7, movement tasks for operators of electronic control systems excavating gravel revealed that the shortest movement time was moving the finger, taking an average time of 1.1 seconds to complete. The longest movement tasks were reaching the arm and turning the head with average task times of 2.0 seconds and 1.3 seconds. Variation was also consistent with that found within the other models in which longer tasks yielded in no variation and shorter tasks (e.g. moving the finger) yielded in higher variation at 20%.

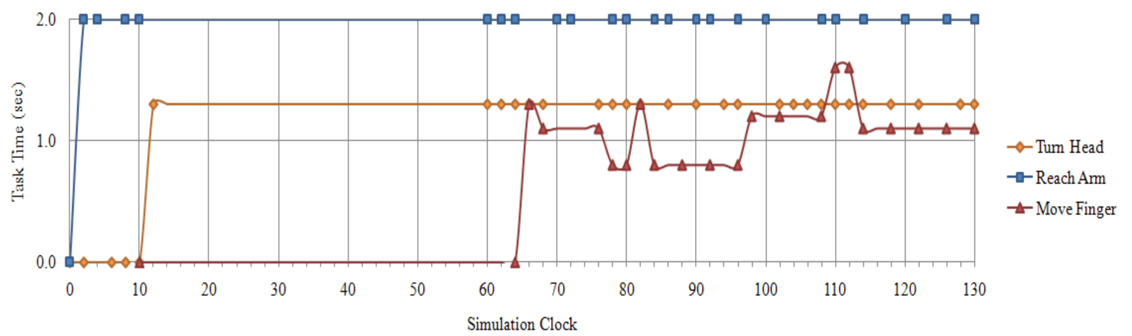

Figure 7.7. Movement Tasks for Electronic-Gravel Model.

The longest operational task for electronic control systems in gravel terrain was checking the monitor with a mean time of 4.6 seconds; whereas, the shortest task was pressing the joystick button yielding an average time of approximately 1.9 seconds. Like the other simulation models, Figure 7.8 indicates that the most variation was evident in shorter tasks (e.g. pressing the joystick button at 80%) and the least variation with longer tasks (e.g. checking the monitor panel or turning the starter switch at 0%).

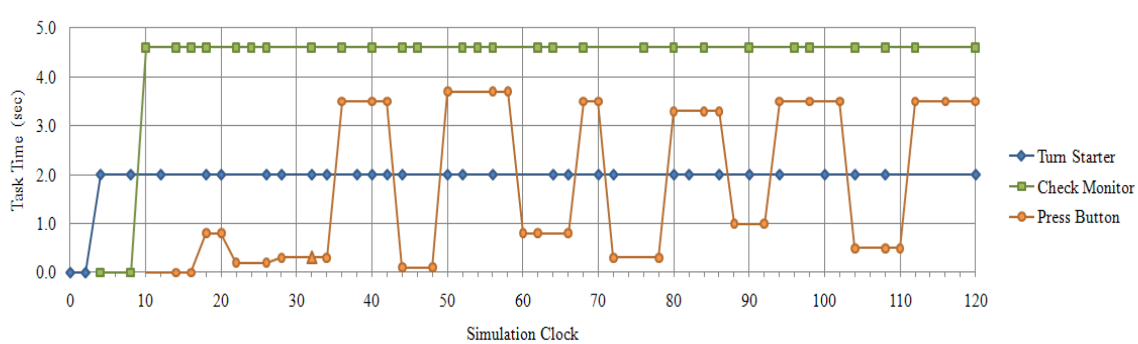

Figure 7.8. Operation Tasks for Electronic-Gravel Model.

7.1.2 Experimental Results

Prior models yielded relevant data regarding the processes associated with various tasks and operations throughout the excavation process with respect to emergent design changes and the role of the environment. The following sections examine the significance of such effects on human performance from an empirical study in terms of completion time and workload.

7.1.2.1 Descriptive statistics. Descriptive statistics for overall performance for completion time and workload are summarized in Table 7.5 and Table 7.6. A complete table of results for each of the simulation models can be found in Appendix A.

Operators using electronic control systems to excavate soil yielded in the lowest mean completion time of 159.9 seconds; whereas, operators using hydraulic control systems to excavate gravel yielded in the longest mean completion time of 383.8 seconds. Overall, completion times with electronic control excavator systems were lower in both environments as compared with hydraulic control excavator systems. Operators also yielded shorter completion times when excavating soil terrain. Both of the prior cases resulted in high variation.

Table 7.5. Performance Model Summary for Completion Time (sec).

Descriptive Statistics	**Hydraulic**		**Electronic**	
	Soil	**Gravel**	**Soil**	**Gravel**
Mean	232.3	383.8	159.9	358.5
Standard Deviation	163.9	360.8	113.7	373.4

Cognitive workload was quantified in each of the four simulation models as a percentage of the effort exerted by the human operator versus the effort exerted by the excavator system for multiple excavation tasks. These tasks were represented graphically as a percentage during model execution in order to assess the impact of workload on performance during excavation processes. Table 7.6 presents descriptive statistics for operator workload associated with digging tasks.

Table 7.6. Performance Model Summary for Workload (%).

Descriptive Statistics	Hydraulic		Electronic	
	Soil	Gravel	Soil	Gravel
Mean	41.1	41.3	62.8	68.8
Standard Deviation	8.0	10.9	14.2	15.2

Results from Micro Saint performance models revealed that the most cognitive workload occurred with electronic control systems in gravel terrain where the human operator exerted an average of 68.8% of the effort needed to accomplish the task; whereas, the least amount of workload was experienced with hydraulic control systems in soil terrain, yielding a value of 41.1%. With respect to control type, hydraulic control systems required less cognitive workload (e.g. 41.1% for soil and 41.3% for gravel) than electronic control systems (e.g. 62.8% for soil and 68.8% for gravel).

7.1.2.2 Inferential statistics. A 2x2 factorial design was conducted to investigate the impact of control and the environment on excavator operator performance. For this type of design, a two-way analysis of variance (ANOVA) was appropriate. Such an analysis is based on the assumption of normality (i.e. data is distributed symmetrically about its mean). Therefore, caution should be used when using such analyses for experimental studies. A model adequacy check was performed to check the simulated model data for assumptions. Residual analyses from the adequacy check indicated a violation of normality in the simulated data (i.e. skewed right). Though a log transformation was used to minimize the deviation, marginal impact was found.

Given that the purpose was to demonstrate the feasibility of the framework, the goal of the study was to provide an approach for modeling performance rather than to analyze its effects. Therefore, the analysis of results only contributes a small portion to the value of the theory presented in the framework. More importantly, ANOVA is generally robust to violations of normality (Maxwell & Delaney, 1990). Research by Lindman (1974) noted that distributional skews do not typically have a substantial effect on the F-statistic when using the F-distribution. Peres-Neto and Olden (2001) also found that “ANOVA exhibits smaller rates of Type-I error as compared with the Kruskal-Wallis test” (p. 85). Since research debates the negligibility of violations, ANOVA results can often be relied on when distributional assumptions are violated, validating their use in this study. Further explanation is provided in Chapter 8.

A two-way analysis of variance (ANOVA) was used to determine the impact of the environment and control type on operator performance as measured by the completion time of the excavation process as well as operator workload. With respect to completion time, Table 7.7 results revealed a significant main effect for the environment (F (1, 396) = 39.6, p < 0.0001).

Table 7.7. ANOVA-2x2 Factorial Design for Completion Time.

Source	DF	Type I SS	Mean Square	F-Value	Pr > F
Control	1	238,344.1	238,344.1	3.08	0.0800
Environment	1	3,063,357.6	3,063,357.6	39.60	<0.0001
Control*Environment	1	55,208.6	55,208.6	0.71	0.3987
Error	396	30,632,144.1	77,353.9		
Total	399	33,989,054.3			

However, no significant effect was found for excavator control type (F (1, 396) = 3.08, p = 0.0800). Also, no significant effect was found for the interaction between control type and the environment (F (1, 396) = 0.71, p = 0.3987). This can be seen in the plot in Figure 7.9.

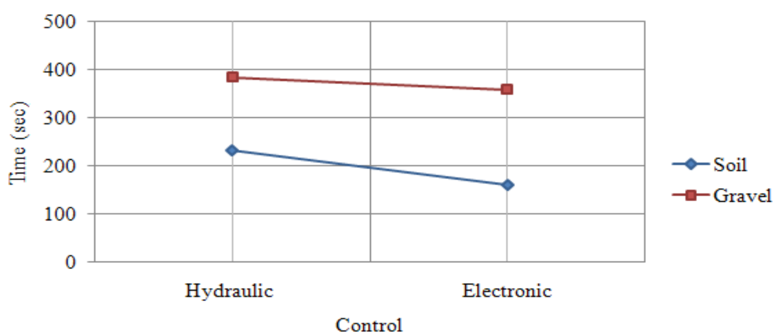

Figure 7.9. Interaction Plot for Completion Time.

In contrast, for operator workload associated with digging in the excavation process, results revealed a significant main effect for control type (F (1, 396) = 394.0, $p <$ 0.0001). A significant main effect was also found for the environment (F (1, 396) = 6.3, p = 0.0123) as seen in Table 7.8.

Table 7.8. ANOVA-2x2 Factorial Design for Workload.

Source	DF	Type I SS	Mean Square	F-Value	Pr > F
Control	1	60,614.4	60,614.4	394.0	<0.0001
Environment	1	973.4	973.4	6.3	0.0123
Control*Environment	1	858.5	858.5	5.6	0.0186
Error	396	60,917.1	153.8		
Total	399	123,363.5			

Workload estimates also yielded significant results for the interaction between control type and the environment (F (1, 396) = 5.6, p = 0.0186) as seen in Figure 7.10. Analysis of the interaction revealed a significant effect on workload when sliced by electronic control (F (1, 396) = 11.9, p = 0.0006). No significant effect was found when sliced by hydraulic control (F (1, 396) = 0.01, p = 0.9138). When sliced by environment, both soil terrain (F (1, 396) = 152.9, p < 0.0001) and gravel terrain (F (1, 396) = 246.7, p < 0.0001) yielded significant effects on workload.

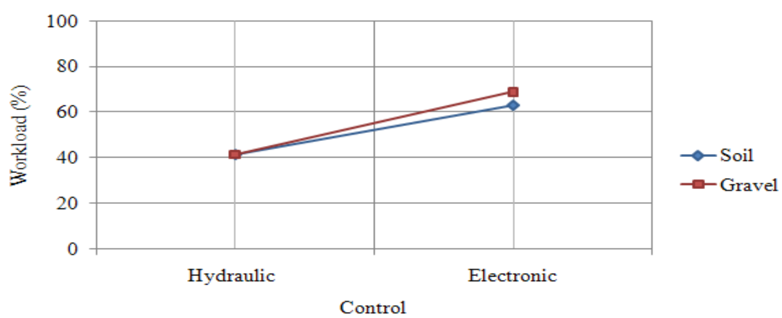

Figure 7.10. Interaction Plot for Workload.

7.2 Jack Human Performance Models

Four physical performance models were developed in Jack software based on excavator control type (e.g. hydraulic vs. electronic) and environment (e.g. soil vs. gravel). Model development involved defining the digital human, scheduling work tasks, and representing the excavator system. Since task and timing inputs were required to simulate performance, data which was used to create the network models in Micro Saint was also used to schedule the work tasks executed by the digital human in Jack software; thus, ensuring consistency between both cognitive and physical models. Unlike Micro Saint, Jack models concentrated on tasks in the active work phase (i.e. digging process) in order to assess the portion of excavation work where physical performance occurs.

7.2.1 Experimental Results

In Jack software, multiple analyses were run to assess such performance in terms of energy, fatigue, and recovery. The following sections describe the results found from those analyses. Compiled data sets of model output for each measure can be found in Appendix B.

7.2.1.1 Descriptive statistics. Energy expenditure rates were computed using embedded algorithms in Jack software to quantify physical exertion of the human operator during digging operations. Model results in Table 7.9 reflect that excavator operators expend energy at higher rates when using electronic control systems and while excavating soil terrain environments.

Table 7.9. Energy Expenditure Rate (kcal/min) for Digging Operations.

Descriptive Statistics	Hydraulic		Electronic	
	Soil	**Gravel**	**Soil**	**Gravel**
Mean	1.71	1.47	2.39	1.90
Standard Deviation	1.55	0.93	1.20	1.40

For instance, electronic control systems in soil terrain yielded in the highest mean energy expenditure rate of 2.39 kcal/min; whereas, the hydraulic control systems in gravel terrain yielded in the lowest rate of 1.47 kcal/min. In contrast, variation was higher with hydraulic control systems. The higher degree of variation was found with hydraulic control systems, yielding coefficients of variation at 90% for soil and 60% for gravel terrain environments.

Recovery was also modeled in Jack software as a measure of the physical performance of the human operator given by the difference between the time available (T_a) versus the time needed (T_n) to recover from physical exertion as described in Table 7.10. In terms of this measure, greater recovery time was needed for digging tasks with hydraulic control systems and gravel terrain environments as compared with electronic control systems and soil terrain.

Table 7.10. Recovery Available and Needed (sec) for Digging Operations.

Descriptive Statistics	Hydraulic				Electronic			
	Soil		**Gravel**		**Soil**		**Gravel**	
	T_a	T_n	T_a	T_n	T_a	T_n	T_a	T_n
Mean	11.2	1.9	16.9	7.2	4.5	1.1	3.5	1.6
Standard Deviation	10.4	1.4	17.1	7.2	2.9	1.4	2.3	1.2

For instance, hydraulic control excavator systems in gravel terrain required the most needed recovery time of 7.2 seconds; whereas, electronic control excavator systems yielded the least needed recovery time of 1.1 seconds. In contrast, the most time was available for operator recovery with hydraulic control systems and less with electronic control systems. Such systems yielded available recovery times of 16.9 seconds and 11.2 seconds for gravel and soil terrain; whereas, electronic control systems yielded significantly less available time for recovery. Hydraulic control systems in gravel terrain yielded in the most available recovery time at 16.9 seconds, and the least available recovery time was with electronic control systems in gravel terrain at 3.5 seconds.

Fatigue was described in the integrative framework as a byproduct of the energy expended by the human operator and the amount of time needed to recover from work tasks. Hence, it was modeled to convey the consequences of physical exertion on subsequent performance. Accordingly, fatigue was quantified from Jack output as a product of the human operator's energy expenditure and necessary recovery for each task, yielding in a coefficient of fatigue for digging tasks of the excavation process. Output revealed (Table 7.11) that hydraulic control systems and gravel terrain result in more physical fatigue than electronic control systems in soil terrain.

Table 7.11. Fatigue (kcal/sec) for Digging Operations.

Descriptive Statistics	**Hydraulic**		**Electronic**	
	Soil	**Gravel**	**Soil**	**Gravel**
Mean	1.69	2.83	1.19	1.82
Standard Deviation	4.41	7.62	2.80	1.42

For instance, hydraulic control systems yielded a mean fatigue coefficient of 2.83 kcal/sec and 1.69 kcal/sec for gravel and soil terrain; whereas electronic control systems yielded in lower fatigue coefficients of 1.82 kcal/sec and 1.19 kcal/sec.

7.3 Micro Saint-Jack Integrated Human Performance Models

Relevant findings on cognitive and physical performance during hydraulic excavation processes were revealed from the results of Micro Saint and Jack simulation models. Although both have strengths in predicting a particular facet of human performance, neither tool accounts for the performance modeled by its counterpart. Micro Saint modeled completion time and cognitive workload of the human operator; yet failed to model the operator's physical exertion; whereas, Jack modeled physical measures such as energy, recovery, and fatigue, yet failed to model the cognitive decision making processes of the human operator. Furthermore, data in Jack software cannot be replicated for empirical analysis. Such modeling deficiencies identify a clear limitation when studying cognitive and physical human performance independently; when in reality, both interact to produce human behavior. To compensate for these shortcomings, an integrated model was developed following the framework detailed in Chapter 5, using Micro Saint and Jack software to simulate cognitive and physical performance.

As described in Section 7.1, four Micro Saint and four Jack models were developed to simulate the performance of operators using hydraulic and electronic control excavator systems under two environmental conditions, soil and gravel. Each performance model was run and performance output was obtained. Such models were integrated by interchanging corresponding sets of inputs and outputs, enabling models to "speak" to one another and comprehensively model human performance. Simulated Micro Saint output (Appendix A) of representative digging tasks were used as cognitive inputs into Jack software, yielding physical performance estimates for energy and recovery from which estimates of fatigue were derived as described in Section 7.2. Performance models were then bridged together by modeling the simulated Jack fatigue coefficients (Appendix B) back into the corresponding Micro Saint task network models as physical performance variables to convey the bi-directional relationship of cognitive and physical performance; thus, producing an integrated human performance model.

7.3.1 Task Analysis

For the integrated models, tasks analyses were used to decompose work processes and provide a better understanding of human performance as described in Section 7.1.1. The following sections provide details from the results of those analyses.

7.3.1.1 Hydraulic control-soil terrain. Findings of the task analysis for operators of hydraulic control systems in soil terrain were consistent with those identified in Section 7.1. Work tasks were also defined in the three phases. Such tasks consisted of monitoring, positioning, and digging processes which were facilitated by cognitive and physical procedures. Physical tasks involved manipulation of controls; whereas, cognitive tasks involved the selection of the proper decision making strategies.

Integrated movement tasks under such conditions consisted of turning the head, extending the leg, reaching the arm, and tilting the hand as seen in Figure 7.11. The longest task time was observed with reaching the arm which yielded an average time of 2.7 seconds followed by extending the leg with an average time of 1.8 seconds. The shortest tasks consisted of turning the head with an average of 1.2 seconds and tilting the hand with approximately 1.1 seconds. As consistent with earlier findings, tasks yielding longer completion times generally resulted in less variation than those with shorter times (e.g. tilting the hand at 23%).

