ABSTRACT

Title of dissertation:	OPTIMIZING MASS CUSTOMIZATION THROUGH INTERACTION VARIABILITY AND MANUFACTURING TRADE-OFFS
	Kailyn Cage, Doctor of Philosophy, 2018
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Design methods that consider the complete physical system (human interfaces and functional capacities of human interfaces) and incremental distinctions in humans are not widely applied. Human beings vary from a cognitive and physical standpoint. Manufacturing approaches have attempted to implement mass customization to provide end users with personalized products. However, these approaches are limited since (1) mass customization is orthogonal to human variability and (2) manufacturing costs are increased, through additional time and parts, required when mass-producing customized products. This research facilitates the integration of traditional engineering performance metrics and biomechanics creating manufacturable innovations in customized design that target population accommodation. The present method captures (1) human and product interface interactions, (2) interaction accommodation, (3) the impact of interaction accommodation on en-

gineering performance metrics (thermal, structural, fluid, reliability, etc.), and (4) number of products required to accommodate the population. Engineering design techniques provide a structured method for reducing product and performance metrics which provide the foundational framework for the optimization model(s) integrating this method. Optimization enables optimal performance metrics constrained by population accommodation, producing the product metrics and the number of products required to accommodate the population. This work is a novel approach for addressing complex questions for interaction variability in mass production targeting population accommodation while maintaining product performance, which facilitate addressing larger problems of mass customization in mass production.

OPTIMIZING MASS CUSTOMIZATION THROUGH INTERACTION VARIABILITY AND MANUFACTURING TRADE-OFFS

by

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Dedication

In Loving Memory of David A., Quenton B., and Brenda M.

Your lives and legacy have profoundly impacted my life and shaped the trajectory of my purpose

Acknowledgments

"Failure to consider the most vulnerable people in our society == Societal Failure"

I am grateful, first and foremost, to the universal God for my ancestors, whose generational knowledge has been transformative in my life. To my mother, who has given me life, encouragement, persistence and love, thank you. You are my gift. To my father, who has cultivated in me a love of knowledge and understanding, thank you. You are my inspiration. To my village, my sisters and brothers, relatives and lifelong friends, I am indebted to you. You are the best parts of me.

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List of Abbreviations

1D	One Dimensional
3D	Three Dimensional
ABS	Acrylonitrile Butadiene Styrene
AHP	Analytic Hierarchy Process
AM	Additive Manufacturing
ANSUR	Army Anthropometric Survey
AQFD	Analytic Hierarchy Process with Quality Function Deployment
AROM	Active Range of Motion
ASTM	American Society for Testing and Materials
CAD	Computer-aided Design
DAQ	Data Acquisition System
DfHV	Design for Human Variability
DIP	Distal Interphlangeal Joint
DOE	Design of Experiments
EES	Engineering Equation Solver®
FDM	Fused Deposition Modeling
FEA	Finite Element Analysis
FROM	Functional Range of Motion
GCM	Global Criterion Method
HP	Heat Pipe
HX	Heat Exchanger
IP	Interphlangeal Joint
LANL	Los Alamos National Laboratory
MC	Mass Customization
MCP	Metacarpophlangeal Joint
MOO	Multi-Objective Optimization
NHANES	National Health and Nutrition Survey

PDP	Product Development or Design Process
PIP	Proximal Interphlangeal Joint
PLA	Polylactic Acid
PUR	Polyurethane
QFD	Quality Function Deployment
ROM	Range of Motion
SOD	Stand-off Distance
STL	Stereolithography

Chapter 1: Introduction

Characteristics of human beings vary, cognitively and physically. These characteristics impact end user performance, product performance, satisfaction, and usability. Human characteristics relate to manufacturing processes since human expertise, physical labor, or product utilization is associated with the design process from conceptualization, to mass production, to the purchase of the product. In relation to the manufacturing process, the physical capabilities of human beings can vastly differ based on the physical characteristics associated with anthropometry, force, tactility, maneuverability, and reach. Current human factors design approaches do not comprehensively consider the distinctions in human beings from both the variation in human parameters (static) perspective and the interaction capacity of human parameters (dynamic) perspective. Most researchers and methods, e.g. Design for Human Variability, place emphasis on the static perspective. The results produce designs that address specified requirements better than traditional processes but fail to comprehensively, in a static and dynamic manner, improve the design and manufacturing approach (additive or subtractive approaches), for the user population.

In an effort to address human variability and/or preferences, in product development, mass customization (MC) has been introduced, in marketing and operations research. MC is a method to address the individual needs and/or preferences of customers while maintaining the economic benefits of a mass production business model. More specifically MC is defined in the following quote: "At its core, Mass Customization is a tremendous increase in variety and customization without a corresponding increase in costs. At its limit, it is the mass production of individually customized goods and services. At its best, it provides strategic advantage and economic value [4]. Unfortunately, many manufacturers have difficulty adopting MC because of costs associated with tooling [5]. Nevertheless, manufacturing approaches have attempted to implement MC to provide customers with personalized products. As a result, two limitations have arisen (1) MC is centered on aesthetic customer preferences and is orthogonal to human variability and (2) manufacturing costs are increased through partial customization. Moreover, the costs of incorporating preference in mass production exponentially increases due to parameter modifications for differentiated products in manufacturing equipment, additional production time, and restricting or rebalancing production lines.

Interaction variability is introduced in this work and addresses MC from an objective perspective that customizes products based on human parameters and interactions between the product and human parameter. The method relies on the underlying assumption that user preferences and/or needs are dependent on accommodation. Accommodation in this work is the defined as consideration of human parameters and their function capacities during product use. The interaction variability method seeks to address the "customer need aspect of MC, which impacts but not specifically addresses customer preference. Traditionally, MC fails to address human variability as a dependency of customer preference, which may impact satisfaction. While human variability fails to consider interactions and the functional capacity of human parameters, which is assumed to impact customer satisfaction.

Traditionally, human factors methods are applied to the design of work or the fit of the person to a product. These methods rely of adjustability of products and humans to fit workspaces and human parameters to guide the dimensions of products, respectively. Current methods only address static applications and lack standardization often requiring experts or thoroughly trained engineers, e.g. master degree, to implement these techniques. This work presents a structured, classification scheme for identifying interactions between product and human interfaces based on product function for static and dynamic applications. Moreover, this method is applied in the design conceptualization phase of the design process. The fundamental contribution and emphasis of this work, compared to traditional methods, lies in three distinct focuses surrounding the dynamics of interactions.

1. Structured scheme for identifying and mapping human and product interfaces, along with human parameter functionality that is standardized and repeatable.

2. Design dimensions driven by interactions and population variability of interactions for both static and dynamic applications compared to percentile-based design.

3. Interaction design space for capturing multitudinous distinct interactions for individuals and capturing measurable differences amongst the population.

Additive manufacturing (AM) is defined as "the process of merging materials in a layer by layer fashion to make objects based on 3D model data [6, 7]. AM is distinct from traditional manufacturing process which are typically subtractive, removing material to make 3D objects, in nature [7]. Customized products my lead to more complex product designs, AM addresses design complexity less the costs associated with tooling and promotes MC based on the agile nature of the process. Although AM addresses the complexity of implementing MC approaches, design methodologies that address human variability in a static (anthropometric) and dynamic (interactive) approach for additive manufacturing have not been developed. Furthermore, the integration of MC in AM fails to comprehensively consider the tradeoffs between interaction variability specifications (human interaction factors) and manufacturing process specifications (manufacturing characteristics). This can lead to lower product adoption, use errors, and increased manufacturing costs.

Human variability and manufacturing tradeoffs can be modeled through the use of optimization approaches. Optimization is a good tool for assessing tradeoffs and determining optimal solutions that assist in identifying an optimal solution set. Historically, optimization has been applied to manufacturing processes to high performing, consistent products to tolerance specifications [8]. More recently, optimization techniques have been developed to optimize AM processes through minimizing process energy and part errors [9–12]. However, there have been limited attempts to use optimization techniques in the manufacturing of parts or products that directly interface with end users. Optimization enables products to be designed to address the needs of a diverse end user population while maintaining functional performance goals of the product impacted by manufacturing process parameters.

The rigorous nature of this work is centered in the complexity of hybrid systems, from a human and hardware perspective. Manufacturing provides an approach for identifying relationships amongst these perspectives of the hybrid system, which is essential in the design of safety critical product applications. Design for manufacturing methods were developed to improve process performance and reduce costs [13]. The manufacturing process has often been evaluated separately from product variety related to human variability. There is an innate challenge in integrating the fields of biomechanics, mechanical engineering design, manufacturing, and optimization in an effort to produce comprehensive and reliable products that address interaction variability and product performance through manufacturing, without sacrificing quality or cost in production.

This research intends to address product design limitations through identifying interaction variability from a biomechanics viewpoint at the musculoskeletal level. Interaction variability, the main theoretical contribution of this work, will be integrated into a novel multidisciplinary method consisting of biomechanics, mechanical engineering design, manufacturing, and optimization. Interaction variability indirectly represents MC because product dimensions are altered based on human-component interactions not traditional approaches driven by consumer preference specifications. However, the results, relating to product dimension variation, remain the same assuming that preference and satisfaction is influenced by accommodation, which in this method is defined by population interaction variability. The work provides to notable insights in (1) a method of interaction variability and (2) a process for implementing MC driven by interaction variability and functional product performance, which is impacted by manufacturing process parameters. The output of this method presents a practical optimization solution for optimal product performance given the need to accommodate the MC needs of the population. Thus, this method has the potential to simultaneously satisfy biomechanical needs based on interaction variability and the functional performance requirements of a given product.

The process for implementing this method is encompassed in five steps.

1. Selection of a product application
2. Identification human interaction factors
3. Identification manufacturing characteristics
4. Development of a trade-off model
5. Development of a optimization model

The method was demonstrated on two product applications. The first was a hand-held device, with a focus on the hardware elements (button and casing). The second application was the design of a helmet, including a passive heat exchanger for cooling, which defined the performance objective. The results present an optimization solution that answers two fundamental questions that address MC in mass production from the perspective of accommodation and performance.

1. Can optimal functional product performance be achieved with population accommodation?

2. How many devices are needed to accommodate the population?

This work will assist in providing the optimal design solutions that consider interaction variability for static and dynamic product application and manufacturing characteristics and approaches including innovative and novel fabrication approaches such as additive manufacturing.

Chapter 2: Literature Review

This review provides insight into MC and the subsequent relationship between products and end users. The product is discussed in terms of modularization and product platforms as well as manufacturing characteristics and errors as they relate to AM. Furthermore, the end user is discussed in the context of user-centered design methods and the biomechanical and anthropometric limitations in human beings. In an effort to design a methodology for integrating human interaction factors and machine characteristics in optimization, the exploration of optimization models for humans, manufacturing processes, and both human and manufacturing processes is also reviewed.

2.1 Mass Customization and Alternative Concepts

The concept of MC, originally coined by Davis [14], was established as a business strategy to supply customer product preferences (customization) without sacrificing the profitability of a mass-produced product. MC allows end users, on a large scale, to have an individualized product based on personal preferences within defined constraints. This concept leads to additional benefits of increased end user satisfaction, safety, adoption, performance, usability, and adherence to recommended use.

Researchers suggest that the facilitation of an MC and mass production collaboration is dependent upon manufacturing systems that are easily adaptable to customer needs as well as infrastructural advancements [15].

Economically feasible implementations of MC and mass production methods are not currently available. The adoption of MC in traditional manufacturing has proven to be difficult due to the high costs associated with vast amounts of tooling and the additional time needed in order to enable customization [5]. The complexities of MC, from an economy of scale perspective, are detailed as a constrained model where custom products and high volume with consistent production cycles are impossible in a synonymous state [14, 16]. However, MC provides limitless possibilities for end users to obtain customized products at near mass production efficiency. Additional research is required to overcome the limitations that are inherent in the structural and mass production cycles of products.

The constraints associated with MC and mass production are described in terms of the quality and productivity. These specific constraints necessitate optimization in mass production [17]. The process of *continuous improvement* or optimization of these parameters is called *kaizen*. Blecker and Abdelkafi [16] describe MC constraints as external complexities where the customer needs are segmented as subjective or objective needs [18]. The customer needs often shape MC, so the inability of the customer to correctly identify their needs in the production phase could have huge negative impacts on customer satisfaction of the end product. The supply chain imposes additional constraints in the areas of product architecture design and manufacturing. Product architectures must facilitate easy customization and change overs in the manufacturing process, which may in exchange minimize set-up times, wait times, and costs [16].

Buffington and McCubbrey [19] introduced the concept of generative customization as an alternative method to MC. They describe generative customization as a virtual customer (repository) that provides innovative product options that offer a *innovative continuum*, which connects discontinuous innovation within one system. Buffington and McCubbrey [19] formally define generative customization as "a product conceptualization and fulfillment system that enables customization through a front-end generative design process and a supply chain system that enables innovation." While generative customization utilizes a customer repository to determine product options (taking the actual human out of the equation), MC directly involves the customers and their perceived preferences. A survey to assess US and Swedish customers' willingness to participate in MC found that customers were ambivalent toward MC in mass markets [20]. The customers' ambivalence indicates that the customer may not be certain of their preference. In the context of the proposed research ambivalence may indicate that the designer, as opposed to the user, should be knowledgeable of the user population and responsible for ensuring that a product also meets the physical requirements of an end user. In a comparative study, generative customization was determined as a viable alternative strategy to MC. However, there is a need for empirical research to confirm the effectiveness of the generative customization method [20].