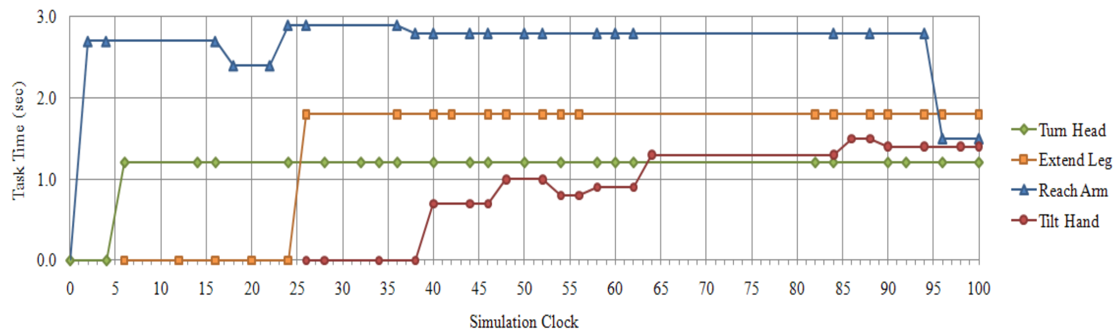

Figure 7.11. Integrated Movement Tasks for Hydraulic-Soil Model.

Operational tasks consisted of turning the starter, checking the monitor panel, as well as engaging the lever and joystick controls. Figure 7.12 illustrates that checking the monitor panel by far yielded the highest time yielding an average time of 6.0 seconds. All other tasks yielded lower values relatively close in nature. Turning the starter switch yielded an average time of 2.0 seconds and pushing the lever yielded an average time of 1.7 seconds. The shortest tasks involved the joystick controller with an average 0.86 seconds for adjusting and 0.84 seconds for pushing or pulling. Again, longer tasks yielded in less variation.

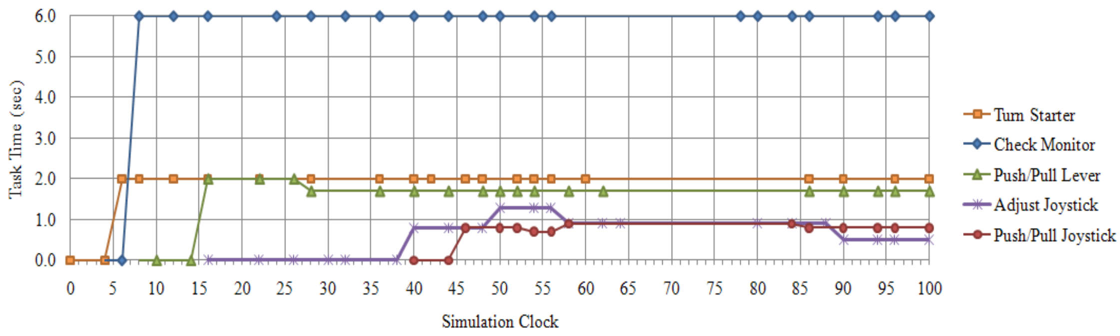

Figure 7.12. Integrated Operation Tasks for Hydraulic-Soil Model.

7.3.1.2 Hydraulic control-gravel terrain. Operators of hydraulic control systems in gravel terrain also engaged in cognitive and physical tasks consisting of monitoring, positioning, and digging (Figure 7.13). The shortest movement tasks for these operators were tilting the hand with an average time of 1.6 seconds, followed by reaching the arm with an average time of 2.5 seconds. As in the prior models, faster tasks generally yielded in the most extreme variation and the least consistency during the simulation with coefficients of variation ranging from 26% to 63%. In contrast, turning the head and reaching tasks took operators longer, averaging 3.5 seconds and 2.6 seconds. These tasks appeared to have consistent trends throughout the excavation.

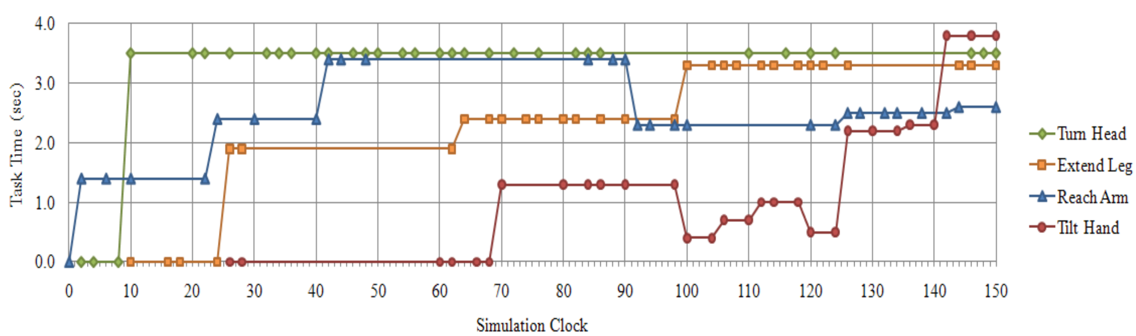

Figure 7.13. Integrated Movement Tasks for Hydraulic-Gravel Model.

Operational tasks for the integrated model revealed that the longest task performed by the human operator involved checking the system's monitor, taking and average time of 10.0 seconds. All other tasks yielded significantly lower values such as pushing or pulling levers, taking an average of 3.9 seconds as well as turning the starter switch taking an average of 2.0 seconds to complete. The shortest times were found to involve the joystick controllers, yielding in an average time of 1.4 seconds for adjusting and 1.3 seconds for pushing or pulling. Figure 7.14 revealed that longer tasks tended to yield in less variation (i.e. checking the monitor at 0%) and shorter tasks with more variation (i.e. pushing or pulling the lever at 29%).

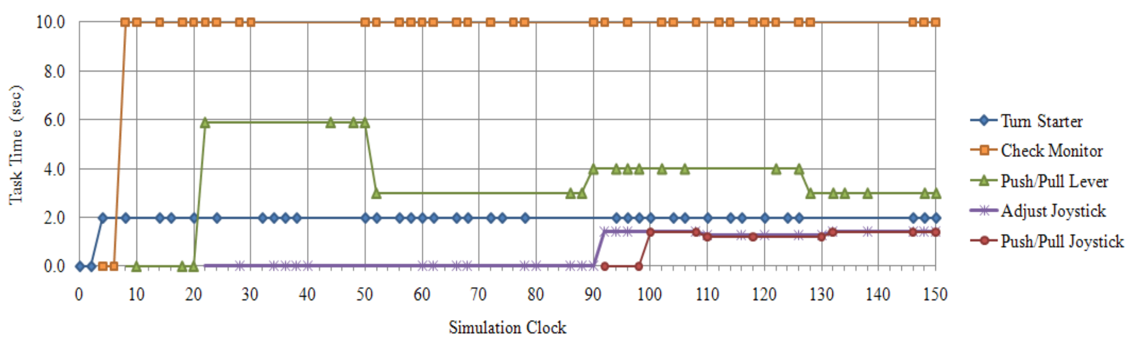

Figure 7.14. Integrated Operation Tasks for Hydraulic-Gravel Model.

<u>*7.3.1.3 Electronic control-soil terrain.*</u> Work processes for electronic control systems excavating soil involved initialization, active work, and finalization tasks with respect to monitoring, positioning, and digging. However, instead of controlling the system through motion of the joystick controllers, these functions were controlled through buttons embedded in the joystick controllers.

Movement tasks consisted of reaching the arm, turning the head, and moving the finger. In Figure 7.15, the shortest movement time for operators of electronic control excavators was moving the finger with an average time of approximately 0.9 seconds, followed by reaching the arm with an average time of 1.5 seconds. Turning the head took the longest time to complete, taking an average of 2.8 seconds with no variation; whereas, moving the finger resulted in high variation at 42%.

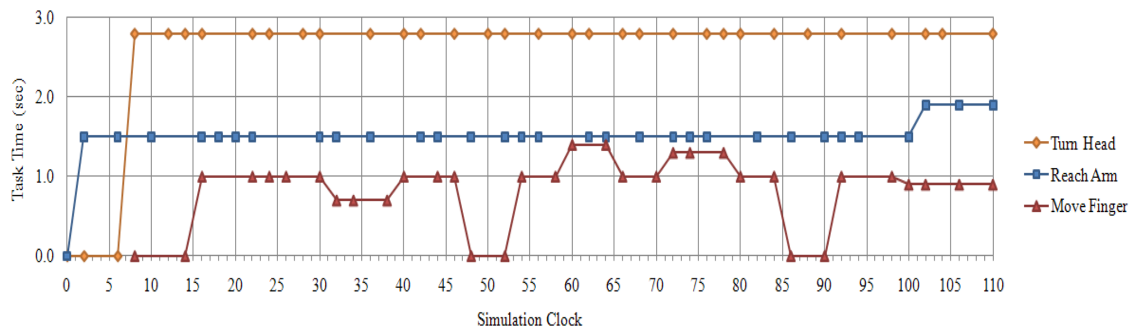

Figure 7.15. Integrated Movement Tasks for Electronic-Soil Model.

Operational tasks for such systems consisted of turning the starter, checking the monitor, and pressing joystick buttons. On average, the longest task was associated with checking the system's monitor panel, yielding in a value of approximately 3.5 seconds, followed by turning the starter switch at approximately 2.0 seconds. The most variable task was revealed to be that of pressing the joystick buttons which yielded an average time of 2.2 seconds. This task also yielded in the greatest amount of variation at 90% as shown in Figure 7.16.

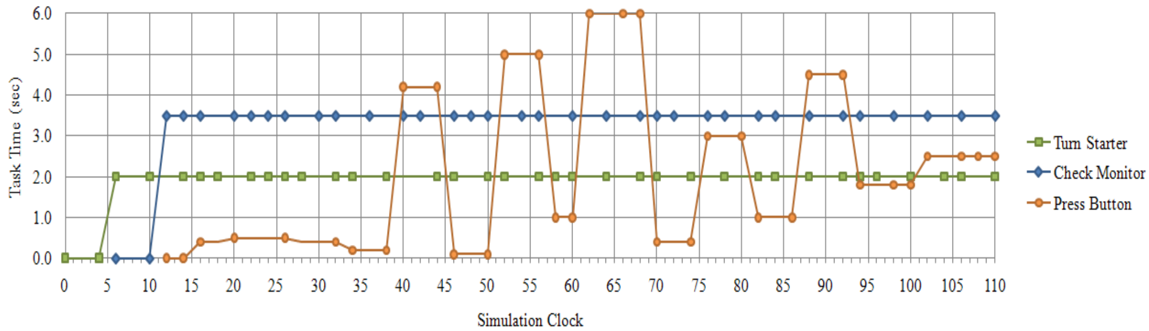

Figure 7.16. Integrated Operation Tasks for Electronic-Soil Model.

<u>7.3.1.4 Electronic control-gravel terrain.</u> Operators of electronic control systems in gravel terrain also executed key tasks consisting of monitoring, positioning, and digging by utilizing joystick controller buttons. Movement tasks in Figure 7.17 revealed that the shortest movement was moving the finger with an average time of 1.2 seconds. The longest movement tasks were reaching the arm and turning the head with average task times of 2.0 seconds and 1.5 seconds. Data trends again revealed that longer tasks yield less variation (e.g. reaching the arm at 0%) and shorter tasks yield in more variation (e.g. moving the finger at 40%).

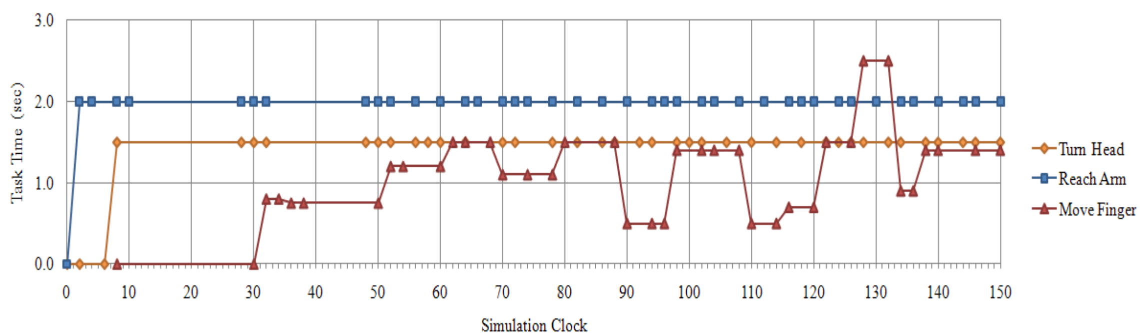

Figure 7.17. Integrated Movement Tasks for Electronic-Gravel Model.

The longest task for electronic control systems in gravel terrain as seen in Figure 7.18 was checking the monitor with a mean time of 10.0 seconds; whereas, the shortest task was turning the starter, yielding a time of approximately 2.0 seconds. Like the other models, the most variation was evident in shorter tasks such as pressing the button (e.g. 82%) with an average time of 3.5 seconds, and the least variation was evident in longer tasks such as checking the monitor or turning the starter at 0%.

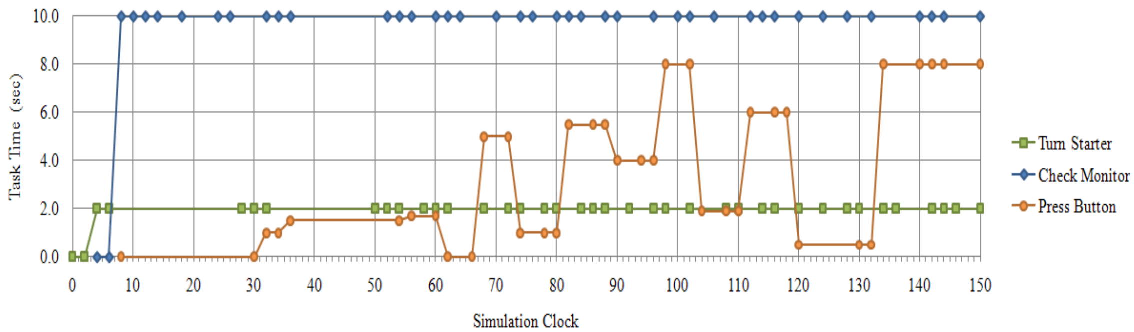

Figure 7.18. Integrated Operation Tasks for Electronic-Gravel Model.

7.3.2 Experimental Results

Prior models yielded relevant data regarding the processes associated with various tasks and operations throughout the excavation process. The following sections examine the significance of those effects through an empirical study.

<u>7.3.2.1 Descriptive statistics.</u> Descriptive statistics for overall performance of each of the integrated models are summarized in Table 7.12 and Table 7.13. A compiled set of integrated simulation data can be found in Appendix C.

In the integrated models, completion time (Table 7.12) was assessed subject to the effects of physical fatigue. From the results, it was found that operators of electronic control systems in soil terrain yielded in the lowest mean completion time of 165.7 seconds; whereas, operators of hydraulic control systems in gravel terrain yielded in the longest mean completion time of 392.9 seconds. In general, completion time with electronic control was lower in both environments as compared with hydraulic control. Soil terrain also yielded lower completion times than gravel terrain for both systems.

Table 7.12. Performance Model Summary for Integrated Completion Time (sec).

Descriptive Statistics	Hydraulic		Electronic	
	Soil	Gravel	Soil	Gravel
Mean	241.6	392.9	165.7	363.6
Standard Deviation	166.6	576.6	125.1	515.9

Workload was also quantified to gauge the affects of physical fatigue on cognitive performance. Table 7.13 results revealed that the greatest workload for digging tasks occurred with electronic control excavator systems in gravel terrain, yielding an average of approximately 79%; whereas, the least workload occurred with hydraulic control systems in soil terrain, yielding a value of 45%. With respect to control type, operators of hydraulic control systems experienced less workload (e.g. 47% for soil and 64% for gravel) than operators of electronic control systems (71% for soil and 79% for gravel).

Table 7.13. Performance Model Summary for Integrated Workload (%).

Descriptive Statistics	Hydraulic		Electronic	
	Soil	Gravel	Soil	Gravel
Mean	46.8	63.8	71.4	78.6
Standard Deviation	14.2	16.8	19.5	15.8

7.3.2.2 Inferential statistics. Assumptions for normality of the ANOVA analysis for integrated models were consistent with those described in Section 7.1.2.2. A two-way analysis of variance (Table 7.14) revealed a significant main effect for the environment (F (1, 396) = 18.9, $p < 0.0001$) on completion time for excavation processes.

Table 7.14. ANOVA-2x2 Factorial Design for Integrated Completion Time.

Source	DF	Type I SS	Mean Square	F-Value	Pr > F
Control	1	277,075.9	277,075.9	1.73	0.1897
Environment	1	3,048,341.4	3,048,341.4	18.90	<0.0001
Control*Environment	1	54,400.9	54,400.9	0.34	0.5608
Error	396	63,563,572.3	160,514.1		
Total	399	66,943,390.5			

However, no significant effect was found regarding the system's control type (F (1, 396) = 1.73, $p = 0.1897$). No significant effect was found for the interaction between the system's control type and the environment (F (1, 396) = 0.34, $p = 0.5608$). A plot of these effects can be seen in Figure 7.19.

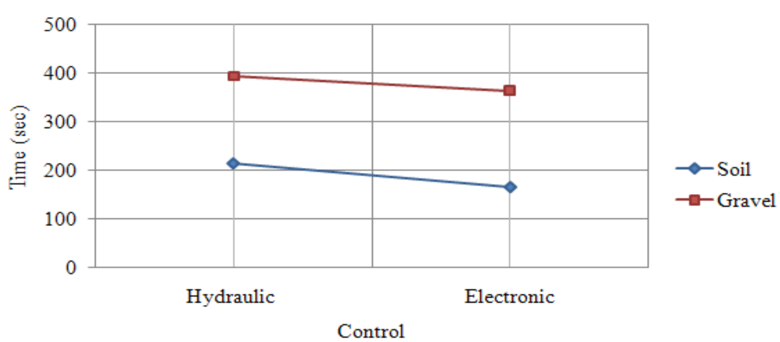

Figure 7.19. Interaction Plot for Integrated Completion Time.

Analysis of workload (Table 7.15) revealed a significant main effect for control (F (1, 396) = 220, $p < 0.0001$) and the environment (F (1, 396) = 29.5, $p < 0.0001$) for digging tasks. A significant interaction effect was also found between control type and the environment (F (1, 396) = 29.5, $p < 0.0001$).

Table 7.15. ANOVA-2x2 Factorial Design for Integrated Workload.

Source	DF	Type I SS	Mean Square	F-Value	Pr > F
Control	1	54,079.5	54,079.5	220.2	<0.0001
Environment	1	7,233.5	7,233.5	29.5	<0.0001
Control*Environment	1	7,233.5	7,233.5	29.5	<0.0001
Error	396	97,278.1	245.7		
Total	399	165,824.6			

Further analysis (Figure 7.20) revealed a significant effect on workload when sliced by hydraulic control (F (1, 396) = 58.9, $p < 0.0001$) and no effect for electronic control (F (1, 396) = 0.0, $p = 1.0000$). When sliced by environment, soil (F (1, 396) = 205.3, $p < 0.0001$) and gravel (F (1, 396) = 44.3, $p < 0.0001$) yielded significant effects.

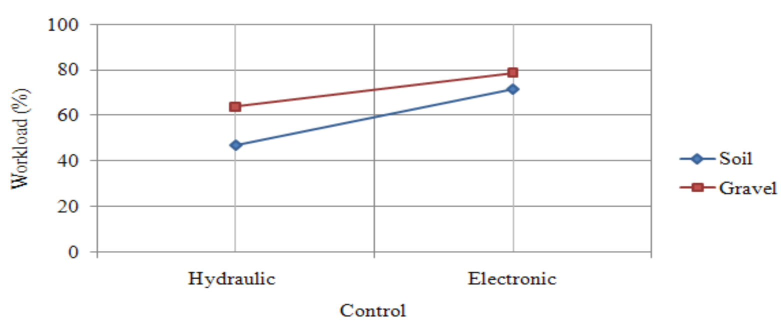

Figure 7.20. Interaction Plot for Integrated Workload.

7.4 Analysis of Non-Integrated and Integrated Models

Data obtained from both sets of performance models yielded in relevant findings in terms of their analyses individually. As can be noted from those findings, differences were observed among integrated models (iHPMs) which considered cognitive and physical performance comprehensively, as well as the non-integrated models (HPMs) which considered both aspects of human performance separately. To conclusively and further demonstrate the value of the integrated human performance modeling approach, it is appropriate to examine the differences between the results in a comparative analysis.

7.4.1 Experimental Results

The following sections examine the experimental results from both the HPMs and iHPMs in comparison to one another; thus, depicting the true impact of model integration on human performance in complex human-machine systems.

7.4.1.1 Descriptive statistics. In terms of completion time, iHPMs which simulated human performance subject to the effects of energy, recovery, and fatigue yielded in longer excavation processes for human operators as compared with HPMs. Overall with each of the models, data revealed similar trends with regard to control type and terrain (i.e. quicker performance with electronic control systems or soil terrain and slower performance with hydraulic control systems or gravel terrain).

As can be seen in Table 7.16, integrated models which were subject to the effects of various physical factors resulted in longer mean completion times than models not considering those factors. For example, the quickest completion times were observed with electronic control systems in soil terrain in which HPMs yielded a mean time of 159.9 seconds; whereas, with the iHPMs, modeling under the same conditions yielded a mean time of 165.7 seconds. Such results convey a divergence between the output of integrated and non-integrated modeling approaches as follows: electronic control-gravel terrain at approximately 1%, hydraulic control-gravel terrain at 2%, electronic control-soil terrain at 3%, and hydraulic control-gravel terrain 4%.

Table 7.16. Comparison of HPMs and iHPMs for Completion Time (sec).

Descriptive Statistics	Hydraulic		Electronic	
	Soil	Gravel	Soil	Gravel
HPMs	232.3	383.8	159.9	358.5
iHPMs	241.6	392.9	165.7	363.6

When comparing the modeling results for workload, such differences were also evident. In Table 7.17, the greatest workload was observed with electronic control systems in gravel terrain which yielded approximately 69% in the HPMs and 79% in the iHPMs. All models conveyed a divergence in output as follows: hydraulic control-soil terrain at approximately 12%, electronic control-soil terrain at 12%, electronic control-gravel terrain at 13%, and hydraulic control-gravel terrain at 35%.

Table 7.17. Comparison of HPMs and iHPMs for Workload (%).

Descriptive Statistics	Hydraulic		Electronic	
	Soil	Gravel	Soil	Gravel
HPMs	41.1	41.3	62.8	68.8
iHPMs	46.6	63.8	71.4	78.6

7.4.1.2 Inferential statistics. In order to compare the HPMs (i.e. non-integrated models) and iHPMs (i.e. integrated performance models), data obtained from both models was combined into a single dataset. The combined dataset was treated as a 2x2x2 factorial design. Specifically, the analysis was used to determine whether divergences between modeling approaches yield significantly different findings when evaluating human performance in complex systems. With respect to completion time, Table 7.18 shows that significant main effects were found for: control type (F (1, 792) = 4.3, p = 0.0378) and the environment (F (1, 792) = 51.4, p <0.0001). No significant main effect was found for integration (F (1, 792) = 0.2, p = 0.7634).

Table 7.18. ANOVA-2x2x2 Factorial Design for Completion Time.

Source	DF	Type I SS	Mean Square	F-Value	Pr > F
Control	1	514,680.7	514,680.7	4.3	0.0378
Environment	1	6,111,726.0	6,111,726.0	51.4	<0.0001
Control*Environment	1	109,603.0	109,603.0	0.9	0.3374
Integration	1	10,784.7	10,784.7	0.2	0.7634
Control*Integration	1	729.1	729.1	0.0	0.9376
Environment* Integration	1	9.3	9.3	0.0	0.9930
Control*Environment* Integration	1	1.5	1.5	0.0	0.9972
Error	792	94,195,692.6	118,934.0		
Total	799	100,943,227.4			

In Figure 7.21, no significant interaction effects were found for: control type and the environment (F (1, 792) = 0.9, p = 0.3374), control type and integration (F (1, 792) = 0.0, p = 0.9376), the environment and integration (F (1, 792) = 0.0, p = 0.9930), or for control type, the environment, and integration (F (1,792) = 0.0, p = 0.9972).

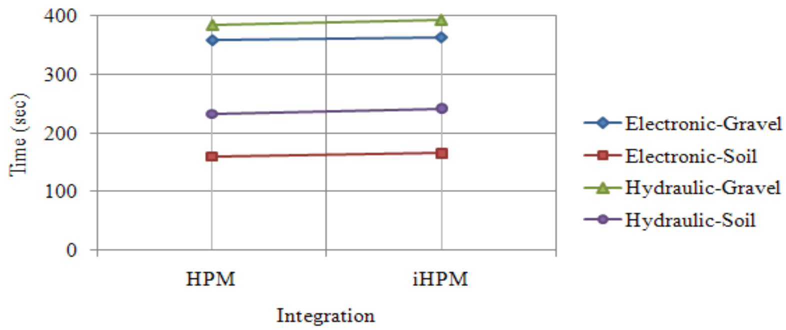

Figure 7.21. Multi-Way Interaction Plot for Completion Time.

Results for the analysis of cognitive workload for the 2x2x2 factorial design can be seen in Table 7.19. The table shows that significant main effects in this experiment were found for: excavator control type (*F* (1,792) = 573.6, *p* < 0.0001), environmental terrain (*F* (1, 792) = 33.8, *p* <0.0001), and human performance model integration (*F* (1, 792) = 181.3, *p* < 0.0001).

Table 7.19. ANOVA-2x2x2 Factorial Design for Workload.

Source	DF	Type I SS	Mean Square	F-Value	Pr > F
Control	1	114,600.8	114,600.8	573.6	<0.0001
Environment	1	6,757.0	6,757.0	33.8	<0.0001
Control*Environment	1	1,554.0	1,554.0	7.8	0.0054
Integration	1	36,220.9	36,220.9	181.3	<0.0001
Control*Integration	1	93.2	93.2	0.5	0.4948
Environment* Integration	1	1,449.9	1,449.9	7.3	0.0072
Control*Environment* Integration	1	6,537.9	6,537.9	32.7	<0.0001
Error	792	158,195.2	199.7		
Total	799	325,408.9			

Figure 7.22 shows that significant interaction effects were also found for: control type and the environment (F (1, 792) = 7.8, p = 0.0054) and for the environment and integration (F (1, 792) = 7.3, p = 0.0072). No significant interaction effect was found for control type and integration (F (1, 792) = 0.5, p = 0.4948). However, a significant 3-way interaction effect was found for control type, the environment, and integration (F (1, 792) = 32.7, p < 0.0001).

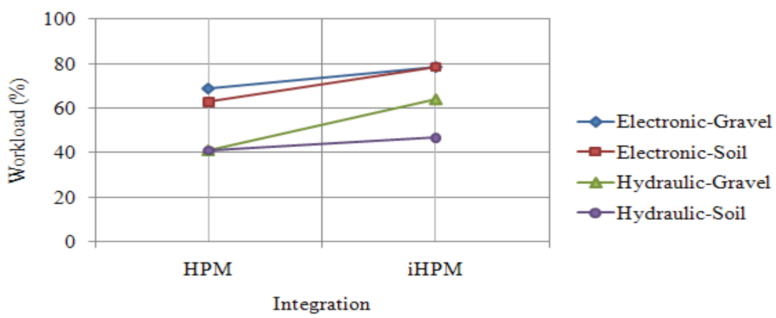

Figure 7.22. Multi-Way Interaction Plot for Workload.

When sliced by control type and the environment for workload with regard to the interaction of control, the environment, and integration, Figure 7.22 also shows that significant effects were found for: electronic control in gravel terrain (F (1, 792) = 23.8, p < 0.0001), electronic control in soil terrain (F (1, 792) = 62.5, p < 0.0001), hydraulic control in gravel terrain (F (1, 792) = 127.3, p < 0.0001), and hydraulic control in soil terrain (F (1, 792) = 8.2, p = 0.0043).

Significant effects on workload were also found for the interaction of control type, the environment, and integration, when sliced by control and integration for:

electronic control in the HPM (F (1, 792) = 9.2, p = 0.0026) and hydraulic control in the iHPM (F (1, 792) = 72.4, p < 0.0001). No significant effects were found for electronic control in the iHPM (F (1, 792) = 0.0, p = 1.000) or for hydraulic control in the HPM (F (1, 792) = 0.01, p = 0.9243).

Lastly, when sliced by the environment and integration for workload, significant effects were found for the interaction of control type, the environment, and integration for: gravel terrain in the HPM (F (1, 792) = 190.0, p < 0.0001), gravel terrain in the iHPM (F (1, 792) = 54.5, p < 0.0001), soil terrain in the HPM (F (1, 792) = 117.8, p < 0.0001), and soil terrain in the iHPM (F (1, 792) = 252.5, p < 0.0001).

Results of both Micro Saint and Jack HPMs revealed a variety of data and trends regarding cognitive and physical human performance in the case study of the hydraulic excavator. More importantly, the iHPMs were developed based on the parameters of the human performance modeling framework as well as outputs from derived performance models. Much of the data obtained from those models reference the strengths of an integrated approach to human performance modeling, giving insight into specific areas of human performance and their correlation. Chapter 8 discusses the fluid power case study in detail and examines implications from these findings.

CHAPTER 8

DISCUSSION

Studies on human performance in fluid power make it possible to gain extensive knowledge on human-machine interaction, understand human mental and physical capabilities, and better support human needs. More importantly, it was necessary to develop an approach to more accurately predict complex human behavior which has perplexed researchers, resulting in modeling difficulties which produced inaccurate assessments of performance. Through the development of a human performance modeling framework that identified the necessary elements and parameters to include when modeling, the cognitive and physical factors which shape human behavior were able to be accounted for in integrated simulation models.

A case study and an empirical study were used to demonstrate the viability of the integrated approach in a real world domain while considering various conditions with respect to the factors presented in the framework. The framework contributes to the improvement of research methods by providing the required guidelines for developing human performance models. Such guidelines yielded in meaningful findings, providing an opportunity for the evaluation, improvement, and selection of more efficient processes and systems. The most salient contribution, however, is that the integrated framework bridged the gap between independent models to accurately depict human performance. The following sections describe in further detail the relevance of the integrative framework as well as implications from its findings.

8.1 Significance of the Integrated Framework

The integrated modeling framework was developed for the purpose of fully capturing the complexity and variability of human performance with complex systems by taking into consideration cognitive and physical factors. Targeting complex human-machine systems, the framework's structure served as a method by which to ensure that the appropriate elements and parameters were considered when predicting human performance. Furthermore, components comprising the framework's structure were demonstrated with a case study in fluid power and quantified through both non-integrated and integrated human performance models. As described in Section 7.4, such models provided significant findings and implications regarding the impact of various factors on human performance. More importantly, the framework itself provided further value to understanding the mechanisms of human performance within complex systems.

8.1.1 HPMs

The integrative framework specified the use of multiple tools to accurately model both facets of human performance. Hence, Micro Saint and Jack, cognitive and physical simulation tools, were chosen in order to model human performance with respect to the framework's structure.

8.1.1.1 Cognitive performance. Cognitive functioning was modeled using Micro Saint software and allowed for representation of internal performance at the task, system, human, and environmental levels. From this aspect, it was found that the mental processes of human operators occurred through information acquisition and analysis, decision and action selection, as well as action implementation (Parasuraman et al., 2000). For instance, the framework uncovered that operators of hydraulic excavator systems perceived dynamic stimuli not only from the environment, but also from entities existing within the environment (e.g. excavator system or workers). From this information, the operators then formed work goals (e.g. position, dig, or move) and evaluated alternatives (e.g. work methods) to best achieve desired performance outcomes.

Cognitive models also revealed that operators were more efficient at completing work with newer electronic control systems; however, a tradeoff exists wherein these operators experienced more cognitive workload with the newer design. The cognitive component of the framework aided in determining that when interacting with complex systems, the potential exists for human operators to be exposed to additional work demands due to the many panels and instruments that must be simultaneously and continuously controlled (Nikolova et al., 1993; Zhang, 2000). Such tasks over prolonged periods can induce higher amounts of cognitive workload. Much of the workload can be attributed to by monitoring which was required throughout the excavation process, dividing the operator’s attention between supervision and execution tasks. This task along with the digging task, contributed to high workload as denoted in Table 8.1.

Table 8.1. Levels of Cognitive Effort and Workload Experienced.

Workload	Effort	Implication
≤ 50%	Low	Operator workload less than system. No design intervention necessary for performance improvement.
≥ 50%	High	Operator workload greater than system. Design intervention necessary for performance improvement.

In addition to the mechanics of the system, workload for this task was increased by cognitive factors such as memory of training skills and attention to dynamic variables in the environment such as people or other machines. Cognitive tasks can further impact performance by creating a tradeoff between cognitive goals and effort (Nikolova et al., 1993; Hockey, 1997). Hancock et al. (1993) determined that "workload is assumed to increase as the distance from the goal and time constraints are increased" (p.20). Such a concept was validated in the simulation models when sustained effort created performance variations and high workload. For example, as workload for monitoring tasks progressed, more variation was exhibited in both digging and positioning tasks. Hence, it can be inferred that such operations resulted in higher levels of effort from the operator in order to compensate for inadequate functional or processing capacity; thus, resulting in increased workload (Hockey, 1997). Without considering the cognitive aspects of performance required by the framework, it would not be possible to ascertain the effects of work strategies on system design on human performance.

Despite the value given by modeling human cognition, it was not without challenge. As stated in Chapter 7, the data analyzed in the study violated the assumption of normality. Examination of the models indicated that such a violation is partially attributable to the modeling of cognitive decision processes. In the Micro Saint models, decision processes were modeled based on various work alternatives (i.e. repeating the digging cycle, repositioning the system, or ending the excavation process). Likelihoods were assigned for each alternative based on probabilities derived from the decisions made by excavator operators in the collected data. Given the range of weights for each alternative of the human operator, models have the potential to run for substantially longer periods of time for a single iteration; thus, resulting in the variation found in the cognitive performance models and violation of the normality assumption.

8.1.1.2 Physical performance. In contrast, physical functioning was modeled using Jack software that allowed for representation of the external state of performance at the task, system, and human levels. By incorporating a physical perspective, the framework enabled the shift between mental processing and action to be modeled within various phases of the excavation process. According to the framework, human performance occurs dynamically through a series of states, transitioning from internal cognitive functioning to external physical functioning. For instance, from the study it was found that the operator's physical motor responses have an effect on subsequent performance.

The framework specified physical performance be gauged; thus, it was assessed in terms of energy, recovery, and fatigue. In hydraulic excavation processes, digging tasks required the most physical work due to the manipulation of joystick controllers. Energy expenditures were found to be higher with electronic controls systems and gravel terrain as compared to hydraulic control systems and soil terrain. Such findings are partially attributable due to the newer design requiring rapid discrete movements of the finger as opposed to the older design requiring slower sequential movements of the wrist. This notion was also verified by results indicating that operators completed work processes slower with hydraulic control systems. Since newer controllers lack feedback, operators may be more likely to overly apply high amounts of pressure to joystick buttons, resulting in the variability found in such tasks. Furthermore, in terms of recovery it was found that more time was needed for operators of hydraulic control systems and gravel terrain than electronic control systems and soil terrain. Though electronic control systems required more energy for the digging task, energy was expended at a greater rate with hydraulic control systems due to the physical design of the joystick controllers and conditions in the environment.

More importantly, the degree of fatigue experienced with electronic control systems and in soil terrain was less than that of hydraulic control systems and in gravel terrain. Table 8.2 describes levels of physical fatigue experienced and their implication regarding the design of the system wherein lower levels indicate no or slight physical fatigue and higher levels indicate moderate or extreme physical fatigue.

Table 8.2. Levels of Physical Exertion and Fatigue Experienced.

Fatigue	Exertion	Performance Implication
≤ 0	None	No fatigue experienced. No ergonomic intervention necessary.
1 - 2	Low	Slight fatigue experienced. No ergonomic intervention necessary.
3 - 4	Medium	Moderate fatigue experienced. Consider ergonomic intervention.
≥ 5	High	Extreme fatigue experienced. Ergonomic intervention necessary.

In general, low levels of physical exertion were revealed, implying that no ergonomic intervention was needed under those conditions. However, with hydraulic control systems in gravel terrain, it was found an elevated degree of exertion and moderate fatigue signaling, that ergonomic intervention may be necessary for performance improvement. Intervention may be necessary under such work conditions since hydraulic excavators still require direct human operation (Zubko, 2007). For instance, operators often work over prolonged periods; in some cases up to ten hours a day, placing them at risk of cumulative trauma or injury if the system is not properly designed. A task such as bending the wrist is a repetitive movement and a major contributor to this risk. Consequently, without considering physical performance as specified by the integrative framework, it could not be understood the differences between the design of excavator system and the risk placed on the human operator when performing excavation processes.