The effectiveness of MC as a complementary, niche, internet fulfillment mechanism (internet product orders) is discussed by Buffington [20]. MC has not been adopted, as predicted, due to the limited strategic information regarding implementation in a mass production environment. The lack of MC adoption results in an undue cognitive load on the customer based on the requirement to choose the correct design that matches their individualized preferences [20]. On the other hand, Campbell et al. [21] discusses the positive benefits achieved through "Computer-aided Consumer Design" in regard to product customization with predefined constraints. *Computer-aided Consumer Design* allows a customer to interact with a product in the prototype phase before the product is manufactured. The pre-manufacture interaction phase allows for customer preference specifications to be incorporated in the final product. The customer product adjustments were focused on manipulating the shape, color, and size of products with certain parameters being fixed to maintain manufacturability [21]. This research suggests that guided design for MC denotes viable options for effectively and costly implementing MC.

The aforementioned literature supports the potential of MC as an effective user-centered product development approach, when incorporated with mass production manufacturing. However, there is a need for novel methodologies that facilitate the incorporation of MC in a mass production manufacturing environment at lower costs. For effective and feasible implementation of such novel methodologies, it is essential to define constraints for human interaction factors with products in order to maintain the quality, performance, safety, decision-making, customization, etc. of the product. The next section discusses the advantages and limitations of AM as a mass production approach that affords feasible solutions for providing customized products at nominal costs.

2.2 Manufacturing Characteristics

AM has the potential to assist in addressing the cost prohibitive nature of MC, combined with other subtractive processes. However, process constraints and cost restrictions for AM will drive the MC integration process, which is true for all manufacturing approaches. Process constraints consist of the physical limitations of machines that perform specific tasks in the production line. The specific limits of each machine in the production line impose constraints on the product being produced. Process or production line limitations are sometimes considered but often not fully understood at the product conceptualization phase of the product development or design process (PDP). This aspect of the review focuses on the Manufacturing characteristics of different AM applications which are useful because AM processes often combine many tasks into one machine that are typically completed by multiple machines in traditional production cycles. AM was selected as the focal manufacturing approach for this work because there is limited information on AM process parameters compared to subtractive processes. Additionally, AM process parameters heavily influence that material properties (thermal and mechanical) of manufactured parts [31]. This is important for research efforts in AM for future integration with subtractive manufacturing processes for the creation of more efficient production facilities. Thus, in an effort to understand and describe manufacturing characteristics the following sections will detail the AM design process, the different AM processes and major errors, and the use of modularization and product platforms to feasibly implement MC through mass production.

2.2.1 Origins of the Additive Manufacturing Design Process

Rapid prototyping, which has the potential to expand to rapid manufacturing, often has a bi-fold meaning of an expedited manufacturing approach for end-use parts and the use of an additive manufacturing approach in the development process as discussed by Hopkinson, Hague, and Dickens [22]. The authors replaced the term 'layered' with 'additive' because of the expected advances in the future AM processes including multi-axis building. Rapid prototyping was first implemented by Battelle Memorial Institute in the 1960s, where lasers were used to create solid objects with photopolymers; however, the inception of AM, which replaced the term rapid prototyping, is accredited to the introduction of stereolithography (STL) in 1987 [7].

The implications of AM and areas of the PDP where AM techniques are generally applied are discussed by Gibson, Rosen, and Stucker [23]. Authors mention that in early stages of the PDP, AM provided rough visualizations of parts and components due to the speed at which prototypes could be produced. On the other hand, AM techniques that are applied later in the PDP as a part in the final design usually require some post processing. The AM process consists of eight stages that describe the process from the computer-aided design (CAD) part to the physical part produced as mentioned in Gibson et al. [23]. The stages include: (1) CAD; (2) STL Conversion; (3) AM Machine Transfer and STL Manipulation; (4) Machine Set-up; (5) Build; (6) Removal; (7) Post-processing; (8) Application.

The design implications of rapid prototyping are discussed by Hague, Campbell, and Dickens [24].The authors discuss the commonalities between AM and rapid prototyping as they relate to processes where the CAD model transitions to a physical part and the speed of the production cycle without regard for tooling or molding requirements. Rapid prototyping technologies include STL, laser sintering, etc. Rapid prototyping has the potential to reduce or eliminate the elements of geometry, material choice, rationalization or components, and costs as contributors to design obstacles in the PDP [24]. However, there are many critical design constraints that impact rapid prototyping including surface finish and build speed, representation of different material properties in CAD models, limited variety of materials, recycling, product liability, and intellectual property rights.

A framework for the implementation of AM techniques is provided by Mellor, Hao, and Zhang [25]. Their methodological framework includes External Forces, AM Strategy (Alignment to Business Strategy), AM Technology (AM Standards), Organizational Change (Business Size); Systems of Operations (Design for AM); and AM Supply Chain (Material Suppliers). Each category has a different set of factors that impact the implementation of AM. In order to merge the AM design process with the PDP, the machine characteristics and limitations should be clearly identified along with the specific technique or process, given the part constraints.

2.2.2 Additive Manufacturing Processes and Major Errors

In order to identify the characteristics associated with AM processes it is essential to understand the challenges and errors that result from AM machine controls. Literature on the most prevalent errors and potential solutions will be discussed.

AM is currently seen as a process of adding material to make objects from 3D model data, usually completed through the addition of layers on top of layers as opposed to more traditional methods [25]. Traditionally, AM was conducted in three processes laser sintering, melting of metallic powders, or extrusion of polymer filaments. The American Society for Testing and Materials (AMST) expanded the number of AM approaches, defining seven different AM processes including VAT Photopolymerisation, Material Jetting, Binder Jetting, Material Extrusion, Powder Bed Fusion, Sheet Lamination, and Directed Energy Deposition [6]. Moreover, Levy, Schindel, and Kruth [26] specify that AM applications of the higher level processes include STL, solid ground curing, lamented object manufacturing, fused deposition modeling, selective laser sintering, and 3D printing.

Each AM process starts with a CAD file, which requires formal adaptation to meet the part specifications before conversion to an STL file. Formal adaptation is the process of ensuring that a part meets the specifications of the manufacturing process and machine tolerances. This is usually done through geometric dimensioning and tolerances in the CAD file which should be maintained in the STL file conversation. One of the formal adaptation requirements for tolerances is slice thickness. A general procedure for adaptive slicing was developed by Jager, Broek, and Vergeest [27], where they compared zero and first order algorithms for adaptive slicing to determine layer thickness, given a user defined error (δ). The authors outlined the four-step procedure in the following manner. (1) Analysis of CAD model for preservation of important features during approximation; (2) Segmentation of CAD model and slicing direction determination; (3) Application of adaptive layering to CAD segments based on user defined maximum error for 2.5D or ruled slices; (4) Reconstruction of slices with vertical or sloping sides. The first order approximation, which refers to rule slicing, reduced the number of layered slices required for part formation. The application of an adapting slicing approach further reduces the costs and time associated with AM.

Other problems that contribute to the major errors in AM occur during the part build. For example, after the CAD file has been formally adapted per build requirements and converted to an STL file, errors generally occur as the part begins printing. Several researchers have evaluated the impact of AM on part design and two major problems have been widely identified with AM technologies. (1) shrinkage and (2) thermal warpage [28–30]. Thermal warpage in part design was further investigated at Los Alamos National Laboratory, where a temperature-controlled chamber was used to reduce part warpage [31]. In addition, accuracy in geometric dimensioning and tolerances are negatively impacted through AM processes due to solidifying and binding of material to a less than exact tolerance [32]. The simulation of manufactured parts based on a virtual model allows for the calculation of geometric dimensioning and tolerance errors [28]. Five geometric dimensioning and tolerance errors were identified including: (1) circularity, (2) flatness, (3) cylindricity, (4) circular runout, and (5) total runout [28]. The effect of thermal distortion in part layers [29, 30], which heavily impacts geometric dimensioning and tolerances and final part errors, has not been investigated in many AM technologies including laser melting or sintering until recently [29, 32].

The most common limitations in AM are summarized into ten challenges discussed by Oropallo and Piegl [33]. The author's mention that the identified challenges need to be overcome in AM in order to enable efficient product development. The challenges listed include: shape optimization (cellular structures); design for 3D printing (CAD software); pre and post processing (STL format); printing methods (layered manufacturing); error control (errors before printing); multi-material printing (modeling multiple materials); hardware and maintenance issues (process issues); part orientation (methodology); slicing, and speed (adaptive slicing). The authors state that failure to address these challenges will inhibit the ability to produce products on a massive scale i.e. MC. However, Ghariblu and Rahmati [34] found a new effective approach that combines additive and subtractive approaches that may prove beneficial with further research. Subtractive approaches include well established processes using machines such as mill or lathe that remove material until a part is formed which is opposite of additive approaches that add material until a part is formed.

The errors identified in the literature have a significant impact on the product reliability and post-processing. This is important because specific AM approaches may reduce product quality, which will directly impact the ability to meet customer needs. Future research is required to optimize these approaches and reduce the most detrimental errors through identifying and controlling for AM constraints.

2.2.3 Modularization and Product Platform Design

Modularization and product platforms have the ability to facilitate mass production for AM. Customization can occur at several different magnitudes, from individual or small groups to populations. Moreover, modularization and product platforms will reduce production costs by minimizing the need to develop customized tooling.

Modularization is described, by Davis [14], as a form of MC at the end of the production line; it is formally defined as the standardization of parts with a customized final product at the end of the production cycle. Hwang, Moon, Ho, and Noh [35] describe the facilitation of MC through product platforms, where product platforms are defined as common platforms designed for a multitude of differentiated products. Research that attempts to address mass customization through product platform/family and modularization has been introduced over the last decade. Module-based design concepts were used to generate different product platforms, which were evaluated through universal design principals and a game theoretic approach (coalition and Bayesian games) [36, 37]. More specifically Ki Moon and McAdams [36], utilized the universal design concepts to create three modules including (1) universal (2) accessible (3) typical. The universal design concepts inspired the introduction of a new product family approach where a platform is increased to combine common modules and varietal modules [38]. The generation of new product platforms based on the combination of modules provides a medium between high level platforms which share more common elements and low level platforms which share less elements and has a direct link to customization.

It is evident that product platforms play a critical role in modularization. The role of product platforms, described by Ben-Arieh [39], is considered to be integral for the facilitation of product customization by Smith [39]. The fundamental problems with product platform formation is described as the (1) maintenance of the part family relationship during platform configuration and (2) justification of the platform is only achieved with the accomplishment of efficient mass production [39]. To address these fundamental problems, an optimization model was developed for single and multiple platforms with consideration of demand uncertainty at the lowest production cost [39, 40]. The objective of the single platform optimization problem was to minimize the costs associated with production, assembly, manually adding components to the platform, and removing components from the platform [39]. The objective of the multiple platform optimization problem is to minimize the cost associated with set-up for each platform, selecting a set of components to include with each platform, and assigning products to each platform [39]. Through the identification of an optimal product platform, MC can be feasibly addressed at an optimal production cost.

In order to identify optimal product platforms that enable MC, Chowdhury and Siddique [41] examined shape matching and commonalities in 3D CAD models. The dimension and position of each feature in a product component was compared with a quantitative commonality value. On the other hand, Seung, Simpson, Shu, and Kumara [42] used a fuzzy clustering method to identify common modules for a service based product platform. MC in this instance is narrowed through clustering which enables an efficient and feasible service product platform. In essence this means that the amount of options, which is directly related to customization, are reduced to enable a feasible service platform.

Product platform design facilitates modularization, which supports MC. Through the effective implementation of optimal product platforms/families, costs are reduced and production is more efficient. This ultimately results in a better product that considers product design input and minimizes production expenses resulting in a quicker turn around for demanded products. In the next section the differences in the parameters of human beings, which impact design constraints, will be discussed along with design approaches developed to analyze these differences.

2.3 Human Characteristics

Humans vary in several different aspects including cognitive, behavioral, sociological, biological, and physical dimensions. The impact that human variability has on product usability is extensive. Usability applies to all aspects of a system in which a human would interact; it includes learnability (system is easy to learn), efficiency (system is efficient), memorability (system is easy to remember), errors (system has low error rate), and satisfaction (system is pleasant to use) [43]. While human variability encompasses many dimensions, the focus of the presented literature and the proposed methodology will be on physical constraints, which may limit functional device interaction. In order to comprehensively describe these constraints, user-centered/universal design, human variability, and end user errors will be discussed.

2.3.1 User-Centered Design

User-centered design encompasses several design techniques that aim to comprehensively account for the needs of users at different phases and by different means (qualitative and quantitative) throughout the design process. The International Standards Organization, in six principals, defines user-centered design. The principals are defined in the Human-centered Design for Interactive Systems International Standards Organization's standard and include: (1) the design is based upon an explicit understanding of users, tasks, and environments; (2) users are involved throughout design and development; (3) the design is driven and refined by the user-centered evaluation; (4) the process is iterative; (5) the design addresses the whole user experience; and (6) the design team includes multidisciplinary skills and perspectives [44]. The application of user-centered design is essential in order to adequately design for the intended population. Failure to consider user centered design principals in consumer products often results in a "bad design" as defined by Norman [45]. The limitations associated with adequately applying these principals are that they are qualitative in nature and are hard to objectively measure. Moreover, they require subjective human input that is usually collected through participatory design approaches such as interviews, focus groups, surveys, etc. [46]. The most prominent limitation of the human input collection methods is that they consist of feedback from individuals and small groups. Thus, the designs derived are often not generalizable or representative of the entire population.

2.3.2 Human Variability

Design for Human Variability (DfHV) attempts to address the subjective nature of user-centered design by focusing on quantifying and integrating human physical attributes the design process. Garneau, Nadadur, and Parkinson [47] define design for human variability (DfHV) as *"the design of artifacts, tasks, and environments that are robust to the variability in their users."* Human variability is described as the anthropometric differences in human beings [48]. Anthropometry is defined as the study of the measurement of the human body [49]. Ergonomics is broadly focused on the "study of interaction between people and machines and the factors that impact the interaction" [50]. Anthropometry and ergonomics are extremely important for product design due to the fact that people use products and poor interactions may decrease the perceived quality or usefulness of a product, increase the occurrence safety issues, and human errors due to functional use, musculoskeletal disorders, etc. The original intent of accommodating human parameters in design was to ensure universal operation and design for all users in the population [49, 51]. The application of anthropometrics may impact the size and shape of components in a design, which could provide a better fit for the end user.

In addition to the general field of ergonomics, DfHV is another field that has spawned from the use of anthropometrics in the design process. New concepts of sizing and adjustability are introduced with applications in product platforms and modularity. The benefits of applying DfHV, based on population databases, to product platforms provide the ability to minimize platform variants based on the population segments. The anthropometric metric databases used to model populations in majority of the applications of DfHV include the National Health and Nutrition Survey (NHANES) I II and III and the Army Anthropometric Survey (ANSUR) I and II. The application of DfHV in product platforms provide and foundation for MC to be integrated with mass production. Garneau and Parkinson [52] present one major limitation associated with DfHV methods, the use of outdated military databases as a source of optimization when these databases do not currently reflect the growth of our population in the US.

2.3.3 Universal Design

A commonly applied subset of user-centered design is universal design. Universal design has been applied in several applications to narrow, evaluate, and select the best product platform options. Universal design principals are listed in seven concepts, as described by Connell et al. [53]; equitable use, flexibility in use, simple and intuitive use, perceptible information, tolerance and balance, low physical effort, and size and space for approach and use. Universal design has been used qualitatively and quantitatively to assess and measure the accessibility of the design.

Through the application of game theory techniques, such as the coalition game and the Bayesian game, universal design techniques have been applied to product family and platform design. Similar to the coalition game approach described in

Hwang et al. [35]; Moon and McAdams [36, 37] used a Bayesian game approach to model uncertainties in market environments when evaluating and selecting modules and platforms for universal product families. Universal product families were defined, by the authors, through the incorporation of universal design principals with modularity and product platform designs. The platforms for universal product families of TV remote controls and light-duty trucks were determined through the application of universal design principals to describe modules that were considered accessible. One limitation to this approach is the application of the Function-Universal Principal Matrix, which encompasses two sources of subjectivity for the accessibility of impairment and the usability level.

Universal design was established with the intention to produce designs that are appropriate for all users; however, design methods are not comprehensive enough to truly design for all users. In many instances, user groups contain small sample sizes and results are generalized for an entire sub-set of the population. In addition, universal design principals are qualitative in nature, which requires human interpretations that can lead to bias and subjectivity in designs that are intended for all people. There is a need to expand the representativeness of universal designs in the population and remove subjectivity in the design process.

2.3.4 Use Errors

Inappropriate design accommodation for end users can also lead to use errors in device interaction. Use errors occur at points of user interaction with artifacts, which may include artifact systems consisting of hardware or software elements. Use errors are defined as three forms of errors, slips (attention failures), lapses (memory failures) and mistakes (performance (rule-based), and planning (knowledge-based)) errors [54]. These errors may occur at points of interaction in the output (information provided to user) or input (user performs action on system) state of a system [55]. End use errors impact a product's market success. In addition, products that predispose end users to use errors are not easily correctible through labeling and may present end users with negative safety consequences [55]. Norman [45] discusses the cognitive models of the designer and the user in the design of product and concludes it is essential to build corrective models between the designer model and the user model while satisfying the functional requirements of the product.

Another limitation lies in the failure to consider human variability and the resultant errors that follow. The US recorded over 5.5 million accidents, including 30,500 deaths, associated with household products in 1995 as cited by Correia, Soares, Barros, and Campos [56]. The errors that occurred as a result of pressure cookers and power drills were analyzed. Researchers assigned fault in both case studies to the product design and not the end user [56]. Additional research revealed products (power drill and pressure cooker) that had low usability scores, which may indicate that the design of the product negatively interacts with the physical limitations of the user [57]. The outcome provides an example of the catastrophic events that may occur when human variability is not considered in design. In addition, it raises the question of who takes responsibility for the errors that result in failures and or safety hazards to the end user.

In an effort to include the end user in the design process for AM build prototypes, Campbell et al. [21] conducted research to create a unified model between the designer and the end user (or customer) in the *"Customer Interaction through Function Prototypes"* methodology. This methodology has been extended in *"Computer-aided Consumer Design"*, which was developed to support AM techniques and allows for the end user to interact with a generic prototype, within a defined set of constraints, to enable mass customization. This interaction between the end user and the prototype conveys the necessity to identify all human errors and account for the potential errors through the incorporation of adjustments in the design process.

The AM process does not explicitly adjust for human errors associated with the end user and the product. Errors need to be addressed and reconciled before a finalized product can be delivered. Methods that guide designers to minimize the potential for human errors have not been developed. In the effort to expand design parameters and design for human variability, parameter ranges will be identified and optimized leading to a quantified user centered design, which is expected to minimize human use errors. The final section will provide insight into optimization methods applied in AM and traditional manufacturing approaches related to human and manufacturing parameter optimization.

2.4 Optimization Models

In order to effectively implement MC through mass production, it is essential to better understand the physical limitations of AM processes (machine parameters and characteristics) and human variability (human parameters and interaction factors). With a comprehensive understanding of physical machine and human parameters, optimization techniques can be applied to effectively design for the physical needs of the human population while also optimizing the performance and/or quality of the product. Optimization tools are required to efficiently produce products at the lowest cost while satisfying all requirements (product, machine, and human parameters). Challenges to successfully optimize products given the aforementioned parameters include parameter accuracy, optimization in run time, and complexity with large numbers of design variables. Thus, understanding human or decision-based, manufacturing, and human and manufacturing based optimization models will enable the effective reduction of costs (time, financial resources, and man power), increases in product quality, and the facilitation of design for mass customization.

2.4.1 Decision-Based Optimization Models

Optimization models for humans are subjective and generally implement decision-making models and trade-off analyses. Several game theoretic approaches such as Bayesian and coalitional games have been applied to assist in the selection of a design approach or concept [58]. The application of these games has been applied with the incorporation of disability or universal design based functions to ensure that all customers (anthropometry tables) and their device action function relationships (through action-function diagrams) are considered in the design [59, 60]. Current methods in game theory and human variability optimization do not consider human-device mapping for product interaction descriptions, which limit the direct incorporation of these relationships into the PDP.

Other studies have utilized the coalition and Bayesian games to develop product platform strategies for universal product families. A strategy quality function was applied to assess human variability in product and service designs through the application of functions that act as tradeoff models when incorporated in the games [35–37, 61]. Additional service-based platform optimization techniques developed to select the optimal service platform, used fuzzy clustering to identify the common modules that determined the most appropriate platform [42]. Based on the published literature, there are very few optimization models that focus on the physical variations for users. Furthermore the techniques presented do not apply traditional optimization techniques for obtaining optimal product solutions.

Nadadur and Parkinson [62] proposed a Multi-objective optimization(MOO) technique with consideration of human variability in terms of comfort, safety and profit goals of the company. These objectives were applied to an aircraft seat (height and pitch) where 4,000 human models were generated through the NHANES III anthropometric database. The researchers framed and suggested a MOO approach for solving the problem however the optimization problem was not actually solved in this paper. The future investigation of this type of optimization work was suggested. Although the optimization problem was not solved, the methodology presented provides support for consideration of human variability in optimization models. Limitations of the present methodology are the inclusion of designer's subjective comfort rating in the model and the consideration of profit without the manufacturing costs and constraints. Garneau and Parkinson [63] proposed an optimization approach that measured grip quality as an accommodation metric where the model evaluated options for handle sizes and increased costs. Researchers suggested future research is necessary to investigate a robust objective function considering variance for different applications in target user populations.

2.4.1.1 Robust Optimization and Variability

Robust optimization may be used to model the uncertainty in human or manufacturing process variability data. It is defined by data that is either stochastic or uncertain. Robust optimization is distinct from stochastic optimization because it assumes probability distributions are unknown and data resides in an uncertainty set [64]. Robust optimization is directly applicable for the concept of interaction variability, which seeks to define design spaces for human-component interactions, because information is limited. More specifically, interaction variability in a new concept, thus there is no information on probability distributions and the data is uncertain due to the wide range of postures attributed to a single interaction.

Robust optimization can handle continuous and binary data with decision rules and is applicable for traditional forms of human factors data such as preference [64–66]. In addition, nonlinear problems are that contain nonlinear perturbations in uncertainty data have been addressed with affine, which maintain points, lines, and relationships of data sets, and non-affine transformations and other approaches [65, 67, 68]. However, human variability methods that incorporate anthropometric data assume a bi-modal distribution for female and male populations, which create an optimization problem that is both nonlinear and non-convex. Non-convex, nonlinear problems are generally deemed intractable and ambiguous for efficient solutions [64,65,67]. Although recent method have achieved tractable solutions to non-convex problems using robust methods [69]. Thus, with knowledge of errors to inform the uncertainty set, robust optimization provides a feasible approach that can optimize objective non-convex human variability data. Unfortunately, knowledge or errors for related to human variability and interaction variability is unknown.

Other alternatives to robust optimization methods include: *Chance-based constraints*, which allows constraints to be violated up to a specified probability limit [70]; *Reliability optimization*, which focuses on the components and distributions of component failure [71, 72]; and *demand maximization*, which maximizes the potential market based on assumptions regarding demand [73]. Each approach is a viable alternative that is appropriate for modeling human variability but assumes information regarding the problem is complete and available. In instances where information is not complete the benefits of these approaches are overshadowed.

Suggestions for future research can be addressed through the application of an optimization model that accounts for the number of artifacts required to satisfy a target population. This would demand additional insights into errors related to anthropometric datasets. The errors could be formed to account for the differences in existing datasets and current population parameters. There is currently no research being conducted to assess interaction variability with consideration of human parameters (static) and human parameter and component interactions (dynamic) for the purposes of optimization. It is essential to comprehensively understand the physical variation in users and optimize design parameters based on this variation in order to comprehensively apply MC principals.

2.4.2 Manufacturing-Based Optimization Models

MOO approaches allow for the selection of objectives associated with a device or design to be established and then optimized based on performance. Ho, Xu, and Dey [74] discuss the different multi-criteria decision making approaches that have been applied in supplier evaluator and selection processes. The most commonly used multi-criteria approach is the data envelopment analysis. Paul and Anand [11] developed an optimization approach for metal powder based AM processes that considered the process energy, part errors, and part strength as criteria. Other applications of MOO approaches have been applied in several AM processes including stereolithography, fused deposition modeling, selective laser sintering, and laminated object manufacturing to optimize the build orientation of the design or part [75–77]. MOO approaches have not been widely applied to all seven AM processes or specific applications of these processes. However, they have been applied in the selection of other manufacturing approaches Gurumurthy and Kodali [78]; and in the selection of cutting fluids for green manufacturing techniques [79]. Mellor et al. [25] mentions supply chain as a critical component in the implementation of an AM technique. The supply chain is defined with respect to the producers of AM applications and the buyers of the technology that produce parts for customers as a two-fold supplier information feedback loop [25]. Moreover, utilizing multi-criteria decision-making approaches is a common technique in supplier evaluation and selection; however, these approaches have presented issues with the time consuming aspect of determining consensus and subjectivity in popular approaches such as analytic hierarchy process with goal programming and data envelopment analysis, respectively [74]. While the application of MOO techniques are useful in different selection and manufacturing applications, in order to effectively utilize AM as an economic, quality, and performance alternative to traditional manufacturing techniques, with the ability to meet the MC requirements, additional methods and optimization techniques are required. Additional methods should focus on the additive manufacturing approaches that maintain quality and cost and optimize time intensive approaches for efficiency through standardization across manufacturing approaches and machines.