8.1.2 iHPMs

As demonstrated by this research, many challenges plague human performance in complex systems, especially in the fluid power domain. Such complexities have caused the need for an integrative approach that considers performance in multiple regards. As described in the prior sections, findings produced relevant implications in terms of the mechanisms of human behavior. Together, integrating cognition as well as physical functioning in human performance models provided a higher degree of insight on the interaction between such factors that could not be explained when assessing performance independently.

8.1.2.1 Performance interaction. Integration of human performance models demonstrated that both design and dynamic conditions impacted performance. In particular with the integrated model, it was determined that the environment had a significant impact on the completion of excavation processes wherein additional time was necessary in gravel terrain. Such conditions and attention to hazardous factors (e.g. overloading or unbalanced weight) consume mental resources, causing additional demands on the human operator. As a consequence of these demands, more cognitive workload also occurs in gravel terrain which was determined to also significantly impact performance. Furthermore, the arrangement of buttons embedded in the joystick controllers failed to match the human operator's mental models, resulting in high cognitive workload. Models showed more variation under these conditions, leading to the potential for increased errors. High workload also resulted in more energy being required for operators of electronic control systems and in gravel terrain. Hence, the framework uncovered a link between the physical amount of energy required for the job, the rate of work, and the human's cognitive activity.

From the integrated models, it was also determined that longer completion times, high workload, and energy rates were correlated to more fatigue and greater recovery time being needed; especially with hydraulic control systems and in gravel terrain. These notions lead to three significant ideas that can be formed regarding the impact of such findings from the integrated human performance models. Foremost, both rapid and prolonged work can cause operators to utilize methods reducing accuracy, increasing the risk of error (Hockey, 1997). In reality, excessive cognitive or physical exertions with complex systems can lead to costly mistakes which endanger human workers as well as the surrounding environment. Additionally, when multiple variables consume the operator's attention (i.e. monitoring tasks, controls, etc.), the operator can become mentally overloaded, inhibiting performance and jeopardizing safety (Svensson et al., 1997). Lastly, although operators may perform tasks adequately, excessive workload causes inadequate performance over prolonged periods (Mazaeva, Ntuen, & Lebby, 2001). Over time as workload increases, performance variations result. These variations increase the difficulty of work tasks and cause operator fatigue, slowing the overall work process.

8.1.2.2 Performance representation. More importantly, without the framework and integration of performance models, it would not be possible to conclusively confirm or deny that the design of a particular system yields in better performance than another system. Following their introduction, system manufacturers marketed the notion that electronic control was more efficient and less fatiguing than traditional hydraulic control, without having concrete empirical evidence to prove those statements. Though different in various areas of assessment, model integration with the framework uncovered that overall performance is better with emergent electronic control mechanisms.

For instance, electronic control systems yielded in faster completion times, less recovery time needed, and less fatigue experienced than hydraulic control systems which only fared better in terms of cognitive workload and energy expenditure (Table 8.3). Integration of the data conveys the bi-directional relationship between cognitive and physical factors to form a comprehensive representation of performance. Without the integrative framework, it would only be possible to gauge one facet of performance, making any findings inconclusive. Such notions are verified by the losses in accuracy between both HPMs and iHPMs. Through integration, however, modeling accuracy is improved; thus, reducing errors and overestimations of performance efficiency.

Table 8.3. **Summary of Model Performance for Excavator Systems.**

Human Performance	Excavator System	
	Hydraulic Control	Electronic Control
Cognitive Model		
Completion		x
Workload	x	
Physical Model		
Energy	x	
Recovery		x
Fatigue		x
Integrated Model		
Completion		x
Workload	x	

Though HPMs and iHPMs yielded in similar results for completion time and workload, integration of performance models through the framework allowed for examination beyond the surface to obtain a more accurate depiction of performance. For instance, integrated models produced significantly different results in terms of the workload experienced by the human operator for the environment and control type. By accounting for physical factors (e.g. energy, fatigue, and recovery) along with cognition which triggers action, models captured the bi-directional relationship which impacts performance; thus, making a difference in performance predictions.

Integration clearly aids in understanding of human behaviors to help designers to create systems that facilitate human interaction. In the fluid power domain, the integrative framework proved advantageous for the assessment of human performance with regard to constraints such as time, capital, and safety. For cognition, it was uncovered what strategies are employed by human operators; when, where, and how tasks are performed; as well as why work is done in a particular manner. In contrast, for physical performance, it was determined which systems and conditions cause extreme exertions as well as how adequate or inadequate rest impacts subsequent work. Implications of such findings yield benefits including the evaluation of work processes which revealed that as demands increase (i.e. speed, time), performance deteriorates as a consequence; and that cognitive workload is linked to energy and control which are significant to work productivity. Hence, by modeling the effects of performance in complex systems, designers will have the ability to better design intelligent automated systems that increase efficiency, improve work methods, and operator satisfaction.

8.2 Implications of the Fluid Power Case Study

A fluid power case study was presented in Chapter 6 to demonstrate a viable domain for the application of the integrated human performance modeling framework. From this framework, a study was performed to gain insight on the effects of various factors on human performance. Upon analysis of the results in Chapter 7, implications were drawn regarding cognitive and physical performance of excavator operators utilizing such systems under a set of selected conditions. The following subsections discuss details regarding the impact of system control and the effects of the environment on human performance as measured by task completion time and workload analysis for various tasks of hydraulic excavation processes as well as the value of the framework for modeling human performance.

8.2.1 Hydraulic Excavation Work Processes

Hydraulic excavation processes involve a variety of tasks critical to human performance based on interaction with the system. As established by the composition of the task analysis, human operators manage the complexity of such work through series of phases which decompose difficult work processes into simple sub-tasks. These work phases consisted of: initialization to activate and monitor the system; active work to execute excavation tasks; and finalization to complete work tasks and deactivate the system. To carry out such phases and complete these processes, both the human and the system carry out work tasks. With regard to the human, the operator is primarily responsible for cognitive decision making processes and manipulation of system controls; whereas, the system is responsible for majority of the physical processes for work.

Movement tasks denote the operator's functional activities concerning a particular work goal. With regard to such tasks, it was revealed that the mean time to perform a work operation can be influenced by the length of the work, methods employed by the operator, design of the system, and the difficulty of the task (Keller, 2002). The primary difference among all movement tasks, however, was in their degree of variation throughout the excavation process. Movement tasks within performance models yielding longer task times such as reaching the arm, turning the head, and extending the leg or foot appeared more consistent than tasks such as tilting the hand or pressing the button with shorter task times.

Times for such tasks were also shorter during the beginning of the excavation process and shifted during the middle the excavation process. Shifts of this nature can be explained by the point at which one work phase ends (i.e. initialization phase) and the other begins (i.e. active work phase), or the job requiring the human operator move or re-position the excavator for continuation of the excavation process being performed. In contrast, tilting the hand and pressing the joystick button to control rotation of the excavator's cab, arm, and bucket attachment, required the least amount of time in comparison with other movement tasks. As a result of the quickness of such performance, it yielded in the highest variation and was the most unstable task of all movements, showing little consistency throughout the excavation process. Such extreme variations can be explained due to the multiple objectives that can be accomplished by excavator operators when tilting the hand or pressing the buttons. For instance, tasks associated with these movements consist of scooping dirt from trenches, digging surface areas, and rotating the body of the excavator cab. Each task serves a unique purpose in the excavation process; therefore, various times were undertaken.

From this data it can be seen that the majority of the tasks involved in hydraulic excavation processes are manual and repetitive in nature, perpetuating the risk of serious injury. Since task times for reaching movements are shorter at the beginning and the end of the excavation and longer during the middle of the process when actual work is performed, it indicates that operators are likely to be experiencing fatigue. To eliminate awkward postures from this type of movement and minimize the fatigue experienced by operators, designers of excavator systems should consider the placement of controls. Movement tasks were also indicated as the most unstable in both the hydraulic and electronic systems. Although the variation of movement tasks can be explained by the various reasons excavator operators must tilt the hand or wrist and press buttons, processes of this nature potentially lead to stress and an increased amount of concentration or workload. To resolve these types of issues involving the hand and wrist, it is recommended that an aid be implemented to reduce the amount of stress, displacement, and force required to manipulate the joystick; thus, promoting better coupling with the controller and to reduce the amount of force or the degree of deviation at the wrist when using the joystick.

Operational tasks help convey the operator's intent as well as the means by which to accomplish a goal. With regard to these tasks, pushing or pulling the joystick and pressing joystick buttons required relatively less time in comparison with other tasks. Such tasks began during the initialization phase of the excavation process and were carried out through finalization. Much of the variation for these tasks occurred during the active work phase (i.e. middle) of the excavation process; whereas, the tasks showed more consistency during initialization (i.e. beginning) and finalization phases (i.e. end) of the work process. Such variation occurred due to the range of motion associated with tilting the hand or the force exerted when pressing buttons to complete work tasks. These changes may have also been attributed to the operator adapting to the work environment throughout the excavation process. In contrast, adjusting the joystick did not begin until the middle (i.e. active work phase) of the excavation process. These tasks showed an increasing trend, indicating that the workload may be increasing or that discomfort is being experienced as work progresses and the job becomes more difficult.

Examining both movement and operational tasks simultaneously revealed a direct relationship with regard to time and the resultant degree of variation. For instance, for both hydraulic and electronic control systems, movement tasks such as turning the head was followed by the corresponding operational task of checking the monitor; thus, presenting a connection between the physical movement triggered by the operator's intention and action to reach the desired work goal. Another relevant relationship that was realized from the task analysis was that the time during the excavation process in which a particular task occurred, correlated to the progression of the work phase. As earlier described, excavation processes occurred in three phases: initialization, active work, and finalization.

In both hydraulic and electronic control systems, manipulation of the joystick controller or joystick buttons presented variation at similar points during the excavation process. For example, during the active work stage, more variation and longer task times were present. From the output, it can also be noted that changes for both movement and operational tasks occur following initialization (i.e. at the beginning of the active work phase). Such changes are most likely due to a shift from tasks that are more cognitive (e.g. monitoring and decision making) during the initialization phase to tasks that are more physical and require action during the active work phase. Furthermore, when movement and operator tasks are less often used (i.e. during initialization and finalization), variation in performance stabilizes. Other generalizations from the output that can be made are that movement tasks show less stability throughout the excavation process and that operator tasks are subject to the effects of these movement tasks.

8.2.2 Excavator Control and Human Performance

Analysis of hydraulic excavation processes revealed that many conditions are likely to pose significant effects on human performance. From the task analysis data, it was found that excavator operators utilized various methods to execute work processes based on the design of the system's controls. With hydraulic control systems, movement of the controller itself was employed; whereas, with electronic control systems, buttons embedded in the joystick controller were employed to carry out similar work tasks. More importantly, it has been believed that emergent designs of system controls are more efficient as compared with traditional hydraulic control designs.

Though not found to be significantly different, results from the analysis of the case study revealed that operators using electronic control systems took less time to complete excavation processes as compared to those of traditional hydraulic control systems. Differences in process completion can be explained by quicker execution of individual work tasks with electronic control systems whose design allows operators to select a desired control pattern based on personal preference and job type; thus, reducing the physical requirements to carry out work. Hence, operators can perform more efficiently by better managing goals, demands, and resources. In addition, variation between both control types differed. Systems with hydraulic control yielded in less variation than those equipped with electronic control. Higher variation can be attributed to by the lack of feedback in electronic controls, indicating a tradeoff between operator efficiency and consistency with regard to excavator control type. For instance, in hydraulic systems, tactile feedback is provided through hydraulic tubes beneath the joysticks which give operators a sense of the environment; whereas, electronic system joystick controls have a spring center mechanism which feels the same regardless of the state of the machine.

This lack of feedback causes operators to increase force or the amount of pressure applied to controllers to execute a system function, making work processes more challenging from a remote sense of the work environment. A potential remedy to such an issue would be the introduction of haptic technology to restore the feedback necessary to effectively complete work tasks and further enhance performance with electronic control systems. Haptic control can replace much of remote sensation which was lost in electronic controllers by aiding the operator with mechanisms that respond to force in the work environment. In combination, both electronic control and haptic feedback can yield in ergonomic benefits such as greater comfort and reduced fatigue to improve performance efficiency.

Unlike completion time, control was found to have a significant impact on the degree of workload experienced by the human operator. In particular, it was found that cognitive workload was lower in hydraulic control systems as compared to electronic control systems. In prior research, it has been suggested that the mechanics of the system can affect the degree of mental workload experienced by the human operator. It has even been found in some cases to increase workload (Parasuraman et al., 2000). Considering this perspective, cognitive workload may be higher with electronic control systems due to the design of its controllers which fail to match the mental models of the human operator. For instance, with hydraulic control systems, the range of motion in the joystick controls match the resultant movements carried out by the system (i.e. downward motion produces a lowing movement of the system's arm). However, in electronic control systems, joystick button mappings failed to match the human operator's mental models; thus, violating expectancies. One method of improving such matters is to reconfigure the layout of the joystick buttons to match system functions and the operator's mental model of what should occur when a particular button is pressed.

From a physical standpoint, diverse results were found with respect to both systems. With regard to energy, it was found that operators of hydraulic control systems expended less energy than operators of electronic control systems. Unexpected results could have possibly occurred given that operators were slower in completing work processes with hydraulic control systems. This implies that these operators executed tasks at a slower rate, yielding in less energy; whereas, operators were faster at completing work processes with electronic control systems, implying that quicker execution yields in more energy.

Workload for these systems was also consistent with these findings. Despite the amount of energy expended, operators of electronic control systems required less time to recover and experienced less fatigue. Such performance is result of electronic controllers requiring physical movements that are less extreme. For instance, in hydraulic control systems, operators must tilt the wrist to control system functions. If improperly or repetitively performed, it can result in fatigue due to awkward postures or deviations. In electronic control systems, however, the operator carried out identical functions by moving the finger; thus, reducing the time and effort needed to perform the work task.

8.2.3 Environmental Conditions and Human Performance

As confirmed by the empirical study, the environmental conditions under which excavation tasks were performed had a significant impact on human performance. For the two test conditions, it was found that operators completed work processes more quickly when excavating soil terrain as opposed to gravel terrain with both hydraulic and electronic control systems. The difference in the overall process completion times and more efficient performance in soil terrain can be explained by the elevated degree of difficulty in performing excavation processes under demanding environmental conditions. Though soil can vary extensively, it generally offers a sufficient degree of porosity and permeability to facilitate excavation.

Likewise, gravel can also vary tremendously (i.e. ranging from fine pebbles to course boulders); however, it generally results in less efficiency due to its higher mass and weight in conjunction with the capacity of the system. In some circumstances, this type of environmental terrain can be difficult to permeate or can even become impermeable. Such difficulties alter the methods implemented by operators to accomplish work goals, resulting in the higher degree of variation seen within the models. In the real world, gravel terrain environments impose additional demands that the operator must take into consideration when undertaking work processes (e.g. load weights, balance, and bucket capacity), adding to the complexity and difficulty of the work task. Thus, it is clear that the environment is a substantial factor in human performance with hydraulic excavator systems regardless of control type. Therefore, a greater emphasis should be placed on designing systems by considering the environmental conditions under which they will be used to aid operators in better managing work processes.

Furthermore, the environment also had a significant effect in terms of the workload experienced by the human operator. From the models, it was found that operators experienced more cognitive workload in gravel terrain as compared with soil terrain. Likewise, operators also required more time to complete work processes in gravel terrain due to additional considerations such as load weight, balance, and bucket capacity; thus, increasing the complexity and difficulty of work.

From a physical perspective, more energy was needed in soil terrain than in gravel terrain. Similar to completion time, less recovery time was needed and less fatigue was experienced with soil terrain as compared to gravel terrain. This could also be attributable to the difference in time taken to complete work processes and the degree of difficulty in both environments. For instance, work was completed more efficiently in soil terrain versus gravel terrain due to the complexity of the work task; therefore, operators needed less recovery and experienced less fatigue due to a lesser amount of workload which facilitated the work process.

CHAPTER 9

CONCLUSION

9.1 Summary of Dissertation

This research has demonstrated the volatility of human performance in complex human-machine systems. Within the fluid power domain, where demands for versatility are constant, complexity has also significantly increased. Subject to such requirements, hydraulic excavator systems have advanced from hydraulic to electronic control mechanisms; however, because these changes offer varying degrees of simplicity, comfort, and feedback, the impact of design on human performance presents an ever challenging issue.

Of the past literature which investigated such matters, much was limited in viability due to the complexity and variability of human behavior. Chief issues determined within past studies not only consisted of research lacking the investigation of human performance in fluid power systems; more importantly, there was found to be an overemphasis on system performance rather than on human performance, and a substantial lack of knowledge on the interaction between the cognitive and physical factors contributing to human performance. As a result, research credibility and model accuracy was jeopardized.

The premise of this dissertation has concentrated on correcting methods that neglect performance shaping factors and enhancing predictive capabilities through the conception, development, and implementation of an integrative framework, and an empirical study on human performance models that take into consideration both cognitive and physical components. Extensive research was explored in order to gain thorough knowledge of human performance at a theoretical level and to plan procedures which facilitated the integration of human performance models.

The integrated framework itself described the modeling approach and the required parameters for the creation of integrated human performance models; thus, serving as a set of procedures and blueprint for model development. Requirements for understanding performance consisted of: establishing the levels at which performance should be assessed to identify the levels of abstraction at which performance can be affected; defining states of human performance to convey the transition from internal to external functioning; and differentiating between cognition and physical action to define key components of human performance. Integration requirements consisted of: extracting performance variables to quantify performance; selecting the appropriate modeling tools to simulate cognitive and physical performance; linking performance measures to convey the bi-directional relationship between performance factors; and integrating representations to create a comprehensive model of human performance.

To illustrate how the integrative framework could be utilized to model human performance in complex systems, a case study in fluid power was described to demonstrate its viability in hydraulic excavation processes with respect to its described structure and modeling parameters. Based on the parameters of the framework, cognitive, physical, and integrated simulation models were derived and compared through an empirical study to assess the effects of a subset of factors identified in the case study on performance during hydraulic excavation processes. Various system configurations and environmental conditions were found to have a significant impact on human performance as well as a clear correlation between cognition and physical action. More importantly, variance between non-integrated and integrated models which considered performance independently and collectively, confirmed an increase in model accuracy when using the framework's human performance modeling approach.

9.2 Contribution of Research

Using an integrated approach to human performance modeling provided unprecedented value in enhancing the quality of research on human performance. Such an approach promoted the realization of knowledge concerning the characteristics and role of the human operator, the distribution of work between the human-machine system, as well as the interaction among the task, human, system, and the environment. The theoretical framework in this research acted as a set of procedures for better models of human performance to be developed. Specifically, it developed a set of procedures to accurately model human performance by considering cognitive and physical factors which were overlooked in traditional research models as well as identifying, defining, and correlating the factors which should be considered when modeling human performance. By creating an integrated performance model to study performance in existing and emergent fluid power systems, it was possible to determine the effects of various factors on human performance, assess the degree of workload experienced by the human operator, identify usability and ergonomic issues with excavator system designs, and propose recommendations for improvements in emergent systems. Furthermore, the framework expanded beyond the realm of past approaches and overcame modeling deficiencies to bridge the gaps in traditional research by acknowledging the interactions that produce human behaviors and by representing various components contributing to human performance within multiple modeling tools.

More importantly, this research addressed the voids found within prior research models. Foremost, it concentrated on human performance in the fluid power domain where there has been a lack of effort and studies which have inappropriately concentrated on the system rather than on human performance. However, by utilizing this approach, the excavation process was able to be selected as an applicable domain for the development of human performance models that concentrated on the human operator while considering technical aspects such as system mechanics. A breadth of knowledge was also gained on the interaction between the cognitive and physical factors contributing to human performance. Insight was found regarding human capabilities and limitations with regard to system design, work processes, and the environment; thus, improving usability, ergonomics, and human performance while reducing operational errors, demands, and fatigue. Completion of such research endeavors in this area yielded in a better understanding of the factors to be considered when modeling human performance, identification of the human factors which influence performance, and examination of the factors that cause or amplify variance in human performance models to conclusively provide the foundation for more realistic representations of human performance in simulation models.

9.3 Future Work

Despite these contributions, there are still many relevant human performance issues to consider with regard to complex human-machine systems. Therefore, in order to further develop the capacity of such technology, matters of cost, safety, design, and operator workload which affect overall efficiency of the system must be continually optimized. Modelling the tasks and processes of fluid power systems such as the hydraulic excavator allowed for the successful examination of efficiency and the investigation of human performance. For instance, Micro Saint and Jack were effectively integrated to accurately represent the human-system design in complex settings and to ensure that problems associated with human performance were clearly identified. Findings from the study revealed the importance of analyzing design changes in fluid power systems before implementation and marketing to its intended users. It was found that the environment was critical to performance in terms of process completion time; whereas, controls were important to performance in terms of the workload experienced by the human operator. Furthermore, newly implemented electronic controls were more effective at enhancing overall operator performance, yet improvements are still needed to provide more feedback and better match mental models. Integrating all aspects of human performance to truly depict the complexities of human behavior in the real world remains a challenge; thus, maintaining the need for alternative techniques that address the inadequacies of past performance models (Gore et al., 2008).

9.3.1 Limitations

As prior noted, it is not possible to develop a human performance modeling framework that is applicable to all systems. Therefore, research using the integrative framework is limited to the scope of its parameters. Foremost, the framework developed herein, is limited in application to the area of complex human-machine systems; particularly, those involving cognitive and physical tasks. Furthermore, although integrated, the chosen tools (e.g. Micro Saint and Jack), were initially limited because the cognitive tool had no physical modeling capability and the physical tool had no cognitive modeling capability or ability to be replicated for trial studies. Consistent with prior research, the complexity of modeling of cognitive processes also resulted in variability which caused a violation of normality for the data analysis. Lastly, the framework offers a broad range of elements (e.g. functions, variables, metrics, etc.) that can be chosen by the researcher based on the chosen tool and the research domain. Hence, the capability of the chosen tools can limit the overall ability to represent certain parameters identified in the framework.

9.3.2 Recommendations

Despite these limitations, this research provided great value in demonstrating the use and value of creating integrated human performance models. Furthermore, a variety of alternatives exist to address such limitations and provide opportunities for future research endeavors. For instance, the integrative framework provides opportunities for application with other complex human-machine systems as well as other domains where humans are required to manage cognitive and physical tasks. Suitable areas include the transportation (e.g. aviation), the manufacturing (e.g. automated assembly operations), as well as further investigation in the construction industry (e.g. cranes or lifts).

As citied, a variety of other software is also available which has the capabilities to model either cognitive or physical human performance. Beyond those identified in this research, emergent software is available that attempts to model human performance more accurately by representing both facets of human performance as well as a host of factors that affect human performance within the framework. The Integrated Human Performance Modeling Environment (IPME), is one tool that provides an integrated approach to simulation and modeling tools for assessing human performance in complex environments. The software not only allows for cognitive and physical performance to be assessed in a single tool, but it also allows for closer examination of the broad aspects (e.g. task, human, system, and the environment) which affect human performance on a deeper more characteristic level. Like Micro Saint and Jack, the tool can model the human's cognitive capabilities (e.g. mental ability, training, or fatigue) as well as physical characteristics (e.g. dimensions of the hands or fingers). However, it also provides environment models which simulate factors such as temperature, lighting, and humidity; task functions such as the time given to perform or failure probabilities; as well as micro models of human behavior to simulate conditions such as reaching within work zones. Multiple runs (i.e. iterations) can also be set up for simulation under various experimental conditions. Therefore, given the additional capabilities with IPME software, it is possible to discover other links and correlations between the factors in the framework that were unable to be modeled by the initial tools. With these considerations, the scope of problems addressed through human performance modeling can be increased by simulating performance and providing solutions on complex human behavior to help identify and resolve problems associated with human performance.

As established by this research, the integrated approach provided a strong foundation for the enhancement of the practices and methodologies used to model human performance in complex systems by coupling the interaction among the task, human, system, and the environment. Its structure acted as a guide, linking commonly misrepresented and overlooked elements for better predictions of human performance by understanding human behavior and its shaping factors. The example of its application through a case in fluid power further validated its theoretical contribution, demonstrating the feasible development of better models. By studying human performance with fluid power systems such as the hydraulic excavator, insight was gained on human-system interaction, capabilities and limitations, as well as the relationship between cognitive and physical performance. Such insight can be used to optimize the excavation process and operational procedures, overcoming current limitations and expanding the future capabilities of fluid power technology. Through continual development, integrative approaches will further provide value by increasing the accuracy and validity of models to ultimately close the gap between existing and emergent research methods that model human performance in complex systems.

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APPENDIX A

MICRO SAINT MODELS & DATA

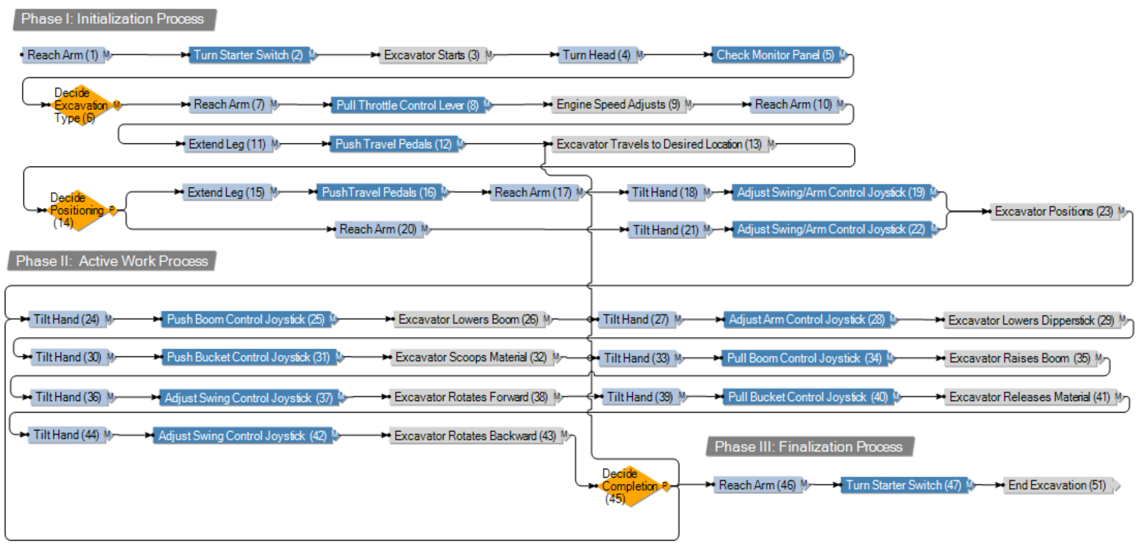

Figure A.1. Task Network Model for Hydraulic Control Excavator System.

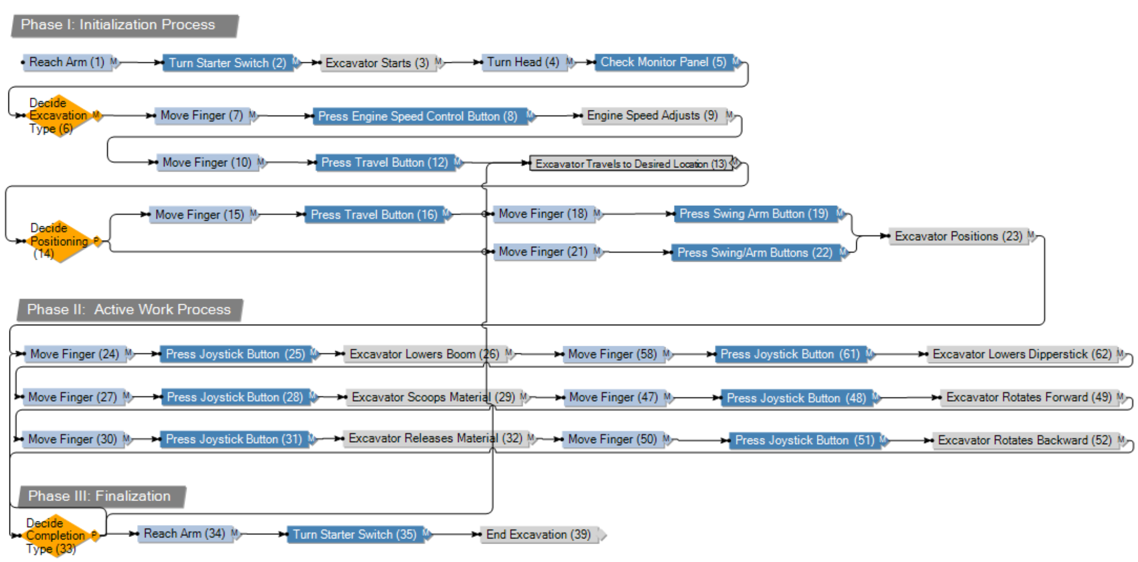

Figure A.2. Task Network Model for Electronic Control Excavator System.

Table A.1. Completion Time (sec) for Hydraulic-Soil Model.

#	Completion Time	#	Completion Time	#	Completion Time	#	Completion Time
1.	390.2	26.	912.8	51.	144.3	76.	104.6
2.	225.7	27.	95.4	52.	125.8	77.	315.2
3.	267.8	28.	106.4	53.	75.6	78.	114.7
4.	123.0	29.	118.3	54.	396.4	79.	315.2
5.	426.7	30.	405.1	55.	81.1	80.	249.4
6.	82.6	31.	85.0	56.	139.0	81.	566.4
7.	178.7	32.	128.6	57.	389.9	82.	167.1
8.	96.3	33.	133.9	58.	131.3	83.	128.1
9.	99.9	34.	124.1	59.	179.2	84.	143.5
10.	105.3	35.	163.8	60.	141.3	85.	101.5
11.	573.0	36.	191.6	61.	149.8	86.	338.6
12.	407.1	37.	405.9	62.	352.7	87.	258.3
13.	226.7	38.	248.1	63.	376.1	88.	305.1
14.	257.9	39.	240.9	64.	220.5	89.	409.1
15.	753.0	40.	918.5	65.	112.9	90.	145.0
16.	309.0	41.	348.8	66.	119.2	91.	126.0
17.	268.5	42.	92.7	67.	199.7	92.	377.1
18.	135.5	43.	163.1	68.	84.6	93.	159.3
19.	152.7	44.	96.0	69.	302.2	94.	119.4
20.	158.4	45.	98.5	70.	231.1	95.	173.4
21.	123.2	46.	209.6	71.	141.7	96.	154.1
22.	382.1	47.	120.6	72.	270.4	97.	201.6
23.	86.6	48.	162.4	73.	111.9	98.	448.0
24.	82.3	49.	140.4	74.	233.5	99.	401.1
25.	551.4	50.	109.3	75.	248.2	100.	162.7

Table A.2. Completion Time (sec) for Hydraulic-Gravel Model.

#	Completion Time	#	Completion Time	#	Completion Time	#	Completion Time
1.	563.9	26.	148.4	51.	369.6	76.	306.7
2.	370.2	27.	205.3	52.	627.0	77.	196.2
3.	148.6	28.	159.0	53.	464.3	78.	176.5
4.	269.4	29.	146.2	54.	154.2	79.	318.8
5.	169.7	30.	665.5	55.	164.0	80.	242.1
6.	242.2	31.	151.8	56.	159.3	81.	148.5
7.	1439.8	32.	172.6	57.	313.2	82.	160.2
8.	236.5	33.	345.3	58.	147.6	83.	149.7
9.	437.7	34.	235.4	59.	148.4	84.	616.0
10.	159.7	35.	778.5	60.	459.2	85.	183.7
11.	164.4	36.	190.5	61.	501.1	86.	731.5
12.	173.6	37.	477.5	62.	162.5	87.	170.0
13.	1449.8	38.	155.3	63.	394.2	88.	673.4
14.	1578.0	39.	451.7	64.	264.5	89.	1529.0
15.	441.8	40.	494.6	65.	225.2	90.	356.5
16.	216.9	41.	494.6	66.	146.7	91.	187.3
17.	139.3	42.	240.2	67.	365.4	92.	149.7
18.	146.1	43.	419.4	68.	138.6	93.	154.4
19.	409.6	44.	434.0	69.	2348.6	94.	161.5
20.	539.4	45.	366.3	70.	193.3	95.	297.5
21.	437.1	46.	152.4	71.	802.9	96.	165.9
22.	153.0	47.	155.4	72.	326.7	97.	133.3
23.	145.9	48.	205.8	73.	760.4	98.	290.6
24.	916.3	49.	789.1	74.	178.8	99.	287.0
25.	223.4	50.	722.2	75.	215.6	100.	632.5

Table A.3. Completion Time (sec) for Electronic-Soil Model.

#	Completion Time	#	Completion Time	#	Completion Time	#	Completion Time
1.	117.5	26.	94.1	51.	83.1	76.	91.7
2.	121.2	27.	93.6	52.	81.2	77.	89.9
3.	143.1	28.	90.2	53.	81.2	78.	85.4
4.	144.7	29.	85.7	54.	76.3	79.	85.0
5.	145.4	30.	82.4	55.	726.2	80.	82.4
6.	161.8	31.	78.8	56.	72.1	81.	81.1
7.	169.4	32.	77.9	57.	71.4	82.	80.4
8.	170.1	33.	76.2	58.	69.2	83.	79.8
9.	195.0	34.	75.9	59.	432.3	84.	78.4
10.	196.5	35.	75.8	60.	289.6	85.	75.4
11.	207.0	36.	71.7	61.	269.2	86.	441.5
12.	218.7	37.	376.8	62.	230.6	87.	312.7
13.	453.7	38.	350.8	63.	226.1	88.	248.4
14.	672.1	39.	283.5	64.	202.0	89.	226.0
15.	74.6	40.	195.2	65.	193.9	90.	225.5
16.	78.1	41.	180.4	66.	180.3	91.	204.5
17.	78.1	42.	169.7	67.	177.7	92.	167.0
18.	78.4	43.	167.1	68.	177.6	93.	152.1
19.	78.6	44.	165.6	69.	173.7	94.	133.0
20.	82.1	45.	164.5	70.	171.0	95.	133.0
21.	86.1	46.	157.1	71.	166.5	96.	127.4
22.	88.9	47.	140.1	72.	148.7	97.	124.0
23.	90.2	48.	136.4	73.	122.7	98.	118.1
24.	96.1	49.	121.5	74.	115.5	99.	117.0
25.	97.9	50.	113.5	75.	112.4	100.	114.6

Table A.4. Completion Time (sec) for Electronic-Gravel Model.

#	Completion Time	#	Completion Time	#	Completion Time	#	Completion Time
1.	858.6	26.	334.9	51.	202.6	76.	156.7
2.	785.2	27.	334.7	52.	192.6	77.	156.3
3.	779.4	28.	331.2	53.	190.8	78.	156.3
4.	704.7	29.	322.8	54.	188.8	79.	154.5
5.	681.9	30.	317.0	55.	187.8	80.	154.5
6.	225.1	31.	310.8	56.	187.0	81.	152.7
7.	629.5	32.	292.0	57.	186.5	82.	152.6
8.	573.5	33.	291.7	58.	184.6	83.	150.7
9.	534.3	34.	291.1	59.	184.4	84.	150.2
10.	524.1	35.	290.4	60.	1824.9	85.	148.6
11.	506.9	36.	285.8	61.	182.5	86.	147.9
12.	498.7	37.	278.6	62.	181.8	87.	147.3
13.	461.1	38.	278.3	63.	180.2	88.	146.3
14.	451.8	39.	266.1	64.	1776.1	89.	145.2
15.	416.0	40.	265.0	65.	175.3	90.	144.0
16.	414.3	41.	2426.9	66.	173.0	91.	143.2
17.	411.4	42.	241.3	67.	172.0	92.	143.2
18.	392.8	43.	231.3	68.	170.3	93.	142.7
19.	380.5	44.	222.1	69.	169.5	94.	138.9
20.	371.8	45.	220.5	70.	165.7	95.	137.7
21.	367.9	46.	218.0	71.	165.2	96.	134.2
22.	366.0	47.	211.2	72.	164.7	97.	1319.9
23.	342.3	48.	210.3	73.	164.5	98.	130.2
24.	340.3	49.	210.2	74.	160.6	99.	1256.1
25.	335.0	50.	205.3	75.	160.6	100.	1104.2

Table A.5. Workload (%) for Hydraulic-Soil Model.