2.4.2.1 Product Family Optimization

Manufacturing and supplier optimization techniques have a more comprehensive history of implementation in industry. However, more recent optimization techniques are focused on applying optimization approaches in MC and product platform frameworks. While Section 2.2 outlines product platform design and modularity approaches, here we discuss methods for product platform and architecture optimization. In an overview of optimization and artificial intelligence methods for product family and product platform designs, Simpson [80] notes that many methods identify a platform design prior to optimization. However, this poses a limitation because designers would like to explore platform commonality levels to determine which "variables to make common and unique within the family [80]. In addition, suboptimal product families were revealed in the application of MOO because market demand and manufacturing costs are not explicitly modeled [80].

Product family optimization techniques have been applied in an effort to implement MC frameworks. Tseng et al. [81] developed a method for designing product architectures for commonality in product families to facilitate MC. In this approach, a MOO model was applied to objectives subject to technical constraints based on the technical specifications of different product families [81]. Product families have specific levels of commonality (similar dimensional and functional requirements in product families) that enable manufacturability; thus, the requirements for commonality are technical specifications of product families [81]. In other methods, objectives were developed to determine the value of alternative platform designs and scalable product platforms to produce product families for firms [82, 83]. The research surrounding optimization in product families indicates the importance of the selection of product architectures in manufacturing. Product family optimization is ann area that has not been widely explored in AM approaches and may be essential as AM evolves.

In other applications of MOO, modules were evaluated in terms of commonality to determine the optimal product platforms each of which out-performed the individual designs that did not utilize component sharing [84]. This specific optimization application was applied to telecommunication subsystems across three different spacecraft vehicles [84]. A multi-objective particle swarm optimization approach was applied to determine the optimal product platform design variables in terms of commonality and design variation within the product family [85]. Design variation was determined through the use of the product family penalty function developed by Messac, Martinez, and Simpson [86]; and applied in later research studies [85, 87]. Product family penalty function was applied in another multi-objective evolutionary optimization approach called the Epsilon-dominance Non-dominated Sorted Generic Algorithm-II, in order to optimize commonality and performance in the selection of a product family [87]. Based on the literature, commonality is an important measure to determine product families but approaches to determine or establish commonalities prior to product conceptualization have not been discussed in the literature. Thus, there is a need to select approaches that assist in establishing commonality in order to maximize efficiency in the development of product families, which is important for large scale manufacturing in AM and MC.

The application and validation of optimal product family techniques and methodologies in AM are limited. Optimization methods provide specific advantages, over the traditional PDP, for generating higher quality concepts and designs since the problem can be designed comprehensively to include all design variables and constraints. The limitations of comprehensively designing the optimization problem are the high computational power required, computing time, and complexity of the problem. All limitations considered there is still a need to merge AM optimization and product family/platform optimization approaches to address MC at economic costs, while optimizing machine and human constraints. The discussion of optimizing product families/platforms for AM approaches is limited. The merging of AM and product family/platform optimization could occur through the development of a method that considered the selection of a product family approach before the product was manufactured through an AM approach.

2.4.3 Human and Manufacturing Based Optimization Models

There are currently no optimization models that account for human variability (anthropometric and human interaction measures) in products given the limits of machine and human parameters. However, several studies have optimized human related factors (physical, cognitive, and behavioral areas of humans) for manufacturing and end users. While other research fields, e.g. Marketing, attempt to address the market demand and manufacturing modeling limitations lacking in product family optimization literature.

Cognitive and behavioral factors are accounted for in stochastic models for man-machine systems developed by Abbas and Kuo [88]. The cognitive factors consist of stress and fatigue while the machine elements are related to task arrival time and machine state. Other research solely evaluated the human performance or cognitive errors for human-machine optimization models where the performance of systems altered the physical state of the human operator; good and bad operator states were measured as were different system states in stochastic simulations [89,90]. These models only focus on cognitive and behavioral aspects of the human being neglecting the physical parameters of the human which affect either negatively or positively the interactions. The investigation of the human in a physical sense including interactions is necessary in relation to AM and is the primary goal of the present work.

In the field of marketing, researchers have been successful in addressing the market demand limitation in product family optimization discussed by Simpson [80]. Luo et al. developed a method to capture customer preference variation based on product variants in performance usage conditions in a MOO model. Relationships were determined between design alternatives and customer preferences, based on conjoint analysis [91] results, with a mapping function [92]. These relationships allowed the changes in customer preference to be captured for design variation addressing the market demand limitation since design variation is expected to significantly impact customer preference and thus market share [92]. Customer preference described in this method is subjective and does not capture the impact of performance variation on consumer use. Understanding the changes in consumer use with design alternatives may also have a significant impact on customer preference and ergonomic design.

Other optimization models are aimed at customized design for AM. Customized design for AM provides computational models for maximizing design and AM performance in product and AM design processes [38]. Customized design for AM provides designers with a quantitative method from conceptual design phases, which are largely based on customer's perceived satisfaction [38]. The outcome of this approach provides designers with build sequences that affect customized design. While this approach provides insight into product state changes that occur through customer interactions, it does not account for human variability within the customer population or the unintended interactions that may occur between the customer and the product. Authors mention that additional research is required to integrate customized design parameters and AM process machine constraints in order to better facilitate design of demand through Customized design for AM [38]. This suggests that research, which is focused on maximizing the level of human variability integrated into design, is needed in order to effectively optimize customizable end products. The difficulty lies in identifying all sources of human variability and correctly mapping interactions between the human and the designs/products. To maximize human accommodation and product performance and/or quality, the actions of the user should be considered in terms of product interactions to effectively optimize customizable end products in AM approaches, in terms of accommodation/comfort, quality, costs, and performance for customers.

2.5 Summary of Research Gaps

The gaps revealed in this literature review reinforce the need for a structured, objective method to optimize products based on human interaction factors and manufacturing characteristics in a MC design process. There is currently no methods the directly capture interaction variation, researcher rely on customer-choice, aesthetics, and other qualitative and subjective approaches to capture customer preference. The literature has shown that customers have difficulty in identifying their needs [18]. Capturing interaction variation in consumer population will identify the interaction limitations of the population and allow for designers to design safe products that fall within the usability limits of the population. In addition, by designing for interaction variability designers can anticipate the overlap in customer preference.

In many instances standardized approaches are adopted to minimize costs and meet customer needs. However, with highly variable populations that require specialized products, the cost usually increases for the manufacturer resulting in higher prices for end users. AM has the potential to address MC and decrease production costs through the application of modularization and product platforms/families. A methodology that comprehensively identifies all physical sources of human variability (static and dynamic), and measures the most critical sources through quantifiable means for the purposes of mapping human interaction variability does not currently exist. The universal design product platform approaches discussed are limited due to the subjectivity in converting the qualitative principals of universal design to weighted quantitative values. Moreover these methods are not optimized given the variability associated with human-device interactions. Thus, there is a need for a comprehensive optimization method that considers human variability in the design process and minimizes the errors in the AM process.

There are limited resources that comprehensively measure populations with human variability both statically and dynamically, so additional parameters and historic anthropometric databases need to be collected and updated, respectively. Another challenge is characterizing AM processes and specific process applications in order to ensure the highest quality build. The development of a methodology that assists in identifying the gaps in current anthropometric data sources and approaches for developing high quality builds in current AM processes is necessary to push AM into large scale manufacturing domains while applying MC principals and design on demand options for end users. Through the utilization of product platforms and trade-off models between human variability and AM process and machine characteristics, the development of an efficient optimization model is possible while maintaining product cost, quality, and performance.

Chapter 3: Methodology

A process map of the methodology is presented in Figure 3.1. The steps are summarized below and detailed in subsequent sections.

1. Chapter 3: The *first step* consists of identifying the specific application, with an emphasis on products that require direct or indirect interaction with human beings (e.g., helmet, backpack, glucometer). All product components (parts of the whole application) and requirements (e.g., federal product regulations) are also selected for the end product in this step.

2. Chapter 4: The *second step* is the identification of human parameters (musculoskeletal interfaces) that are required for product interaction. Functional classifications (reach, force, tactility, maneuverability) are then identified to determine the specific interaction (e.g., pressing a button) and the level of variation (e.g., range (maximum, minimum) of press force for 95th percentile male) associated with the classification level (e.g., push) of interaction. After the identification of musculoskeletal interfaces and functional classifications, the *anthropometrics* are determined based on the mapping of the aforementioned parameters to anthropometric databases. The *anthropometrics* identified will become constraints in the optimization model in step 5. There are

also used to inform *product metrics* that are involved in a trade-off process in step 4 and as design variables in step 5.

3. Chapter 4: The *third step* is the identification of machine characteristics. This step consists of identifying all characteristics in AM for the 7 AM processes and selecting a specific AM process (e.g., material jetting) and machine type (e.g., Objet 500 Connex 3). The characteristics identified in this step assists in the generation of design variables for the optimization model in step 5 and the *AM process metrics* that will undergo a reduction in the trade-off analysis conducted step 4.

4. Chapter 5: The *fourth step* is the trade-off analysis, which consists of a new design approach based on the application of design methods including the Analytic Hierarchy Process (AHP) and Quality Function Deployment (QFD). This process assists in obtaining a reduced set of metrics for the optimization model in step 5. The metrics being reduced include the product metrics and the performance metrics, which are influenced by the anthropometrics and AM process metrics, respectively.

5. Chapter 6: The optimization and validation are performed in *fifth and final step* of this methodology. The generated design variables are incorporated into the development of objective functions based on the goals of accommodation in product metrics and performance metrics (e.g., surface temperature; yield strength). The generated functions are optimized through the application of a penalty-based optimization with single or MOO depending on the number

of product and performance metrics. The product metrics generated from the optimization model are then built in a CAD environment and computationally or experimentally tested in the targeted population.

3.1 Application Description and Overview

The proposed methodology is applicable across a broad set of applications. However, the fundamental characteristics of these applications require either static or dynamic interactions in order to be effectively evaluated with this methodology. Thus, applications are classified as either static or dynamic in this method.

A static application has the capacity to carry out the primary function without interaction after an initial interaction. For example, a lamp has a primary function to provide light in a space. After the initial interaction of turning on the lamp it will perform its function without further interaction. In essence, many static applications have two or less states, in our example of the lamp the states are "lamp on" or "lamp off." Other examples of static applications include: chair, glasses, non-accessible containers, etc.

A dynamic application does not have the capacity to carry out a primary function without interaction after an initial interaction. In many instances dynamic applications have one or more primary functions. For example, a water bottle has two primary functions: (1) to hold, store, or contain liquid and (2) to provide access to liquid. The first function can be accomplished without interaction while the second function requires interaction. There are three states in this dynamic

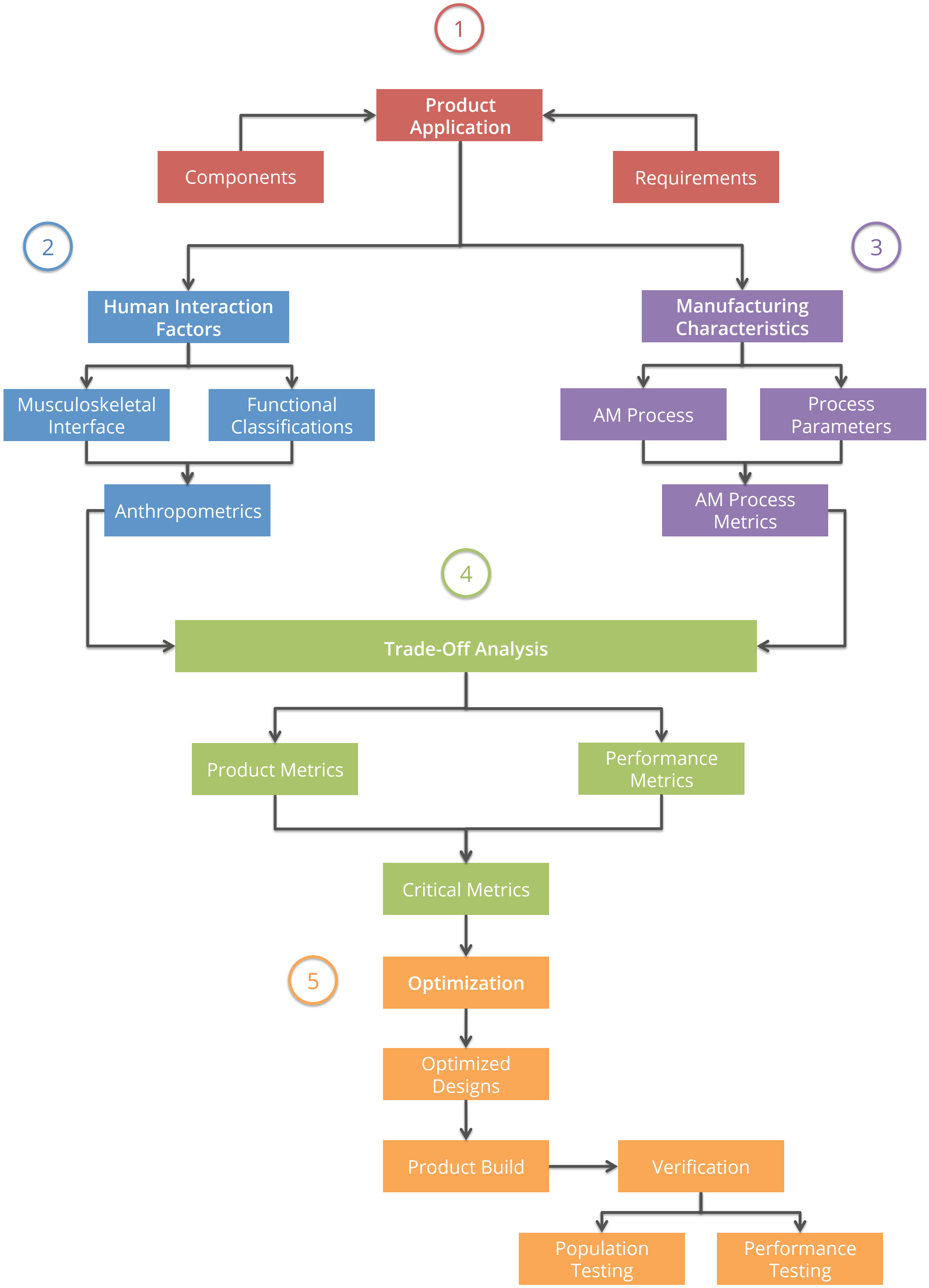


Figure 3.1: Process Diagram for Methodology

application “bottle closed,” “bottle open,” and “liquid released.” After the third state the water bottle will return to one of the previous states. If weight and amount of liquid are considered in the primary function of the device then more states may be important such as the decrease in liquid and weight and the effectiveness of the container, e.g. bottle half full. Other examples of dynamic applications include: tablet, glucometer, vacuum cleaner, etc.

The methodology is presented over the next three Chapters with detailed processes for identifying human interaction factors and manufacturing characteristics (Chapter 4), trade-off analysis (Chapter 5), and optimization (Chapter 6). Each Chapter includes a validation section that validates and verifies new constructs through testing on a set of static and dynamic applications.

Chapter 4: Identification of Human and Manufacturing Parameters

The process diagram, Figure 2, provides a visual overview of the information presented in Chapter 4. Section 4.1 details the process for identifying human interaction factors; Section 4.2 details the process for validating the human interaction process; Section 4.3 details the process for identifying manufacturing characteristics; and Section 4.4 details the process for validating the manufacturing characteristics process.

4.1 Identification of Human Interaction Factors

The identification of human characteristics occurs in three steps. First, the physical elements of the human being that interact with the device must be identified. Next, the type of interaction must be classified. Lastly, the information generated is linked to databases that capture the variation in human physical elements for the population in which the design is intended.

4.1.1 Identification of Musculoskeletal Interfaces

The anatomy of the human being is composed of several systems. Some systems are cognitive while others are physical. This research will focus on physical

Figure 4.1: Process for Human and Manufacturing Parameters

systems, specifically the musculoskeletal system and its associated motions, abilities, and limitations. The musculoskeletal system and elements of the sensory system provide measurable data that is necessary to quantify human variability. Human variability is important since it has the capacity to capture the differences in interactions between musculoskeletal interfaces and product components amongst a range of people.

In order to capture the musculoskeletal interfaces that will interact with the end product, the product idea must first be captured. The product idea consists of the application (product being designed), product components (individual parts of the application), and parameters (measurement limits) of the product. Requirements are functions and behaviors that the product must meet based on the demands of the customer, conceptualization of the product, or the characteristics and limitations of the design process [93]. Once the product idea is selected and the design requirements are established, the elements of the human musculoskeletal system that will interact with the product can be identified.

The musculoskeletal system consists of the human skeletal system and the muscles that support the skeletal structure. There are twelve musculoskeletal areas in the human being. These areas are the braincase, face, ear, throat, vertebral column, thorax, pectoral girdle, arm, hand and wrist, pelvic girdle, leg, and foot [94]. Each of the listed areas acts as a system with its own subset of bones. For example, the hand and wrist consists of 54 bones including phalanges, metacarpals, and the bones that make up the carpal system [94]. The subsets of the musculoskeletal areas (e.g., hand and wrist) are considered the elements (e.g., phalanges) of the area. For the purpose of this method, the musculoskeletal areas will be referred to as musculoskeletal interfaces. It is essential to specify which musculoskeletal interface and interface elements are relevant to the product interaction. Once the interface elements are specified at the appropriate level of detail, the element terms will be translated into common terms for identification in anthropometric databases, for example phalanges $\rightarrow$ fingers.

After identifying common terms, the product components that the human elements interact with are identified. The relevant components of the product are identified through the intended interactions defined by the design requirements. Next, all interactions are identified. The interactions are captured in a detailed manner to ensure that the translated element and the product component interactions are captured and conveyed intuitively to the layperson. For example, thumb (translated element) presses and holds button (product component). The process for characterizing the human-component interaction is the first step to understanding human interactions in order to improve end user satisfaction and accommodation.

4.1.2 Identification of Functional Classifications

After identifying musculoskeletal interfaces and the subsequent interface-component interactions, the functional classifications are defined. Human functions can be classified in four categories.

1. *Reach.* Extension, flexion, and retraction of the limbs in relation to the specific limb when active.

2. *Force Exertion.* Force exerted by the human parameters in relation to the interaction with an object.

3. *Tactility Initiation.* Sensory system that is activated to distinguish surfaces and textures through touch.

4. *Maneuverability.* Ability of the joints and axes of rotation in different limbs and body parts. This includes deviations of the wrist, arms, and lower limbs including legs, ankles, and feet.

The aforementioned functional classifications and the respective classification levels, are highlighted in 4.2. The procedural steps refer to the functional classifications and do note need to be identified in a specific order. The classification levels are the specific measure of each function classification. Functional classifications reach and force were derived from anthropometric databases while tactility and maneuverability were conceptualized in the development of this method. Tactility and maneuverability draw from concepts related to feedback analyzed by the sensory system and the degree of joint fluctuation in a three-dimensional space, respectively.

Data and descriptions of all classification levels were derived from anthropometric databases with the exception of twist and turn (force), sense (tactility) and rotation (maneuverability). Section 4.2 provides validation of the specific sources used to support the inclusion of functional classifications and classification levels. The design team identifies interactions that occur at each classification level of the identified functional classification(s). This process is demonstrated in Chapters 8 and 9 for the glucometer and helmet applications, respectively. Since, interactions are application-specific, thus they are not included in 4.2. The interactions are defined in the demonstration chapters of the methodology.

4.1.3 Mapping to Anthropometric Databases

The identification of the musculoskeletal interfaces and functional classifications allow for the mapping of the identified human parameters to anthropometric databases. The anthropometric databases provide static and dynamic measurements for human parameters, which enables the seamless mapping of musculoskeletal interfaces and functional classifications, respectively. The identified measurements are critical to the optimization model for the prediction of product components dimensions.

The anthropometric databases provide measurements that give insight to the population variability for different body part sizes. Once the appropriate anthropometrics are identified the distributions of each measurement can be observed to obtain an idea of the shape of the distribution. Most anthropometric databases have

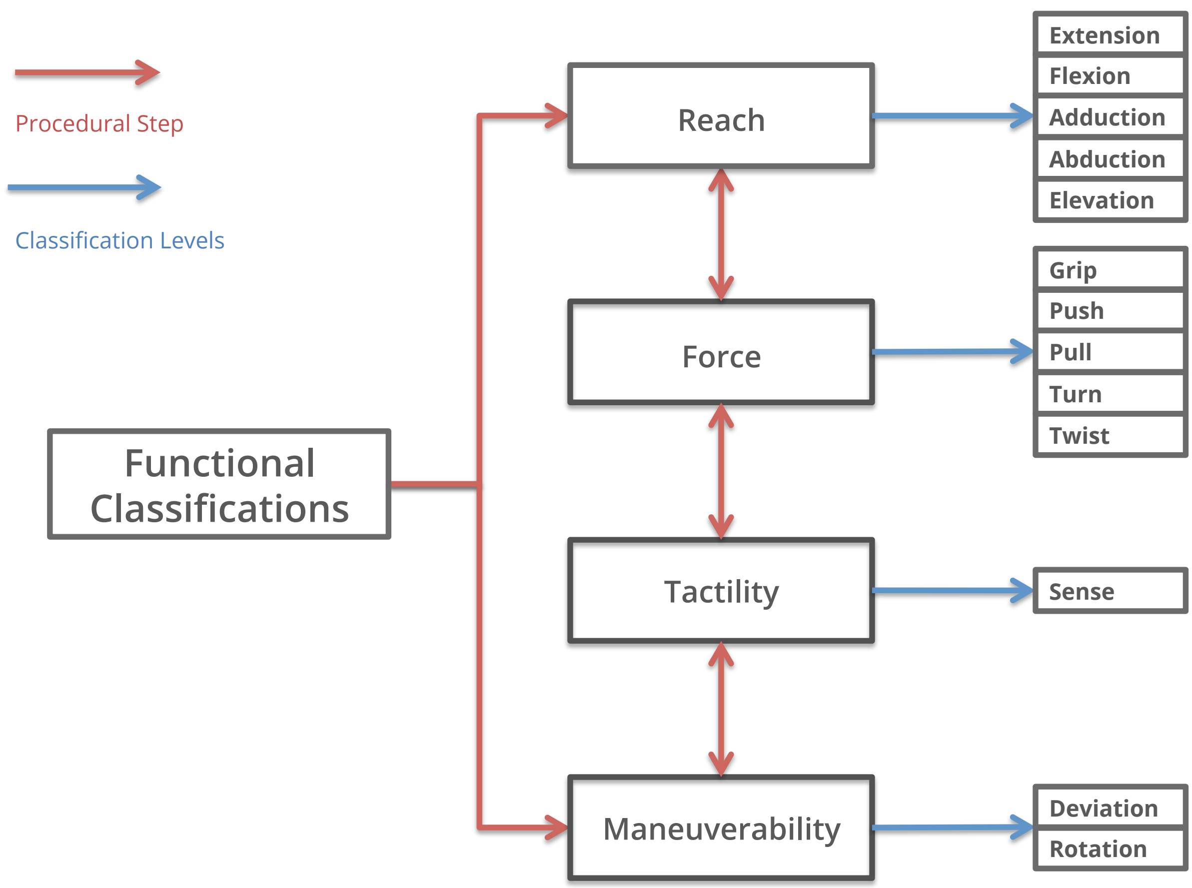


Figure 4.2: Process for Identifying Functional Classifications

an underlying assumption of normality in the distribution. However, the spread of each body part parameter is variable. The most important aspect of obtaining anthropometrics is identifying the correct mapping relationship between the anthropometric value and the musculoskeletal interface or functional classification. The variability ranges for the functional classification levels are determined from federal databases (i.e. NHANES), scholarly research (i.e. Bodyspace by Stephen Pheasant), and anthropometric databases (i.e. ANSUR). For example, NHANES defines physical measures (weight, height, etc.) of people in the population based on physical examinations; The US Department of Defense (DoD) databases define anthropometric data for military personnel; National Institute for Occupational Safety and Health (NIOSH) funds research projects that produce anthropometric datasets for workforce populations to assist in the reduction of workplace injuries; ANSUR defines anthropometric data for army personnel, and NASA databases provides space flight standards for human-system integration from multiple perspectives; etc.

Once an application is selected and a target population is identified, one of the previously mentioned US anthropometric databases can be used to obtain body measurement values for men, woman, and children. There are also international anthropometric databases for products that are expected to be available internationally. In applying most anthropometric database measurements, the designer selects the 5th, 50th, or 95th percentiles of the desired populations based on the population needs. This almost always leaves out some portion of the population [95]. In the proposed approach, instead of attempting to design for the 5th, 50th, or 95th percentiles of the specified population, the distributions of appropriate anthropometrics will be modeled. From these distributions, the optimization model can estimate the fit of various product components in the population and minimize extreme dynamic interactions in the user population.

The method for obtaining the appropriate anthropometric values for the musculoskeletal interfaces and the functional classifications has been discussed. In the case where a parameter is not available in the database then it can be empirically collected from the target population. The data collection process should include all metric values of interest for collection in a sample of the target population. The process for identifying human interaction factors is presented in two primary processes (1) musculoskeletal interface identification and (2) functional classification identification. Figure 4.3 provides a detailed process for the human interaction factors process. The procedural transition step indicates that the interaction is sequential with precedence relationships. The translational transition step occurs when a conversion of syntax is being performed, i.e. phalanges $\rightarrow$ fingers. The mapping transition step identifies the specific interface elements, functional classification level and product components that interact, i.e., fingers map to buttons. In addition, the mapping step, provides a linkage to the anthropometric values based on the common term for the musculoskeletal interface and classification level of the functional classification. Finally, the black arrows represent examples of each term presented in this method.