#	Workload	#	Workload	#	Workload	#	Workload
1.	35.0	26.	55.0	51.	45.0	76.	45.0
2.	35.0	27.	55.0	52.	45.0	77.	46.0
3.	35.0	28.	45.0	53.	45.0	78.	50.0
4.	35.0	29.	45.0	54.	45.0	79.	50.0
5.	35.0	30.	50.0	55.	45.0	80.	50.0
6.	35.0	31.	50.0	56.	45.0	81.	35.0
7.	35.0	32.	50.0	57.	45.0	82.	30.0
8.	35.0	33.	40.0	58.	45.0	83.	30.0
9.	35.0	34.	40.0	59.	45.0	84.	30.0
10.	35.0	35.	40.0	60.	45.0	85.	30.0
11.	35.0	36.	40.0	61.	45.0	86.	30.0
12.	35.0	37.	65.0	62.	45.0	87.	30.0
13.	35.0	38.	65.0	63.	45.0	88.	30.0
14.	35.0	39.	25.0	64.	45.0	89.	30.0
15.	35.0	40.	25.0	65.	45.0	90.	30.0
16.	45.0	41.	25.0	66.	45.0	91.	30.0
17.	45.0	42.	40.0	67.	45.0	92.	30.0
18.	45.0	43.	40.0	68.	45.0	93.	30.0
19.	45.0	44.	40.0	69.	45.0	94.	30.0
20.	45.0	45.	45.0	70.	45.0	95.	35.0
21.	45.0	46.	45.0	71.	45.0	96.	35.0
22.	50.0	47.	45.0	72.	45.0	97.	35.0
23.	50.0	48.	45.0	73.	45.0	98.	35.0
24.	50.0	49.	45.0	74.	45.0	99.	35.0
25.	55.0	50.	45.0	75.	45.0	100.	35.0

Table A.6. Workload (%) for Hydraulic-Gravel Model.

#	Workload	#	Workload	#	Workload	#	Workload
1.	50.0	26.	45.0	51.	48.0	76.	40.0
2.	45.0	27.	45.0	52.	48.0	77.	40.0
3.	45.0	28.	45.0	53.	48.0	78.	40.0
4.	45.0	29.	45.0	54.	48.0	79.	40.0
5.	45.0	30.	45.0	55.	48.0	80.	40.0
6.	45.0	31.	45.0	56.	48.0	81.	25.0
7.	45.0	32.	45.0	57.	48.0	82.	25.0
8.	45.0	33.	45.0	58.	48.0	83.	25.0
9.	45.0	34.	50.0	59.	48.0	84.	25.0
10.	45.0	35.	48.0	60.	70.0	85.	25.0
11.	45.0	36.	48.0	61.	70.0	86.	25.0
12.	45.0	37.	48.0	62.	70.0	87.	25.0
13.	45.0	38.	48.0	63.	40.0	88.	25.0
14.	45.0	39.	48.0	64.	40.0	89.	25.0
15.	45.0	40.	48.0	65.	40.0	90.	25.0
16.	45.0	41.	48.0	66.	40.0	91.	25.0
17.	45.0	42.	48.0	67.	40.0	92.	25.0
18.	45.0	43.	48.0	68.	40.0	93.	10.0
19.	45.0	44.	48.0	69.	40.0	94.	10.0
20.	45.0	45.	48.0	70.	40.0	95.	10.0
21.	45.0	46.	48.0	71.	40.0	96.	25.0
22.	45.0	47.	48.0	72.	40.0	97.	25.0
23.	45.0	48.	48.0	73.	40.0	98.	25.0
24.	45.0	49.	48.0	74.	40.0	99.	25.0
25.	45.0	50.	48.0	75.	40.0	100.	25.0

Table A.7. Workload (%) for Electronic-Soil Model.

#	Workload	#	Workload	#	Workload	#	Workload
1.	55.0	26.	70.0	51.	400.	76.	60.0
2.	55.0	27.	70.0	52.	40.0	77.	60.0
3.	55.0	28.	70.0	53.	40.0	78.	60.0
4.	55.0	29.	70.0	54.	40.0	79.	60.0
5.	55.0	30.	70.0	55.	40.0	80.	60.0
6.	55.0	31.	70.0	56.	80.0	81.	60.0
7.	55.0	32.	70.0	57.	80.0	82.	60.0
8.	55.0	33.	70.0	58.	80.0	83.	60.0
9.	55.0	34.	70.0	59.	80.0	84.	60.0
10.	55.0	35.	70.0	60.	80.0	85.	60.0
11.	55.0	36.	40.0	61.	80.0	86.	60.0
12.	55.0	37.	40.0	62.	80.0	87.	60.0
13.	55.0	38.	40.0	63.	80.0	88.	60.0
14.	55.0	39.	40.0	64.	80.0	89.	60.0
15.	55.0	40.	40.0	65.	80.0	90.	75.0
16.	55.0	41.	40.0	66.	80.0	91.	75.0
17.	70.0	42.	40.0	67.	80.0	92.	75.0
18.	70.0	43.	40.0	68.	80.0	93.	75.0
19.	70.0	44.	40.0	69.	80.0	94.	75.0
20.	70.0	45.	40.0	70.	80.0	95.	75.0
21.	70.0	46.	40.0	71.	80.0	96.	75.0
22.	70.0	47.	40.0	72.	80.0	97.	75.0
23.	70.0	48.	40.0	73.	80.0	98.	75.0
24.	70.0	49.	40.0	74.	80.0	99.	75.0
25.	70.0	50.	40.0	75.	80.0	100.	75.0

Table A.8. Workload (%) for Electronic-Gravel Model.

#	Workload	#	Workload	#	Workload	#	Workload
1.	80.0	26.	50.0	51.	60.0	76.	80.0
2.	80.0	27.	70.0	52.	60.0	77.	80.0
3.	80.0	28.	70.0	53.	60.0	78.	80.0
4.	50.0	29.	70.0	54.	60.0	79.	80.0
5.	50.0	30.	70.0	55.	60.0	80.	80.0
6.	50.0	31.	90.0	56.	60.0	81.	80.0
7.	50.0	32.	90.0	57.	60.0	82.	80.0
8.	50.0	33.	90.0	58.	60.0	83.	80.0
9.	50.0	34.	90.0	59.	60.0	84.	80.0
10.	50.0	35.	90.0	60.	60.0	85.	80.0
11.	50.0	36.	90.0	61.	60.0	86.	45.0
12.	50.0	37.	90.0	62.	60.0	87.	45.0
13.	50.0	38.	90.0	63.	60.0	88.	45.0
14.	50.0	39.	90.0	64.	60.0	89.	75.0
15.	50.0	40.	90.0	65.	70.0	90.	75.0
16.	50.0	41.	90.0	66.	70.0	91.	75.0
17.	50.0	42.	90.0	67.	70.0	92.	75.0
18.	50.0	43.	90.0	68.	80.0	93.	75.0
19.	50.0	44.	90.0	69.	80.0	94.	80.0
20.	50.0	45.	90.0	70.	80.0	95.	80.0
21.	50.0	46.	90.0	71.	80.0	96.	80.0
22.	50.0	47.	90.0	72.	80.0	97.	80.0
23.	50.0	48.	60.0	73.	80.0	98.	80.0
24.	50.0	49.	60.0	74.	80.0	99.	50.0
25.	50.0	50.	60.0	75.	80.0	100.	50.0

APPENDIX B

JACK MODELS & DATA

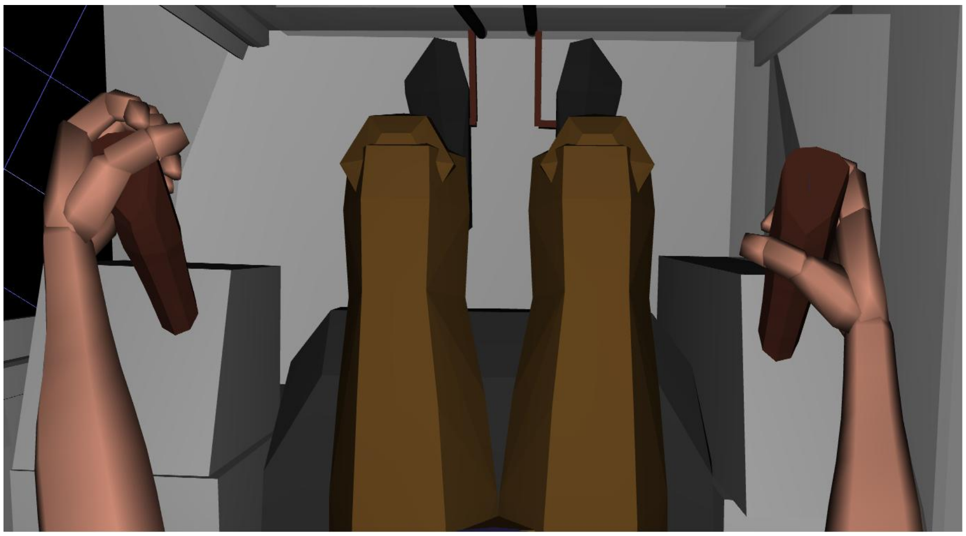

Figure B.1. Digital Human Model for Hydraulic Control Excavator System.

Figure B.2. Digital Human Model for Electronic Control Excavator System.

Table B.1. Original Energy Analysis for Hydraulic-Soil Model.

#	Excavation Task	Task Energy (kcal)	Standing Energy (kcal)	Sitting Energy (kcal)	Bent Energy (kcal)	Energy Exp. Rate (kcal/min)
1.	Tilt Hand	0.032	0.000	0.106	0.000	1.062
2.	Push Boom Joystick	0.029	0.000	0.400	0.000	0.875
3.	Excavator Lowers Boom	0.096	0.000	0.082	0.000	1.776
4.	Tilt Hand	0.032	0.000	0.106	0.000	1.062
5.	Adjust Arm Joystick	0.029	0.000	0.400	0.000	0.875
6.	Lower Dipperstick	0.215	0.000	0.049	0.000	4.399
7.	Tilt Hand	0.032	0.000	0.106	0.000	1.062
8.	Push Boom Joystick	0.029	0.000	0.400	0.000	0.875
9.	Scoop Material	0.425	0.000	0.057	0.000	6.887
10.	Tilt Hand	0.032	0.000	0.106	0.000	1.062
11.	Pull Boom Joystick	0.029	0.000	0.400	0.000	0.875
12.	Raise Boom	0.096	0.000	0.082	0.000	1.776
13.	Tilt Hand	0.032	0.000	0.106	0.000	1.062
14.	Adjust Swing Joystick	0.029	0.000	0.400	0.000	0.875
15.	Rotate Forward	0.107	0.000	0.106	0.000	1.639
16.	Tilt Hand	0.032	0.000	0.106	0.000	1.062
17.	Push Boom Joystick	0.029	0.000	0.400	0.000	0.875
18.	Release Material	0.203	0.000	0.049	0.000	4.199
19.	Tilt Hand	0.032	0.000	0.106	0.000	1.062
20.	Adjust Swing Joystick	0.029	0.000	0.400	0.000	0.875
21.	Rotate Backward	0.107	0.000	0.106	0.000	1.639

Table B.2. Original Energy Analysis for Hydraulic-Gravel Model.

#	Excavation Task	Task Energy (kcal)	Standing Energy (kcal)	Sitting Energy (kcal)	Bent Energy (kcal)	Energy Exp. Rate (kcal/min)
1.	Tilt Hand	0.032	0.000	0.155	0.000	0.984
2.	Push Boom Joystick	0.033	0.000	0.653	0.000	0.857
3.	Excavator Lowers Boom	0.106	0.000	0.106	0.000	1.631
4.	Tilt Hand	0.032	0.000	0.155	0.000	0.984
5.	Adjust Arm Joystick	0.033	0.000	0.653	0.000	0.857
6.	Lower Dipperstick	0.081	0.000	0.065	0.000	1.828
7.	Tilt Hand	0.032	0.000	0.155	0.000	0.984
8.	Push Boom Joystick	0.033	0.000	0.653	0.000	0.857
9.	Scoop Material	0.197	0.000	0.065	0.000	3.278
10.	Tilt Hand	0.032	0.000	0.155	0.000	0.984
11.	Pull Boom Joystick	0.033	0.000	0.653	0.000	0.857
12.	Raise Boom	0.106	0.000	0.106	0.000	1.631
13.	Tilt Hand	0.032	0.000	0.155	0.000	0.984
14.	Adjust Swing Joystick	0.033	0.000	0.653	0.000	0.857
15.	Rotate Forward	0.192	0.000	0.073	0.000	2.949
16.	Tilt Hand	0.032	0.000	0.155	0.000	0.984
17.	Push Boom Joystick	0.033	0.000	0.653	0.000	0.857
18.	Release Material	0.202	0.000	0.057	0.000	3.701
19.	Tilt Hand	0.032	0.000	0.155	0.000	0.984
20.	Adjust Swing Joystick	0.033	0.000	0.653	0.000	0.857
21.	Rotate Backward	0.200	0.000	0.073	0.000	3.038

Table B.3. Original Energy Analysis for Electronic-Soil Model.

#	Excavation Task	Task Energy (kcal)	Standing Energy (kcal)	Sitting Energy (kcal)	Bent Energy (kcal)	Energy Exp. Rate (kcal/min)
1.	Move Finger	0.200	0.000	0.082	0.000	2.816
2.	Press Joystick Button	0.040	0.000	0.122	0.000	1.082
3.	Lower Boom	0.217	0.000	0.049	0.000	4.432
4.	Move Finger	0.200	0.000	0.082	0.000	2.816
5.	Press Joystick Button	0.040	0.000	0.122	0.000	1.082
6.	Lower Dipperstick	0.207	0.000	0.049	0.000	4.266
7.	Move Finger	0.200	0.000	0.082	0.000	2.816
8.	Press Joystick Button	0.040	0.000	0.122	0.000	1.082
9.	Scoop Material	0.202	0.000	0.065	0.000	3.341
10.	Move Finger	0.200	0.000	0.082	0.000	2.816
11.	Press Joystick Button	0.040	0.000	0.122	0.000	1.082
12.	Rotate Forward	0.104	0.000	0.098	0.000	1.682
13.	Move Finger	0.200	0.000	0.082	0.000	2.816
14.	Press Joystick Button	0.040	0.000	0.122	0.000	1.082
15.	Release Material	0.206	0.000	0.049	0.000	4.249
16.	Move Finger	0.200	0.000	0.082	0.000	2.816
17.	Press Joystick Button	0.040	0.000	0.122	0.000	1.082
18.	Rotate Backward	0.104	0.000	0.098	0.000	1.682

Table B.4. Original Energy Analysis for Electronic-Gravel Model.

#	Excavation Task	Task Energy (kcal)	Standing Energy (kcal)	Sitting Energy (kcal)	Bent Energy (kcal)	Energy Exp. Rate (kcal/min)
1.	Move Finger	0.037	0.000	0.090	0.000	1.152
2.	Press Joystick Button	0.033	0.000	0.098	0.000	1.091
3.	Lower Boom	0.213	0.000	0.041	0.000	5.076
4.	Move Finger	0.037	0.000	0.090	0.000	1.152
5.	Press Joystick Button	0.033	0.000	0.098	0.000	1.091
6.	Lower Dipperstick	0.207	0.000	0.049	0.000	4.266
7.	Move Finger	0.037	0.000	0.090	0.000	1.152
8.	Press Joystick Button	0.033	0.000	0.098	0.000	1.091
9.	Scoop Material	0.213	0.000	0.065	0.000	3.478
10.	Move Finger	0.037	0.000	0.090	0.000	1.152
11.	Press Joystick Button	0.033	0.000	0.098	0.000	1.091
12.	Rotate Forward	0.096	0.000	0.098	0.000	1.616
13.	Move Finger	0.037	0.000	0.090	0.000	1.152
14.	Press Joystick Button	0.033	0.000	0.098	0.000	1.091
15.	Release Material	0.194	0.000	0.041	0.000	4.696
16.	Move Finger	0.037	0.000	0.090	0.000	1.152
17.	Press Joystick Button	0.033	0.000	0.098	0.000	1.091
18.	Rotate Backward	0.096	0.000	0.098	0.000	1.616

Table B.5. Original Recovery Analysis (sec) for Hydraulic-Soil Model.

#	Excavation Task	Task Duration	Cycle Time	Recovery Available	Recovery Needed
1.	Tilt Hand	1.08	7.57	6.49	0.12
2.	Push Boom Joystick	4.20	29.41	25.21	3.19
3.	Excavator Lowers Boom	3.14	6.28	3.14	1.59
4.	Tilt Hand	1.08	7.57	6.49	0.12
5.	Adjust Arm Joystick	4.20	29.41	25.21	3.19
6.	Lower Dipperstick	3.35	3.35	0.00	1.85
7.	Tilt Hand	1.08	7.57	6.49	0.12
8.	Push Boom Joystick	4.20	29.41	25.21	3.19
9.	Scoop Material	4.48	4.48	0.00	3.72
10.	Tilt Hand	1.08	7.57	6.49	0.12
11.	Pull Boom Joystick	4.20	29.41	25.21	3.19
12.	Raise Boom	3.14	6.28	3.14	1.59
13.	Tilt Hand	1.08	7.57	6.49	0.12
14.	Adjust Swing Joystick	4.20	29.41	25.21	3.19
15.	Rotate Forward	3.92	7.84	3.92	2.70
16.	Tilt Hand	1.08	7.57	6.49	0.12
17.	Push Boom Joystick	4.20	29.41	25.21	3.19
18.	Release Material	3.55	3.55	0.00	2.13
19.	Tilt Hand	1.08	7.57	6.49	0.12
20.	Adjust Swing Joystick	4.20	29.41	25.21	3.19
21.	Rotate Backward	3.92	7.84	3.92	2.70

Table B.6. Original Recovery Analysis (sec) for Hydraulic-Gravel Model.