The conceptual aspect of this methodology presents the most arduous challenge. The successful development of a streamlined process for mapping the relationship between human anatomy, anthropometry, and product components presents a

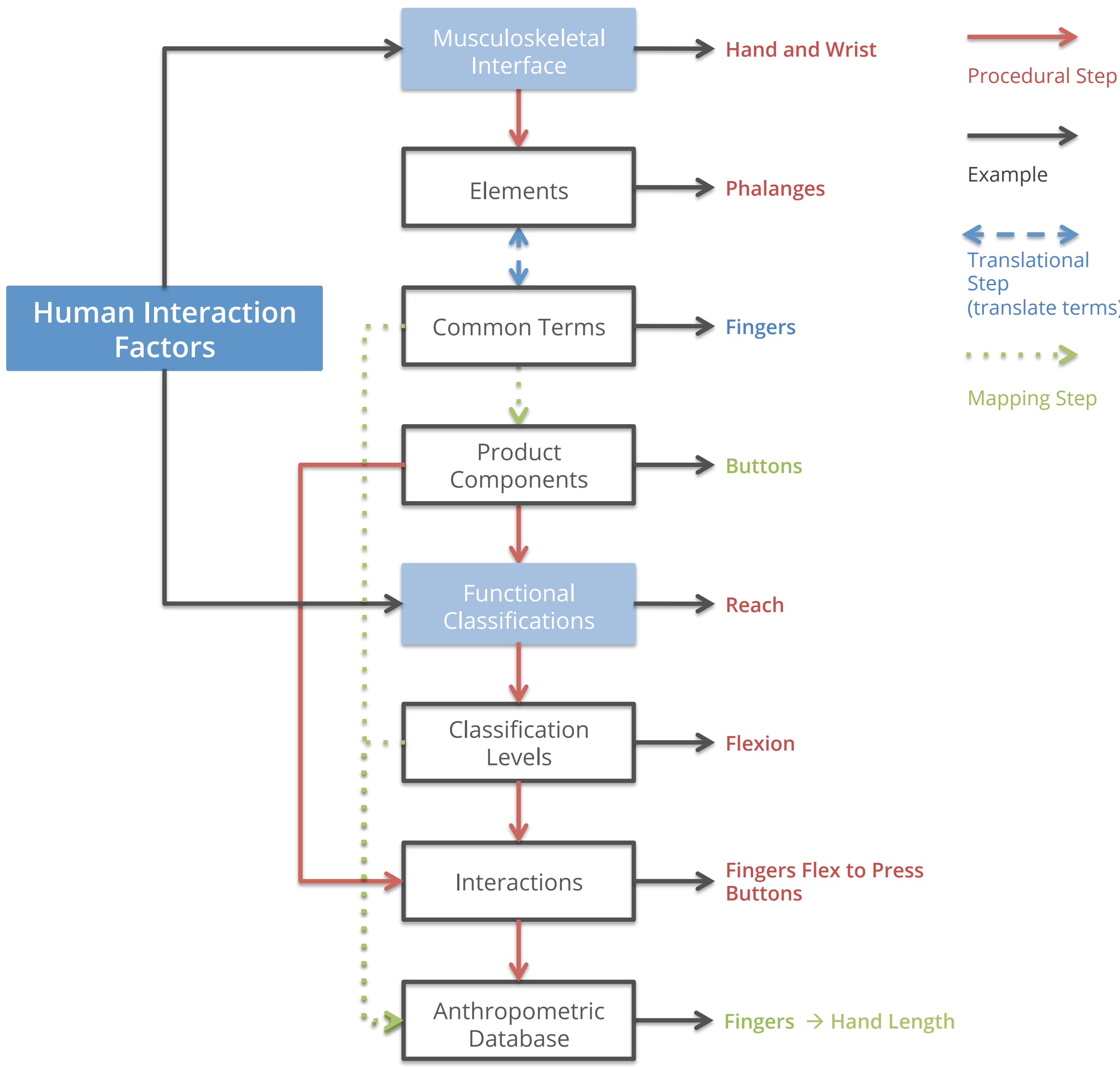


Figure 4.3: Process for Identifying Human Interaction Factors

new conceptual framework for interaction-component mapping. This process allows for thorough and accurate mappings of the human interfaces to the product component. The specificity of the interactions captured is also streamlined between the human interaction elements and the product components, which allows for a greater space to identify and characterize human-component interactions. The characterization of human-component interactions is the first step to understanding human interactions in order to improve end user satisfaction and accommodation.

4.1.4 Summary of Human Interaction Factors

Now that the process for *Human Interaction Factors* has been discussed in detail a summary of all musculoskeletal interfaces, Table 4.1, functional classifications, Table 4.2, and their respective units are presented. The identification of design variables and objective functions, related to these interaction factors, is further investigated in the optimization model, Chapter 6. The summary of the values allow for the easy mapping to the final anthropometrics.

4.2 Validation of Human Interaction Process

The validation process for human interaction factors is presented. Figure 4.4 provides a reminder of the human interaction factors process. More specifically, it outlines the mapping process relationship of among the musculoskeletal interfaces and their respective sub interfaces or elements as well as the functional classifications and levels. The mapping process for each of subprocess of the human interaction

Table 4.1: Musculoskeletal Interface Units for Human Anatomy

#	**Musculoskeletal Interface**	**Units**
1	Braincase	mm
2	Face	mm
3	Ear	mm
4	Throat	mm
5	Vertebral Column	mm
6	Thorax	mm
7	Pectoral Girdle	mm
8	Arm	mm
9	Hand and Wrist	mm
10	Pelvic Girdle	mm
11	Leg	mm
12	Foot	mm

Table 4.2: Functional Classification Units

#	**Functional Classification**	**Units**
1	Reach	mm
2	Force	N
3	Tactility	Hz
4	Maneuverability	Deg

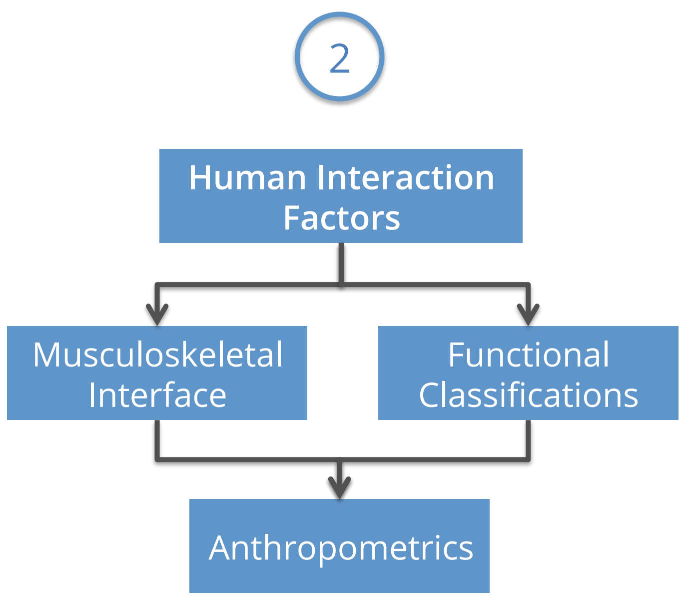


Figure 4.4: Process for Identifying Human Interaction Factors

factors be validated and verified.

The validation square approach was utilized in this step to establish theoretical structural validity for the process of identifying all human interaction factors. Theoretical structural validity is described as the correctness of the method constructs separately and integrated [96]. This form of validity is demonstrated for each construct separately through validation as defined in Seepersad et al. [96] and the integration of the constructs, highlighted in grey, are verified through blind testing [97], depicted in Table 4.3. Construct integration refers to integration of a construct either modified or unaltered into the method.

4.2.1 Validation Protocol and Results for Human Interaction Process

The constructs listed in Table 4.3 were addressed in the following procedures to ensure that *construct mapping* and *interaction conceptualization* processes were valid. A randomized test was conducted to evaluate the correctness of the mappings and the interaction constructs. The process for performing the double blind experiment included the randomization of several tasks for the validation of this entire method, not just specifically the human interaction process. The experimenter as well as the participants was unaware of the task order. However, the individual subtasks for *construct mapping* and *interaction conceptualization* within the human interaction validation procedure were presented in a sequential order.

Participants in the study were provided with a series of supplemental materials to assist their decision making process regarding the engineering design questions

Table 4.3: Validation Constructs for Human Interaction Factor Process

Construct	**Origination**	**Modification**	**Integration**
Area	Table 1.1. Names of Bones in the Human Skeletal pg. 9 [94]	Musculoskeletal Interface	Yes
Singular/Plural	Table 1.1. Names of Bones in the Human Skeletal pg. 9 [94]	Interface Element	Yes
Area/Term $\rightarrow$ Parameter	[94, 98, 99]	Translation	Yes
Sensors, Controls, Connectors	[100, 101]	Product Components	Yes
Reach, Vibrotactile Feedback, Grip Strength, Force	[51, 102]	Functional Classifications	Yes
Posture, Joint Movement	[102]	Classification Levels	Yes
Parameter, Dimension	[51, 102–104]	Measurement	Yes
Interaction	Original Construct	No	Yes

in this study. Correctly identifying and conceptualizing engineering design concepts and human anatomy and functional capacities enabled participants to correctly identify individual parameters and product components to make logical mapping relationships. Providing supplemental material reduces the likelihood of base-rate fallacy and overconfidence errors. Base fallacy errors result from misinformed or misguided subjects while overconfidence errors are a result of poor calibration [105]. Information provided to the participants intended to reduce the possibility of these errors.

The experiment consisted of two tasks to evaluate the interactions developed as a result of the mappings of interface elements and classification levels with product components. The semantics and criteria for interactions were not taught to participants nor were they considered the focal point of the validation procedure. Thus, synonym extraction and mapping was apart of the data analysis process. Future work in this area should provide training to participants including the interaction syntax structure. The anthropometric databases were provide to participants and assisted in estimating the accuracy of the aforementioned mappings. Participants were recruited from the senior level mechanical engineering design course at the University of Maryland, College Park. The inclusion criterion was as follows: participant must have had at least one upper level engineering design course and some knowledge of human anatomy.

4.2.2 Study Procedure

Participants were presented with both a *static* (primary function is performed after initial interaction) and *dynamic* (primary function is not performed after initial interaction) application, as defined Chapter 3. An interaction was demonstrated for both the static and dynamic product. The static product was a pair of sunglasses and the dynamic product was a water bottle.

1. *Static Interaction:* Sunglasses Application

   - Pick up the sunglasses in an expanded arm state with a two-handed pinch grip between the thumb and index finger. Place the lenses in alignment with the pupils and the arms between the braincase and ear.

2. *Dynamic Interaction:* Water Bottle Application

   - Pick up the water bottle with a loose grip. Then, apply a tight grip to the container and lid with two hands in opposite directions apply the torque necessary to unscrew the cap. Remove cap and drink from the container.

Diagrams of the sunglasses and water bottle applications were provided to each participant. Each participant was also provided the supplemental tools necessary to perform the mapping tasks, which consisted of a series of blank tables provided for each task and subtask described below. Participants were also allowed to ask the experimenter any questions regarding the tables provided, interactions, and term clarification, demonstration, or definition.

1. *Task One:* Identify Table Parameters from Source Information

    (a) **Part 1:** Participants were provided with Table 9.2 from Steele and Bramblett [94] and asked to identify and complete the musculoskeletal interfaces, elements, and common terms constructs of the Figure 4.3. Participants were provided access to select anthropometric databases and/or medical dictionaries to complete these three constructs.

    (b) **Part 2:** Participants were provided with a table of version of the functional classifications, Figure 4.2. Based on the musculoskeletal interfaces identified, participants were asked to identify the functional classifications and levels that are active during the demonstrated interaction between the musculoskeletal interface and the product component. Participants were provides access to the same resources available in *Part 1*.

2. *Task Two:* Determining Mappings and Interactions

    (a) **Part 1:** Participants were asked to segment the applications in terms of physical components that require human or user interaction to accomplish the demonstrated interactions. After this, each participant completed the product components handout that was later translated to the product component of the column of the musculoskeletal interface mapping table. The participant then described and wrote the interaction, in the interaction column of the mapping table, which occurred between the product component and the common term, Figure 4.3. This process was repeated of the functional classifications and levels identified in *Part 2 of*

Task 1. The interactions described in this part of the study were based the interaction between the product component and the musculoskeletal interface and the classification levels for each functional classification required to complete the demonstrated interaction for each application.

(b) **Part 2:** Participants were provided with anthropometric measurements tables and asked to determine the specific measurements related to the common terms followed by those related to the classification levels. If expected measurements were not available then participants were asked to provide the needed measurement. Participants were also allowed to ask clarifying questions related to the anthropometric terms.

3. *Task Three:* Identify Application Type

   (a) Participants were asked to identify the category of each application presented. The category of an application is either *Static* or *Dynamic* based on the aforementioned definitions. Participants were provided with a definition of the Static and Dynamic application and asked to correctly identify the category for the sunglasses and water bottle applications. This task was randomized and could have been presented at the beginning or end of the ordered tasks 1 and 2.

4.2.3 Outcome

Each task achieved majority consensus in the participant population. Of the tasks considered important based on the new methodological principals, consensus was achieved at higher magnitudes ranging between 43.75 and 87.5% for human interaction factors mapping. The lower percentages of consensus occurred amongst the population due to the details of the interaction and identifying which musculoskeletal interface directly interacts with the application. Many participants could identify secondary interactions where a part of the body must move to enable a direct interaction with another musculoskeletal interface. It is evident from this study that complexity and the number of components in a product decrease the consensus amongst designers because consensus was achieved at higher rates in the water bottle application compared to the sunglasses application. Participants were also able to consistently identify product components at 93.75% to 100% consistency. Correct identification of static and dynamic applications was achieved at 87% correctness and consistency.