#	Excavation Task	Task Duration	Cycle Time	Recovery Available	Recovery Needed
1.	Tilt Hand	1.61	11.28	9.67	0.04
2.	Push Boom Joystick	8.00	48.00	40.00	16.64
3.	Excavator Lowers Boom	3.97	7.94	3.97	3.10
4.	Tilt Hand	1.61	11.28	9.67	0.04
5.	Adjust Arm Joystick	8.00	48.00	40.00	16.64
6.	Lower Dipperstick	5.08	5.08	0.00	5.61
7.	Tilt Hand	1.61	11.28	9.67	0.04
8.	Push Boom Joystick	8.00	48.00	40.00	16.64
9.	Scoop Material	4.88	4.88	0.00	5.90
10.	Tilt Hand	1.61	11.28	9.67	0.04
11.	Pull Boom Joystick	8.00	48.00	40.00	16.64
12.	Raise Boom	3.97	7.94	3.97	3.10
13.	Tilt Hand	1.61	11.28	9.67	0.04
14.	Adjust Swing Joystick	8.00	48.00	40.00	16.64
15.	Rotate Forward	5.63	5.63	0.00	7.17
16.	Tilt Hand	1.61	11.28	9.67	0.04
17.	Push Boom Joystick	8.00	48.00	40.00	16.64
18.	Release Material	4.16	4.16	0.00	3.47
19.	Tilt Hand	1.61	11.28	9.67	0.04
20.	Adjust Swing Joystick	8.00	48.00	40.00	16.64
21.	Rotate Backward	5.40	5.40	0.00	6.49

Table B.7. Original Recovery Analysis (sec) for Electronic-Soil Model.

#	Excavation Task	Task Duration	Cycle Time	Recovery Available	Recovery Needed
1.	Move Finger	1.00	60.00	5.00	0.12
2.	Press Joystick Button	1.50	40.00	7.50	0.31
3.	Lower Boom	3.32	18.07	0.00	2.08
4.	Move Finger	1.00	60.00	5.00	0.12
5.	Press Joystick Button	1.50	40.00	7.50	0.31
6.	Lower Dipperstick	3.47	17.29	0.00	2.31
7.	Move Finger	1.00	60.00	5.00	0.12
8.	Press Joystick Button	1.50	40.00	7.50	0.31
9.	Scoop Material	4.76	12.61	0.00	4.93
10.	Move Finger	1.00	60.00	5.00	0.12
11.	Press Joystick Button	1.50	40.00	7.50	0.31
12.	Rotate Forward	3.47	17.29	3.47	2.31
13.	Move Finger	1.00	60.00	5.00	0.12
14.	Press Joystick Button	1.50	40.00	7.50	0.31
15.	Release Material	3.49	17.19	0.00	2.34
16.	Move Finger	1.00	60.00	5.00	0.12
17.	Press Joystick Button	1.50	40.00	7.50	0.31
18.	Rotate Backward	3.47	17.29	3.02	2.31

Table B.8. Original Recovery Analysis (sec) for Electronic-Gravel Model.

#	Excavation Task	Task Duration	Cycle Time	Recovery Available	Recovery Needed
1.	Move Finger	1.07	56.07	3.02	2.31
2.	Press Joystick Button	1.22	49.18	6.10	0.19
3.	Lower Boom	2.82	21.28	0.00	1.40
4.	Move Finger	1.07	56.07	3.02	2.31
5.	Press Joystick Button	1.22	49.18	6.10	0.19
6.	Lower Dipperstick	3.47	17.29	0.00	2.31
7.	Move Finger	1.07	56.07	3.02	2.31
8.	Press Joystick Button	1.22	49.18	6.10	0.19
9.	Scoop Material	4.50	13.33	0.00	4.31
10.	Move Finger	1.07	56.07	3.02	2.31
11.	Press Joystick Button	1.22	49.18	6.10	0.19
12.	Rotate Forward	3.47	17.29	4.01	2.31
13.	Move Finger	1.07	56.07	3.02	2.31
14.	Press Joystick Button	1.22	49.18	6.10	0.19
15.	Release Material	3.10	19.35	0.00	1.76
16.	Move Finger	1.07	56.07	3.02	2.31
17.	Press Joystick Button	1.22	49.18	6.10	0.19
18.	Rotate Backward	3.47	17.29	4.01	2.31

Table B.9. Original Fatigue Coefficients (kcal/sec) for Hydraulic Control.

		Hydraulic Control	
#	**Excavation Task**	**Soil Terrain**	**Gravel Terrain**
1.	Tilt Hand	0.017	0.007
2.	Push Boom Joystick	1.366	11.416
3.	Excavator Lowers Boom	0.282	0.657
4.	Tilt Hand	0.017	0.007
5.	Adjust Arm Joystick	1.366	11.416
6.	Lower Dipperstick	0.489	0.818
7.	Tilt Hand	0.017	0.007
8.	Push Boom Joystick	1.366	11.416
9.	Scoop Material	1.793	1.546
10.	Tilt Hand	0.017	0.007
11.	Pull Boom Joystick	1.366	11.416
12.	Raise Boom	0.282	0.657
13.	Tilt Hand	0.017	0.007
14.	Adjust Swing Joystick	1.366	11.416
15.	Rotate Forward	0.575	1.901
16.	Tilt Hand	0.017	0.007
17.	Push Boom Joystick	1.366	11.416
18.	Release Material	0.536	0.899
19.	Tilt Hand	0.017	0.007
20.	Adjust Swing Joystick	1.366	11.416
21.	Rotate Backward	0.575	1.772

Table B.10. Original Fatigue Coefficients (kcal/sec) for Electronic Control.

		Electronic Control	
#	**Excavation Task**	**Soil Terrain**	**Gravel Terrain**
1.	Move Finger	0.033	0.293
2.	Press Joystick Button	0.050	0.025
3.	Lower Boom	0.552	0.356
4.	Move Finger	0.033	0.293
5.	Press Joystick Button	0.050	0.025
6.	Lower Dipperstick	0.591	0.591
7.	Move Finger	0.033	0.293
8.	Press Joystick Button	0.050	0.025
9.	Scoop Material	1.316	1.198
10.	Move Finger	0.033	0.293
11.	Press Joystick Button	0.050	0.025
12.	Rotate Forward	0.466	0.448
13.	Move Finger	0.033	0.293
14.	Press Joystick Button	0.050	0.025
15.	Release Material	0.597	0.414
16.	Move Finger	0.033	0.293
17.	Press Joystick Button	0.050	0.025
18.	Rotate Backward	0.466	0.448

Table B.11. Simulated Energy Analysis for Hydraulic-Soil Model.

#	Excavation Task	Task Energy (kcal)	Standing Energy (kcal)	Sitting Energy (kcal)	Bent Energy (kcal)	Energy Exp. Rate (kcal/min)
1.	Tilt Hand	0.034	0.000	0.098	0.000	1.099
2.	Push Boom Joystick	0.014	0.000	0.114	0.000	0.916
3.	Excavator Lowers Boom	0.210	0.000	0.049	0.000	4.316
4.	Tilt Hand	0.034	0.000	0.098	0.000	1.099
5.	Adjust Arm Joystick	0.014	0.000	0.114	0.000	0.916
6.	Lower Dipperstick	0.210	0.000	0.049	0.000	4.316
7.	Tilt Hand	0.034	0.000	0.098	0.000	1.099
8.	Push Boom Joystick	0.007	0.000	0.114	0.000	0.866
9.	Scoop Material	0.204	0.000	0.098	0.000	2.516
10.	Tilt Hand	0.034	0.000	0.098	0.000	1.099
11.	Pull Boom Joystick	0.014	0.000	0.114	0.000	1.916
12.	Raise Boom	0.196	0.000	0.041	0.000	4.736
13.	Tilt Hand	0.034	0.000	0.098	0.000	1.099
14.	Adjust Swing Joystick	0.014	0.000	0.114	0.000	0.916
15.	Rotate Forward	0.202	0.000	0.171	0.000	1.778
16.	Tilt Hand	0.034	0.000	0.098	0.000	0.110
17.	Push Boom Joystick	0.014	0.000	0.114	0.000	0.916
18.	Release Material	0.218	0.000	0.049	0.000	4.449
19.	Tilt Hand	0.034	0.000	0.098	0.000	1.099
20.	Adjust Swing Joystick	0.014	0.000	0.114	0.000	0.916
21.	Rotate Backward	0.197	0.000	0.163	0.000	1.801

Table B.12. Simulated Energy Analysis for Hydraulic-Gravel Model.

#	Excavation Task	Task Energy (kcal)	Standing Energy (kcal)	Sitting Energy (kcal)	Bent Energy (kcal)	Energy Exp. Rate (kcal/min)
1.	Tilt Hand	0.033	0.000	0.147	0.000	0.999
2.	Push Boom Joystick	0.063	0.000	0.489	0.000	0.921
3.	Excavator Lowers Boom	0.104	0.000	0.106	0.000	1.616
4.	Tilt Hand	0.033	0.000	0.147	0.000	0.999
5.	Adjust Arm Joystick	0.063	0.000	0.131	0.000	1.209
6.	Lower Dipperstick	0.212	0.000	0.065	0.000	3.466
7.	Tilt Hand	0.033	0.000	0.147	0.000	0.999
8.	Push Boom Joystick	0.063	0.000	0.049	0.000	1.866
9.	Scoop Material	0.198	0.000	0.171	0.000	1.759
10.	Tilt Hand	0.033	0.000	0.147	0.000	0.999
11.	Pull Boom Joystick	0.083	0.000	0.049	0.000	1.866
12.	Raise Boom	0.104	0.000	0.106	0.000	1.616
13.	Tilt Hand	0.033	0.000	0.174	0.000	0.999
14.	Adjust Swing Joystick	0.085	0.000	0.041	0.000	2.516
15.	Rotate Forward	0.202	0.000	0.139	0.000	2.004
16.	Tilt Hand	0.022	0.000	0.147	0.000	0.938
17.	Push Boom Joystick	0.063	0.000	0.049	0.000	1.866
18.	Release Material	0.208	0.000	0.057	0.000	3.787
19.	Tilt Hand	0.033	0.000	0.147	0.000	0.999
20.	Adjust Swing Joystick	0.085	0.000	0.041	0.000	2.516
21.	Rotate Backward	0.198	0.000	0.220	0.000	1.549

Table B.13. Simulated Energy Analysis for Electronic-Soil Model.

#	Excavation Task	Task Energy (kcal)	Standing Energy (kcal)	Sitting Energy (kcal)	Bent Energy (kcal)	Energy Exp. Rate (kcal/min)
1.	Move Finger	0.039	0.000	0.082	0.000	1.206
2.	Press Joystick Button	0.009	0.000	0.188	0.000	1.855
3.	Lower Boom	0.191	0.000	0.041	0.000	4.636
4.	Move Finger	0.039	0.000	0.082	0.000	1.206
5.	Press Joystick Button	0.009	0.000	0.188	0.000	0.855
6.	Lower Dipperstick	0.217	0.000	0.049	0.000	4.432
7.	Move Finger	0.039	0.000	0.082	0.000	1.206
8.	Press Joystick Button	0.051	0.000	0.188	0.000	1.037
9.	Scoop Material	0.203	0.000	0.139	0.000	2.010
10.	Move Finger	0.019	0.000	0.082	0.000	1.006
11.	Press Joystick Button	0.017	0.000	0.188	0.000	0.089
12.	Rotate Forward	0.194	0.000	0.049	0.000	4.049
13.	Move Finger	0.039	0.000	0.082	0.000	1.206
14.	Press Joystick Button	0.06	0.000	0.188	0.000	1.077
15.	Release Material	0.207	0.000	4.894	0.000	0.85
16.	Move Finger	0.058	0.000	0.082	0.000	1.396
17.	Press Joystick Button	0.051	0.000	0.188	0.000	1.370
18.	Rotate Backward	0.213	0.000	0.049	0.000	4.366

Table B.14. Simulated Energy Analysis for Electronic-Gravel Model.

#	Excavation Task	Task Energy (kcal)	Standing Energy (kcal)	Sitting Energy (kcal)	Bent Energy (kcal)	Energy Exp. Rate (kcal/min)
1.	Move Finger	0.033	0.000	0.098	0.000	1.091
2.	Press Joystick Button	0.009	0.000	0.179	0.000	0.857
3.	Lower Boom	1.790	0.000	0.033	0.000	5.291
4.	Move Finger	0.033	0.000	0.098	0.000	1.910
5.	Press Joystick Button	0.009	0.000	0.179	0.000	0.857
6.	Lower Dipperstick	0.027	0.000	0.049	0.000	4.266
7.	Move Finger	0.033	0.000	0.098	0.000	1.091
8.	Press Joystick Button	0.055	0.000	0.179	0.000	1.066
9.	Scoop Material	0.196	0.000	0.163	0.000	1.792
10.	Move Finger	0.033	0.000	0.098	0.000	1.091
11.	Press Joystick Button	0.009	0.000	0.179	0.000	0.857
12.	Rotate Forward	0.103	0.000	0.098	0.000	1.674
13.	Move Finger	0.033	0.000	0.098	0.000	1.019
14.	Press Joystick Button	0.064	0.000	1.780	0.000	1.107
15.	Release Material	0.203	0.000	0.041	0.000	4.876
16.	Move Finger	0.049	0.000	0.098	0.000	1.224
17.	Press Joystick Button	0.055	0.000	0.179	0.000	1.066
18.	Rotate Backward	0.103	0.000	0.098	0.000	1.674

Table B.15. Simulated Recovery Analysis (sec) for Hydraulic-Soil Model.

#	Excavation Task	Task Duration	Cycle Time	Recovery Available	Recovery Needed
1.	Tilt Hand	0.98	7.01	6.03	0.09
2.	Push Boom Joystick	0.70	8.56	7.86	0.04
3.	Excavator Lowers Boom	3.43	3.43	0.09	1.76
4.	Tilt Hand	1.01	7.01	6.00	0.10
5.	Adjust Arm Joystick	0.69	8.56	7.87	0.04
6.	Lower Dipperstick	3.42	3.42	0.00	1.87
7.	Tilt Hand	0.97	7.01	6.04	0.09
8.	Push Boom Joystick	0.27	8.56	2.29	7.99
9.	Scoop Material	7.06	7.06	0.00	10.63
10.	Tilt Hand	1.01	7.01	6.00	0.10
11.	Pull Boom Joystick	0.79	8.56	7.77	0.06
12.	Raise Boom	3.05	3.05	0.00	1.42
13.	Tilt Hand	1.08	7.01	5.93	0.12
14.	Adjust Swing Joystick	0.62	8.56	7.94	0.03
15.	Rotate Forward	12.45	12.45	0.00	41.17
16.	Tilt Hand	1.01	7.01	6.00	0.10
17.	Push Boom Joystick	0.68	8.56	7.88	0.04
18.	Release Material	3.31	3.31	0.00	1.73
19.	Tilt Hand	0.95	7.01	6.06	0.09
20.	Adjust Swing Joystick	0.66	8.56	7.90	0.04
21.	Rotate Backward	12.18	12.20	0.02	39.34

Table B.16. Simulated Recovery Analysis (sec) for Hydraulic-Gravel Model.

#	Excavation Task	Task Duration	Cycle Time	Recovery Available	Recovery Needed
1.	Tilt Hand	1.50	11.03	9.53	0.26
2.	Push Boom Joystick	0.94	3.81	2.87	0.08
3.	Excavator Lowers Boom	4.13	8.06	3.93	2.94
4.	Tilt Hand	1.54	11.03	9.49	0.28
5.	Adjust Arm Joystick	0.91	3.81	2.90	0.08
6.	Lower Dipperstick	4.53	4.53	0.00	3.66
7.	Tilt Hand	1.55	11.03	9.48	2.79
8.	Push Boom Joystick	0.99	3.81	2.82	0.10
9.	Scoop Material	12.71	12.71	0.00	41.74
10.	Tilt Hand	1.65	11.03	9.38	0.33
11.	Pull Boom Joystick	0.95	3.81	2.86	0.09
12.	Raise Boom	3.93	8.06	4.13	2.61
13.	Tilt Hand	1.96	11.03	9.07	0.49
14.	Adjust Swing Joystick	0.95	2.83	1.88	0.09
15.	Rotate Forward	10.11	10.12	0.00	24.10
16.	Tilt Hand	1.26	11.03	9.77	0.17
17.	Push Boom Joystick	0.93	3.81	2.88	0.08
18.	Release Material	4.03	4.03	0.00	2.77
19.	Tilt Hand	1.57	11.03	9.46	0.29
20.	Adjust Swing Joystick	0.97	2.83	1.86	0.09
21.	Rotate Backward	16.36	16.35	0.00	76.51

Table B.17. Simulated Recovery Analysis (sec) for Electronic-Soil Model.

#	Excavation Task	Task Duration	Cycle Time	Recovery Available	Recovery Needed
1.	Move Finger	1.00	6.23	5.23	0.09
2.	Press Joystick Button	0.47	14.01	13.54	0.02
3.	Lower Boom	3.14	3.14	0.00	1.46
4.	Move Finger	1.00	6.23	5.23	0.09
5.	Press Joystick Button	0.46	14.01	13.55	0.02
6.	Lower Dipperstick	3.32	3.32	1.67	0.22
7.	Move Finger	1.00	6.23	5.23	0.09
8.	Press Joystick Button	3.67	14.01	10.34	2.12
9.	Scoop Material	10.03	10.03	0.00	23.70
10.	Move Finger	0.55	6.23	5.68	0.02
11.	Press Joystick Button	1.42	14.01	12.59	2.17
12.	Rotate Forward	3.71	3.71	0.00	2.18
13.	Move Finger	1.14	6.23	5.09	0.13
14.	Press Joystick Button	4.19	14.01	9.82	2.92
15.	Release Material	3.48	3.48	0.00	1.87
16.	Move Finger	1.54	6.23	4.69	0.26
17.	Press Joystick Button	3.81	14.01	10.20	2.32
18.	Rotate Backward	3.38	3.38	0.00	1.74

TableB.18. Simulated Recovery Analysis (sec) for Electronic-Gravel Model.