The correction rate of the participants was calculated and analyzed based on the acceptable performance range of 75% to 95% correctness. A range is considered acceptable when a level is not specified, which may prove difficult because a correction rate that is too high (100%) is unreasonable while a correction rate that is too low (50%) may cause system or method failure [106, 107]. A general rule of thumb is 80%, which is often used for statistical power [108].

A correction range was selected because the interests lie in the ability of the most qualified people being able to implement this methodology, implementation by almost everyone (>90%) or less than most (<80%) may indicate simplicity or vagueness, respectively, in the process. Based on the lower ranges of consensus observed, training may be necessary to implement this methodology amongst mechanical de-

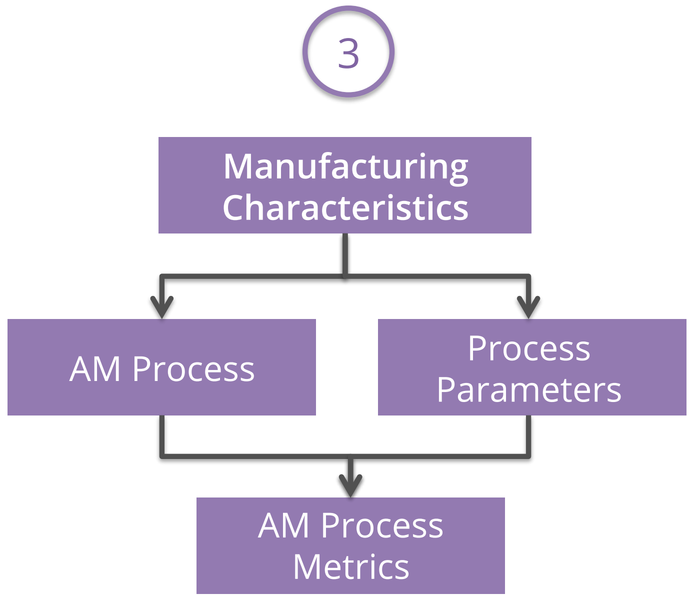


Figure 4.5: Process for Identifying Manufacturing Characteristics

sign students. However, other engineering programs that teach biomechanics may have a more comprehensive understanding of this process. Spelling errors or phrase arrangement (i.e. order of words in a statement) was not considered, only meaning, as it related to the interactions identified.

4.3 Identification of Manufacturing Characteristics

The identification of manufacturing characteristics occurred in two steps, Figure 4.5. In the first step, all characteristics associated with the seven AM processes, as discussed in the literature review, are identified and discussed. In the second step, an approach for identifying the process parameters for an application of an AM process is discussed.

4.3.1 AM Process

There are several types of AM processes defined in the literature review, Chapter 2. It is first important to identify the characteristics including parameters, controls, and constraints or limitations of all AM processes. The general AM process is depicted in Figure 4.6. Each AM process starts with a CAD model (a), followed by an STL file (b), and the final part is produced with an AM process, which all additively layers on material as exhibited in (c). While all AM process build parts layer by layer there are several methods and scientific processes for obtaining an AM part. According to the American Society for Testing and Materials (ASTM) standards for AM terminology, there are several processes and forms of AM. The AM processes that are specific to metals were divided into three categories including power bed systems, laser powder injection systems, and free form fabrication [109]. While all the nomenclature and standardization of AM terms are extremely useful, they vary significantly. Therefore, it is more useful to categorize them by the common processes used to additively manufacture product components and parts [6, 109]. The AM group at Loughborough University provides a detailed guide to classifying the types of AM as defined by Materials [6]. They discuss the seven types of AM processes including vat photo-polymerization, material jetting, binder jetting, material extrusion, powder bed fusion, sheet lamination, and directed energy deposition. There are specific and general characteristics for each of these processes; Table 5 highlights the seven identified AM processes and their inherent characteristics. In the process proposed in this methodology it is important to identify the character-

Figure 4.6: Process for Manufacturing AM Parts

istics that are inherent to the AM process and the part build; these characteristics will act as the manufacturing parameter options for the optimization model.

4.3.2 Process Parameters

After identifying the manufacturing characteristics, designers specify the AM process and application. Additional characteristics associated with the selected AM Process are identified and may be considered as additional variables for the performance objective function. However, the identification and categorization procedure of the AM process and process parameters produces a set of AM process metrics that are reduced in the trade-off analysis step (step 4 of the methodology). During the process of obtaining the AM process metrics, the process parameters that are identified for the AM process application produces a reduced set of metrics that are appropriate for the selected AM process but translatable to the overall manufacturing characteristics. For example, the build area for each approach has some three-dimensional space restrictions. Thus, the specific restrictions will be defined upon the selection of an AM process and application. The AM process application selection is defined based on the product requirements. The emphasis of the function development will be placed on the characteristics that have numerical values and/or ranges, Table 4.4. Traditional characteristics and characteristics that are inherent to the AM process that potentially impact the final part build are included in Table 4.4. Table 4.4 was developed based on the characteristics for each AM process detailed in the ASTM standard and the AM group at Loughborough University [6].

Additional informational on the manufacturing characteristics identified in the seven AM processes is provided, Table 4.4. Similar to the human interaction factors identified, the manufacturing characteristics associated with all AM processes and the process parameters, are represented, Table 4.5. The units for each parameter are also presented. However, the parameter range and AM process applications are not specified in this table since the specific AM process and respective process parameters are expected to vary amongst different design teams and available resources. After selecting an application and defining product requirements, the selection of an AM process, application, and process parameters are determined. The overall manufacturing characteristics still relevant after AM process selection will be significantly decreased. In addition, different applications of AM processes have variable ranges of parameter control, which may be a limiting factor for prototype development and testing. Moreover, the selection of an AM process may provide additional proprietary parameter control that is unknown to researchers that do not own specific AM applications. Thus, these parameters should be added as process parameters for the chosen application. Some manufacturing characteristics are

Table 4.4: 7 AM Processes and Process Parameters

Process Parameters	**AM Process**						
	VAT Photo polymerization	Material Jetting	Binder Jetting	Material Extrusion	Powder Bed Fusion	Sheet Lamination	Directed Energy Deposition
Build Area	○	○	○	○	○	○	○
Layer Height	○	○	○	○	○	○	○
Material	○	○	○	○		○	○
Support Material	○	○		○			
Laser	○				○		○
Blade or Roller	○				○		
Part Density	○				○		
Print Head		○	○		○		
Print Speed			○		○		○
Nozzle Radius				○			
Temperature					○		○
Electron Beam					○		○
Vacuum Pressure					○		
Ultrasonic Weld					○		
Fusion						○	○
CNC Mill					○		
Plasma Arc							○

common to the majority of AM processes while others are only relevant to specific processes. The goal of this procedure is to capture both the inherent differences in the AM processes and the process parameters.

In capturing the inherent differences associated with each AM process, designers can gain a better understanding of which AM processes satisfy product requirements. This is extremely important because the AM process selected will impact the part quality, either positively or negatively. Once the AM process is selected and application should be chosen based on available resources. The identification and refinement of all associated manufacturing characteristics is essential for the trade-off analysis. The trade-off analysis will consider AM process metrics and product metrics for designing an optimal product for accommodation and performance.

4.4 Validation of Manufacturing Characteristics

The identification of the manufacturing characteristics process is outlined in step 3, Figure 4.5. The constructs of this process were identified through a theoretical structural validity approach of the review of literature. The constructs identified and the validation source are presented in Table 4.6.

The constructs listed in Table 4.6 have been identified in the literature. However, research in AM is continuously expanding and growing and the 7 AM processes are expected to expand as additive and subtractive processes began to develop. In addition, the list of characteristics identified for each AM process is not intended to be comprehensive and the design team is expected to add additional relevant

Table 4.5: General AM Process Parameters for Manufacturing Characteristics

#	**Process Parameters**	**Units**
1	Build Area	mm
2	Layer Height	mm
3	Material	kg
4	Support Material	kg
5	Laser	nm
6	Blade or Roller	N
7	Part Density	kg
8	Print Head	mm
9	Print Speed	dps
10	Nozzle Radius	mm
11	Temperature	deg
12	Electron Beam	nm
13	Vacuum Pressure	bars
14	Ultrasonic Weld	N
15	Fusion	N
16	CNC Mill	Hz
17	Plasma Arc	deg

Table 4.6: Validation Constructs for Manufacturing Characteristics

Construct	**Origination**	**Modification**	**Integration**
7 categories of AM processes	[6]	AM Process	Yes
Technical Info, Materials, Pros/Cons	[110]	Process Parameter	Yes

characteristics as research and development in AM progresses.

Chapter 5: Trade-off Analysis

The process diagram for step 4 is presented in Figure 5.1. The trade-off analysis section includes a series of decision-making techniques that assist in reducing the number of product and performance metrics given the anthropometrics and AM process metrics identified. The decision-making techniques include the Analytic Hierarchy Process (AHP) and the 2nd process of Quality Function Deployment (QFD) method. The process for identifying product and performance metrics is described in Section 5.1. The formation process of the AHP method is detailed in Section 5.2, along with discussions of alternative design method options. The output of the AHP's will be used as inputs in the 2nd process of QFD, which is discussed in Section 5.3. Section 5.4 discusses the validation of constructs associated with AHP through literature and analysis of consensus in rating anthropometrics for AHP.

5.1 Identification of Product and Performance Metrics

The anthropometrics selected, Section 4.1, inform the identification of the product metrics. The product metrics assist in the development of the optimization model. Specifically with determining the dimensions of the selected product application, and the number of product applications with different dimensions required

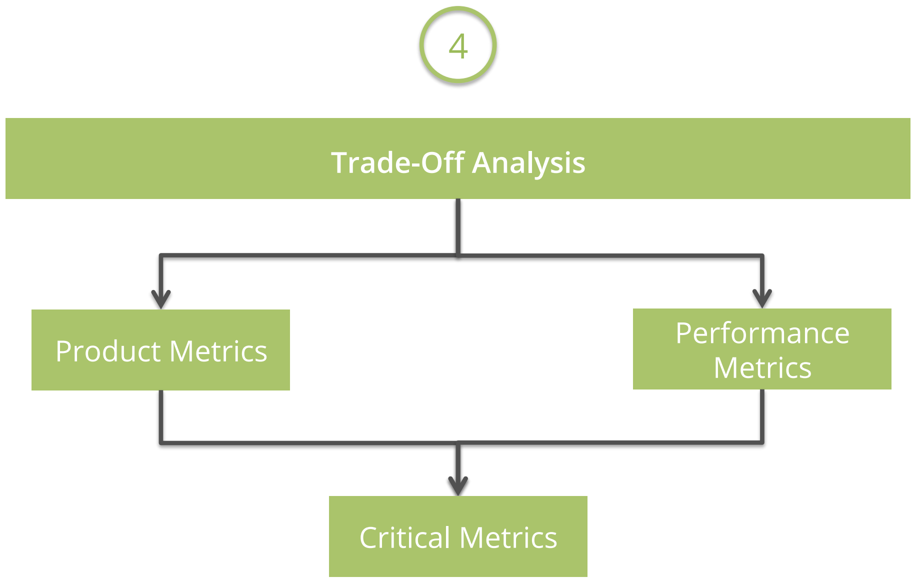


Figure 5.1: Process for Identifying Manufacturing Characteristics

to accommodate the population. The performance metrics also assist the in the development of the optimization problem. The performance metrics integrate the AM process metrics, Section 4.3, to construct the objective function(s).

More specifically, *Human Interaction Factors* and *Manufacturing Characteristics* determine the decision or design variables in the optimization model that will be optimized. Performance metrics associated with the product function and engineering requirements of the product application are directly derived from the process metrics of the manufacturing process. In the demonstration of this method, the manufacturing process is an AM method. Process parameters are expected to impact the final product. Thus, the more information known about the relationship between process parameters and performance metrics based on thermal, structural, material, power, etc. engineering requirements of the product the easier it is to model and optimize the performance metric. In general, the design team determines the performance metrics, which are based on the goal and functions of the product.

Alternatively, human interaction factors in the form of anthropometrics link directly to the product metrics, which drive the shape and fit of the product application. This is generally, all that you will need for static applications. However, for dynamic applications where the interaction space has to be defined fit and the impact of component placement within the interaction space must also be defined. Any functional classification can contribute to a performance metric derived from human interaction factors. In this instance the performance metric would become the objective function, which should be minimized to reduce risk of injury or overexertion on the human parameter during an interaction. This interaction could be driven by feedback of force, tactility, maneuverability, or reach. The process for identifying both the product metrics and the performance metrics are discussed in this section.

5.1.1 Product Metrics

Product metrics are equations or a system of equations that utilize anthropometrics to inform the dimensions of a product application. The product metrics are selected based on any equations that have the capacity to produce the dimensions of the application. Due to the vast number of equations that could aid in the determination of product or application dimensions, a decision-making technique is required to reduce the number of product metric options.