#	Excavation Task	Task Duration	Cycle Time	Recovery Available	Recovery Needed
1.	Move Finger	0.98	7.37	6.39	0.09
2.	Press Joystick Button	0.42	13.08	12.59	0.01
3.	Lower Boom	2.69	2.69	0.00	1.01
4.	Move Finger	1.05	7.37	6.32	0.11
5.	Press Joystick Button	0.42	13.08	12.59	0.01
6.	Lower Dipperstick	3.48	3.49	0.01	1.87
7.	Move Finger	1.50	7.37	5.87	0.25
8.	Press Joystick Button	3.78	13.08	9.30	2.28
9.	Scoop Material	12.25	12.25	0.00	38.28
10.	Move Finger	0.98	7.37	6.39	0.09
11.	Press Joystick Button	0.52	13.08	12.56	0.02
12.	Rotate Forward	3.53	6.96	3.43	1.93
13.	Move Finger	1.31	7.37	6.06	0.18
14.	Press Joystick Button	4.10	13.08	8.98	2.77
15.	Release Material	2.96	2.96	0.00	1.27
16.	Move Finger	1.55	7.37	5.82	0.27
17.	Press Joystick Button	3.83	13.08	9.18	2.35
18.	Rotate Backward	3.43	6.96	3.53	1.80

Table B.19. Simulated Fatigue Coefficients (kcal/sec) for Hydraulic Control.

		Hydraulic Control	
#	**Excavation Task**	**Soil Terrain**	**Gravel Terrain**
1.	Tilt Hand	0.012	0.046
2.	Push Boom Joystick	0.005	0.046
3.	Excavator Lowers Boom	0.457	0.616
4.	Tilt Hand	0.013	0.050
5.	Adjust Arm Joystick	0.005	0.015
6.	Lower Dipperstick	0.483	1.015
7.	Tilt Hand	0.012	0.502
8.	Push Boom Joystick	0.967	0.011
9.	Scoop Material	3.209	15.404
10.	Tilt Hand	0.013	0.059
11.	Pull Boom Joystick	0.007	0.011
12.	Raise Boom	0.336	0.547
13.	Tilt Hand	0.015	0.102
14.	Adjust Swing Joystick	0.004	0.011
15.	Rotate Forward	15.355	8.219
16.	Tilt Hand	0.013	0.029
17.	Push Boom Joystick	0.005	0.009
18.	Release Material	0.461	0.733
19.	Tilt Hand	0.011	0.052
20.	Adjust Swing Joystick	0.005	0.011
21.	Rotate Backward	14.163	31.982

Table B.20. Simulated Fatigue Coefficients (kcal/sec) for Electronic Control.

		Electronic Control	
#	**Excavation Task**	**Soil Terrain**	**Gravel Terrain**
1.	Move Finger	0.011	0.012
2.	Press Joystick Button	0.003	0.002
3.	Lower Boom	0.338	1.836
4.	Move Finger	0.011	0.014
5.	Press Joystick Button	0.003	0.002
6.	Lower Dipperstick	0.058	0.142
7.	Move Finger	0.011	0.032
8.	Press Joystick Button	0.507	0.533
9.	Scoop Material	8.105	13.742
10.	Move Finger	0.002	0.012
11.	Press Joystick Button	0.445	0.004
12.	Rotate Forward	0.529	0.388
13.	Move Finger	0.015	0.023
14.	Press Joystick Button	0.723	5.104
15.	Release Material	9.524	0.309
16.	Move Finger	0.037	0.039
17.	Press Joystick Button	0.555	0.550
18.	Rotate Backward	0.456	0.363

APPENDIX C

INTEGRATED MICRO SAINT-JACK MODELS & DATA

Table C.1. Integrated Completion Time (sec) for Hydraulic-Soil Model.

#	Completion Time	#	Completion Time	#	Completion Time	#	Completion Time
1.	82.7	26.	128.9	51.	422.6	76.	216.8
2.	974.8	27.	385.9	52.	160.8	77.	130.2
3.	274.7	28.	329.3	53.	537.1	78.	447.4
4.	179.2	29.	265.9	54.	132.2	79.	201.7
5.	980.4	30.	478.5	55.	263.7	80.	92.3
6.	182.1	31.	174.2	56.	301.2	81.	322.8
7.	124.9	32.	193.0	57.	288.8	82.	267.0
8.	106.9	33.	118.1	58.	448.4	83.	100.3
9.	139.0	34.	434.1	59.	231.1	84.	625.7
10.	118.6	35.	223.7	60.	101.5	85.	209.1
11.	117.4	36.	84.0	61.	233.1	86.	167.2
12.	231.5	37.	98.5	62.	271.1	87.	94.7
13.	106.3	38.	391.8	63.	399.6	88.	154.4
14.	169.2	39.	277.7	64.	266.0	89.	337.5
15.	173.5	40.	124.6	65.	246.6	90.	331.4
16.	146.2	41.	179.2	66.	131.7	91.	341.0
17.	132.5	42.	781.1	67.	134.9	92.	101.9
18.	118.6	43.	112.9	68.	283.2	93.	163.9
19.	422.8	44.	171.5	69.	297.8	94.	442.0
20.	149.6	45.	115.7	70.	166.2	95.	90.7
21.	200.2	46.	376.1	71.	143.8	96.	102.3
22.	120.9	47.	111.8	72.	157.2	97.	97.3
23.	244.6	48.	215.1	73.	462.9	98.	139.4
24.	177.2	49.	179.8	74.	248.9	99.	127.2
25.	223.5	50.	128.6	75.	245.4	100.	307.0

Table C.2. Integrated Completion Time (sec) for Hydraulic-Gravel Model.

#	Completion Time	#	Completion Time	#	Completion Time	#	Completion Time
1.	381.6	26.	156.8	51.	264.2	76.	388.1
2.	242.4	27.	381.6	52.	229.7	77.	277.3
3.	166.7	28.	242.4	53.	254.2	78.	252.0
4.	176.2	29.	166.7	54.	359.7	79.	1070.9
5.	156.8	30.	176.2	55.	139.6	80.	239.7
6.	381.6	31.	284.7	56.	250.6	81.	175.4
7.	242.4	32.	381.6	57.	1135.6	82.	157.1
8.	166.7	33.	242.4	58.	220.9	83.	426.1
9.	176.2	34.	562.4	59.	242.9	84.	510.0
10.	381.6	35.	176.2	60.	433.7	85.	1038.0
11.	193.9	36.	156.8	61.	384.8	86.	200.8
12.	181.4	37.	381.6	62.	183.4	87.	652.0
13.	5615.2	38.	242.4	63.	245.5	88.	395.6
14.	171.0	39.	166.7	64.	461.6	89.	176.9
15.	461.9	40.	176.2	65.	311.8	90.	303.8
16.	271.4	41.	245.6	66.	149.5	91.	343.6
17.	171.3	42.	178.5	67.	369.7	92.	330.2
18.	407.3	43.	183.9	68.	465.0	93.	235.8
19.	199.9	44.	450.7	69.	190.3	94.	225.8
20.	239.4	45.	1004.5	70.	410.1	95.	209.0
21.	563.4	46.	459.7	71.	166.5	96.	695.8
22.	403.5	47.	303.5	72.	588.8	97.	490.1
23.	526.7	48.	249.9	73.	150.4	98.	212.1
24.	1578.0	49.	262.1	74.	235.0	99.	393.3
25.	436.6	50.	238.8	75.	182.7	100.	500.8

Table C.3. Integrated Completion Time (sec) for Electronic-Soil Model.

#	Completion Time	#	Completion Time	#	Completion Time	#	Completion Time
1.	141.5	26.	88.8	51.	77.1	76.	77.3
2.	133.1	27.	94.7	52.	177.6	77.	109.6
3.	131.5	28.	83.1	53.	76.8	78.	415.0
4.	179.6	29.	193.9	54.	122.2	79.	184.2
5.	110.2	30.	116.3	55.	71.4	80.	207.5
6.	164.2	31.	74.5	56.	90.7	81.	169.7
7.	86.5	32.	111.6	57.	325.1	82.	81.3
8.	81.4	33.	85.0	58.	79.7	83.	65.9
9.	480.8	34.	125.8	59.	83.5	84.	134.2
10.	125.1	35.	88.5	60.	180.3	85.	220.0
11.	80.0	36.	257.6	61.	202.2	86.	138.5
12.	177.5	37.	179.9	62.	177.2	87.	174.9
13.	219.6	38.	138.9	63.	106.2	88.	122.7
14.	74.4	39.	138.1	64.	213.8	89.	680.2
15.	75.4	40.	450.1	65.	116.0	90.	78.9
16.	140.6	41.	270.3	66.	197.1	91.	77.1
17.	78.5	42.	79.1	67.	185.5	92.	184.1
18.	86.5	43.	75.8	68.	75.9	93.	75.2
19.	148.9	44.	85.1	69.	191.2	94.	74.5
20.	230.6	45.	77.2	70.	743.9	95.	70.5
21.	118.6	46.	139.1	71.	427.6	96.	478.6
22.	94.2	47.	80.5	72.	122.2	97.	514.2
23.	137.3	48.	129.5	73.	75.3	98.	244.3
24.	145.5	49.	122.9	74.	355.6	99.	111.1
25.	88.6	50.	218.4	75.	176.5	100.	193.2

Table C.4. Integrated Completion Time (sec) for Electronic-Gravel Model.

#	Completion Time	#	Completion Time	#	Completion Time	#	Completion Time
1.	128.6	26.	167.8	51.	131.7	76.	116.0
2.	388.7	27.	360.9	52.	139.5	77.	252.8
3.	155.2	28.	155.3	53.	199.6	78.	190.6
4.	247.7	29.	401.0	54.	194.8	79.	102.4
5.	121.3	30.	140.7	55.	2823.6	80.	97.8
6.	2223.6	31.	334.1	56.	165.1	81.	261.5
7.	259.9	32.	236.5	57.	200.9	82.	736.3
8.	100.4	33.	215.9	58.	142.0	83.	144.9
9.	203.0	34.	139.5	59.	103.8	84.	106.1
10.	408.0	35.	347.9	60.	565.9	85.	155.8
11.	550.3	36.	1551.0	61.	1936.1	86.	364.2
12.	1433.8	37.	369.4	62.	347.3	87.	155.1
13.	238.0	38.	151.1	63.	243.8	88.	275.0
14.	221.7	39.	244.6	64.	131.1	89.	1430.1
15.	165.3	40.	191.5	65.	125.5	90.	129.5
16.	269.4	41.	183.4	66.	115.7	91.	197.1
17.	121.5	42.	110.3	67.	138.2	92.	361.5
18.	287.3	43.	361.1	68.	219.3	93.	116.8
19.	152.9	44.	120.1	69.	105.8	94.	118.4
20.	795.7	45.	276.0	70.	2215.2	95.	136.0
21.	136.6	46.	269.9	71.	186.3	96.	2294.2
22.	153.9	47.	141.4	72.	186.3	97.	130.6
23.	123.8	48.	270.6	73.	100.0	98.	129.1
24.	145.0	49.	118.2	74.	462.6	99.	592.3
25.	205.5	50.	252.9	75.	111.5	100.	126.1

Table C.5. Integrated Workload (%) for Hydraulic-Soil Model.

#	Workload	#	Workload	#	Workload	#	Workload
1.	45.0	26.	25.0	51.	60.0	76.	75.0
2.	45.0	27.	25.0	52.	60.0	77.	75.0
3.	45.0	28.	25.0	53.	60.0	78.	50.0
4.	45.0	29.	25.0	54.	60.0	79.	50.0
5.	45.0	30.	45.0	55.	60.0	80.	50.0
6.	45.0	31.	45.0	56.	60.0	81.	65.0
7.	45.0	32.	45.0	57.	50.0	82.	65.0
8.	45.0	33.	45.0	58.	50.0	83.	65.0
9.	45.0	34.	45.0	59.	50.0	84.	65.0
10.	10.0	35.	45.0	60.	50.0	85.	65.0
11.	10.0	36.	45.0	61.	50.0	86.	65.0
12.	10.0	37.	32.0	62.	50.0	87.	65.0
13.	10.0	38.	32.0	63.	50.0	88.	65.0
14.	10.0	39.	45.0	64.	50.0	89.	65.0
15.	10.0	40.	45.0	65.	50.0	90.	65.0
16.	45.0	41.	45.0	66.	50.0	91.	65.0
17.	45.0	42.	45.0	67.	50.0	92.	65.0
18.	45.0	43.	45.0	68.	50.0	93.	45.0
19.	45.0	44.	50.0	69.	50.0	94.	45.0
20.	45.0	45.	50.0	70.	50.0	95.	45.0
21.	45.0	46.	50.0	71.	50.0	96.	45.0
22.	45.0	47.	50.0	72.	45.0	97.	45.0
23.	25.0	48.	50.0	73.	45.0	98.	45.0
24.	25.0	49.	50.0	74.	45.0	99.	45.0
25.	25.0	50.	60.0	75.	75.0	100.	45.0

Table C.6. Integrated Workload (%) for Hydraulic-Gravel Model.

#	Workload	#	Workload	#	Workload	#	Workload
1.	65.0	26.	70.0	51.	25.0	76.	75.0
2.	65.0	27.	70.0	52.	25.0	77.	75.0
3.	65.0	28.	70.0	53.	25.0	78.	75.0
4.	70.0	29.	70.0	54.	25.0	79.	75.0
5.	70.0	30.	70.0	55.	75.0	80.	75.0
6.	70.0	31.	20.0	56.	75.0	81.	75.0
7.	70.0	32.	20.0	57.	75.0	82.	75.0
8.	70.0	33.	20.0	58.	75.0	83.	75.0
9.	70.0	34.	25.0	59.	75.0	84.	75.0
10.	70.0	35.	25.0	60.	75.0	85.	75.0
11.	70.0	36.	25.0	61.	75.0	86.	70.0
12.	70.0	37.	50.0	62.	75.0	87.	70.0
13.	70.0	38.	50.0	63.	75.0	88.	70.0
14.	70.0	39.	50.0	64.	75.0	89.	75.0
15.	70.0	40.	70.0	65.	75.0	90.	75.0
16.	70.0	41.	70.0	66.	75.0	91.	75.0
17.	70.0	42.	70.0	67.	75.0	92.	75.0
18.	70.0	43.	45.0	68.	75.0	93.	75.0
19.	70.0	44.	45.0	69.	75.0	94.	75.0
20.	70.0	45.	45.0	70.	75.0	95.	75.0
21.	70.0	46.	60.0	71.	75.0	96.	75.0
22.	70.0	47.	60.0	72.	75.0	97.	50.0
23.	70.0	48.	60.0	73.	75.0	98.	50.0
24.	70.0	49.	25.0	74.	75.0	99.	50.0
25.	70.0	50.	25.0	75.	75.0	100.	50.0

Table C.7. Integrated Workload (%) for Electronic-Soil Model.

#	Workload	#	Workload	#	Workload	#	Workload
1.	98.0	26.	60.0	51.	40.0	76.	70.0
2.	98.0	27.	60.0	52.	40.0	77.	65.0
3.	98.0	28.	60.0	53.	40.0	78.	65.0
4.	98.0	29.	60.0	54.	40.0	79.	65.0
5.	98.0	30.	60.0	55.	40.0	80.	65.0
6.	98.0	31.	60.0	56.	40.0	81.	90.0
7.	98.0	32.	60.0	57.	40.0	82.	90.0
8.	98.0	33.	60.0	58.	40.0	83.	90.0
9.	98.0	34.	60.0	59.	70.0	84.	90.0
10.	98.0	35.	60.0	60.	70.0	85.	95.0
11.	98.0	36.	60.0	61.	70.0	86.	80.0
12.	98.0	37.	60.0	62.	70.0	87.	80.0
13.	98.0	38.	60.0	63.	70.0	88.	80.0
14.	98.0	39.	60.0	64.	70.0	89.	80.0
15.	98.0	40.	60.0	65.	70.0	90.	65.0
16.	98.0	41.	60.0	66.	70.0	91.	65.0
17.	98.0	42.	60.0	67.	70.0	92.	65.0
18.	98.0	43.	40.0	68.	70.0	93.	65.0
19.	98.0	44.	40.0	69.	70.0	94.	65.0
20.	98.0	45.	40.0	70.	70.0	95.	70.0
21.	95.0	46.	40.0	71.	70.0	96.	70.0
22.	95.0	47.	40.0	72.	70.0	97.	70.0
23.	95.0	48.	40.0	73.	70.0	98.	70.0
24.	95.0	49.	40.0	74.	70.0	99.	70.0
25.	95.0	50.	40.0	75.	70.0	100.	70.0

Table C.8. Integrated Workload (%) for Electronic-Gravel Model.

#	Workload	#	Workload	#	Workload	#	Workload
1.	90.0	26.	90.0	51.	95.0	76.	70.0
2.	90.0	27.	90.0	52.	95.0	77.	70.0
3.	90.0	28.	90.0	53.	95.0	78.	70.0
4.	90.0	29.	90.0	54.	95.0	79.	70.0
5.	90.0	30.	90.0	55.	95.0	80.	70.0
6.	90.0	31.	50.0	56.	95.0	81.	70.0
7.	90.0	32.	50.0	57.	95.0	82.	70.0
8.	90.0	33.	50.0	58.	95.0	83.	65.0
9.	90.0	34.	50.0	59.	95.0	84.	65.0
10.	90.0	35.	50.0	60.	95.0	85.	65.0
11.	90.0	36.	50.0	61.	95.0	86.	65.0
12.	90.0	37.	50.0	62.	95.0	87.	95.0
13.	90.0	38.	50.0	63.	70.0	88.	95.0
14.	90.0	39.	50.0	64.	70.0	89.	95.0
15.	90.0	40.	50.0	65.	70.0	90.	95.0
16.	90.0	41.	60.0	66.	70.0	91.	50.0
17.	90.0	42.	60.0	67.	70.0	92.	45.0
18.	90.0	43.	60.0	68.	70.0	93.	45.0
19.	90.0	44.	60.0	69.	70.0	94.	80.0
20.	90.0	45.	60.0	70.	70.0	95.	80.0
21.	90.0	46.	95.0	71.	70.0	96.	80.0
22.	90.0	47.	95.0	72.	70.0	97.	80.0
23.	90.0	48.	95.0	73.	70.0	98.	80.0
24.	90.0	49.	95.0	74.	70.0	99.	80.0
25.	90.0	50.	95.0	75.	70.0	100.	80.0