5.1.2 Performance Metrics

Performance metrics are fundamental engineering metrics for evaluating the quality and/or functionality of a product or application. Performance metrics may be based on requirements that a product must achieve, for functional innovation over competitors, or general performance improvements. Manufacturing characteristics generally affect the performance of a product based on the manufacturing process. The manufacturing process being considered in this methodology is AM, specifically a material extrusion process called fused deposition modeling (FDM). The AM process metrics produced provide the capacity to quantify the effects of manufacturing constraints on product performance. Performance metrics can also be vast, daunting, and costly to estimate. The researcher or organizations' interests also directly influence the performance metrics. Thus, it is essential to understand and model the most important performance metrics that (1) address the interest of the organization and (2) reduce performance metric options to enable the efficient collection of the most critical information for answering the primary research question or problem.

5.2 Analytical Hierarchy Process for Reducing Metric Options

AHP is the most appropriate technique for reducing the product and performance metrics, respectively. AHP is defined as a problem solving method for making a decision considering a set of alternatives when selection criteria represent multiple objectives, have a natural hierarchical structure, or consist of qualitative and quantitative measures [111, 112]. The AHP process consists of performing multiple sets of pairwise comparisons for the identified criteria and options [113]. This method was developed by Saaty and is commonly used in engineering design [113].

In order to narrow the selection of product and performance metrics, two (AHP) analyses are performed. One AHP utilizes the anthropometrics as criteria for the selection of product metric options. The other AHP considers AM process metrics as criteria for the selection of performance metric options. AHP is considered to be an effective method that assists researcher in making consistent comparisons. Thus is necessary for this trade-off method in order to obtain the most appropriate reduced set of product and performance metrics.

5.2.1 AHP for Anthropometric and AM Process Metric Criteria

The process for obtaining the anthropometric and AM process metric criteria for the AHP is detailed in this section. First, the formation of the anthropometric criteria is discussed along with a short demonstration of the anthropometric criteria applied to the AHP process for the design of a helmet. Next, the formation of the AM process metric criteria is described along with a demonstration of the criteria applied to the thermal performance of the helmet.

5.2.1.1 Formation of AHP Criteria: Anthropometrics

The anthropometric criteria are comprised of the specific anthropometric distributions required to capture the human product interactions for a given product or application. The criterion is subject to change upon the specification of a product application. The pairwise comparison, Tables B.23 and 5.2, demonstrates the process for setting up the pairwise comparison as described in Dieter and Schmidt [112]; Saaty [113]. The rows and columns are filled with the criterion. In the instance that one criterion is determined to be more important than another criterion, then the most important criterion will receive a whole number value between two and five in its row column. The reciprocal of the row value will be placed in the column (corresponding with the most important criterion) of the less important criterion. In the event that the criterion is determined to be less important it will receive a reciprocal value between $\frac{1}{2}$ and $\frac{1}{5}$ in its row column and the whole number value in the relative column. In the event that both criteria are considered equal then a value of one will be place in both the row and column. The calculated criteria weight will be determined through a series of three matrix multiplication operations where the first iteration is the criteria ratings squared, the second iteration in the squared criteria ratings multiplied by the squared criteria ratings, and the third iteration is the result of the second iteration squared for a third and final time through matrix multiplication also referred to as the dot product. The eigenvector and normalized value for each row is calculated. The eigenvector is the sum of the row totals represented in Equation 5.1, where $\mathrm{w_i}$ is the value for each column per row. The normalized value is the eigenvectors for each row,$\mathrm{V_j}$ divided by the sum of eigenvectors for all rows, Equation 5.2. The last column will provide the rank order of these criterions. The totals are used to rank the criterion from greatest to least, with the least important values possibly being eliminated. Elimination of criterions may assist the design team reducing time and subsequent costs by eliminating criterions that are not essential to the design. If the design team determines that no criterion should be eliminated, all criterions will be considered and the options will be compared through pairwise comparisons for each criterion.

$$V = \sum_{i=1}^{n} w_i \tag{5.1}$$

$$N = \frac{V_j}{\sum_{j=1}^{n} V_j} \tag{5.2}$$

5.2.1.2 Example of AHP with Anthropometrics

An example of this process, applied to the product metric of a helmet, is provided for clarification. Assume a criteria and normalized comparison matrix for a helmet design is presented, Tables B.23 and 5.2. The anthropometric criterion considering the head breadth (width) and head length is evaluated in the comparison matrix. Designers, in this example, determined that the head breadth and length were equally important. Thus, head breadth received a one in comparison with the head length and the head length received the same value of one.

In this instance, both anthropometric values receive a 1st place rank with a calculated criteria weight of 0.5 based on the normalized eigenvector values from the third iteration of the squared matrix multiplication. Since a helmet is the product of interest, the designer does not need to consider unrelated anthropometrics such at the ear height assuming that it is not a major metric that will help determine

Table 5.1: Criteria Comparison Matrix for Helmet Example

Anthropometric Criteria	Head Breadth	Head Length
Head Breadth	1	1
Head Length	1	1
Total	2	2

the helmet metrics the will be later used to determine fit or accommodation. In this instance, the ear height would not have direct interaction with the helmet because the designer intends on having earphones being build into the helmet, so ear height would be important for earphone design.

Product metrics for the helmet that would assist in determining fit include helmet surface area and helmet circumference, for example. A short demonstration of the full AHP for our example case is provided for robustness. For this example, an AHP tool for R [114] is applied. This tool requires a YAML script, which is a human readable file format commonly used for storing object trees, Figure 5.2. The hierarchical tree for this AHP demonstration is presented, Figure 5.3. The AHP priority calculation, Table 5.4 is based on the eigenvalue calculation method used in Tables B.23 and 5.2. This method show that helmet surface area is the most important metric and the consistency is 0% because there are only two comparisons and one rater that view helmet surface area most important for the length and

Table 5.2: Normalized Comparison Matrix for Helmet Example

Anthropometric Criteria	Head Breadth	Head Length	**Criteria Weight**	**Rank**
Head Breadth	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$	1
Head Length	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$	1
Total	1	1	1	

breadth.

5.2.1.3 Formation of AHP Criteria: AM Process Metrics

The AM process metric criteria are also dependent on the product or application. There is a difference from the anthropometric criteria in that the AM process metric criteria are formulated based on the impact that the manufacturing process parameters have on the performance metric options of interest. In many instances, especially in AM since it is a relatively new manufacturing process, there is little research on the impact of manufacturing parameter control ranges on the performance metrics. This additional research, including design of experiments and surrogate modeling, are required to understand the mathematical relation between the manufacturing parameters and the performance metrics of interest. This process can become very expensive depending on the amount of influential performance metrics. Thus, this process is extremely important for the reduction of performance

```yaml
Version: 2.0
# Start with example
Alternatives: &alternatives
# Just one alternative
  Helmet Surface Area:
    units: mm
  Helmet Circumference:
    units: mm
#
# End of Alternatives Section
#####################################
# Goal Section
#
Goal:
# This goal has 2 criteria and one alternative. Just for demonstration.
  name: Helmet Metric
  preferences:
    pairwise:
      # preferences are defined pairwise
      # 1 means: A is equal to B
      # 5 means: A is highly preferrable to B
      # 1/5 means: B is highly preferrable to A
      - [Head Length, Head Breadth, 1]
  children:
    Head Length:
      preferences:
        pairwise:
          - [Helmet Surface Area, Helmet Circumference, 3]
      children: *alternatives
    Head Breadth:
      preferences:
        pairwise:
          - [Helmet Surface Area, Helmet Circumference, 2]
      children: *alternatives
```


Figure 5.2: YAML format for Helmet Product Metric

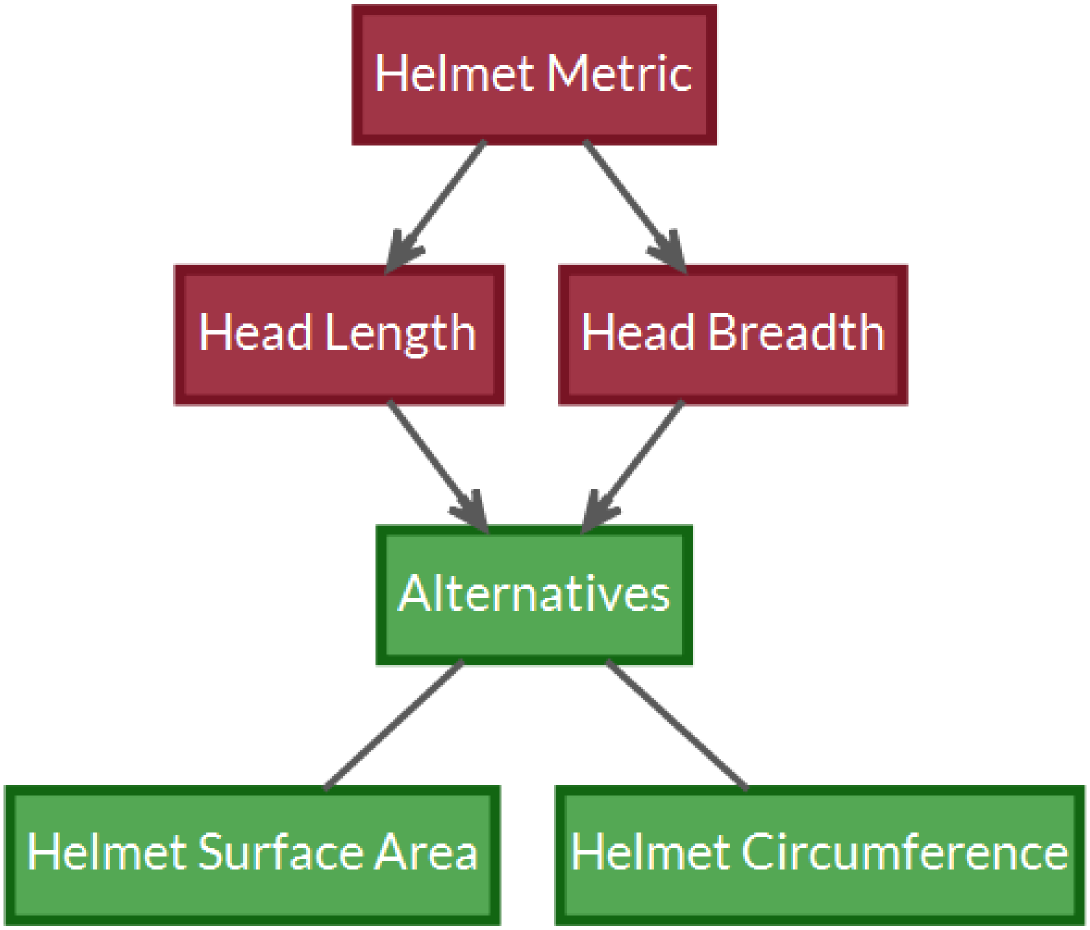


Figure 5.3: Object Tree for AHP

	Weight	Helmet Surface Area	Helmet Circumference	Inconsistency
Helmet Metric	100.0%	70.8%	29.2%	0.0%
Head Length	50.0%	37.5%	12.5%	0.0%
Head Breadth	50.0%	33.3%	16.7%	0.0%

Figure 5.4: AHP Priority Table for Product Metric

metrics options to metrics that provided the most critical information for improving the overall performance of the product.

The criterions in this process are represented by the manufacturing parameters in the AM process. The number of criterion is subject to change based on the selection of a specific AM process and process parameters. The follow section demonstrates the application AM process criteria which are the actual process parameters for an FDM, material extrusion, 3D printer.

5.2.1.4 Example of AHP with AM Process Metrics

The same process described for calculating the criteria and normalized comparison matrices for the anthropometric criteria apply to the calculation of the AM process metric criteria shown in Figures 5.3 and 5.4. Returning to our helmet example, the performance metric of interest is thermal performance. Thermal performance has several performance metric options but this example selected two alternatives: (1) Thermal Conductivity and (2) Surface Temperature. Researchers believe the AM process parameters that impact thermal performance include print speed and nozzle radius. Nozzle radius is believed to have a larger impact on thermal performance than print speed and receives a score of three. Thus, the print speed receives a rating of $\frac{1}{3}$ in comparison to nozzle radius. Overall, this example indicates that nozzle radius is more important to the thermal performance and assigns it a 1st place ranking. The full AHP example for the thermal performance of out helmet example is presented, Figures 5.5 and 5.6. This example reveals that surface

Table 5.3: Criteria Comparison Matrix for Thermal Performance

AM Process Metric Criteria	Print Speed	Nozzle Radius
Print Speed	1	$\frac{1}{3}$
Nozzle Radius	3	1
Total	4	$1\frac{1}{3}$

temperature is the most important thermal performance metric. A comprehensive AHP for a static and dynamic application will be demonstrated for two different products in Chapters 8 and 9.

5.2.2 Evaluation Scheme for AHP

The evaluation scheme consists of a 9-point rating scale and a description for each rating. The design team must decide whether each criterion is more, equal, or less important than a comparative criterion. The maximum and minimum rankings for this scale are 5 and $\frac{1}{5}$, respectively. This process for establishing and ranking the criterion metrics was demonstrated in Section 5.2.1 for the AHP pairwise comparisons, Figures 5.4 and 5.6. This section provides the full criteria weighting scheme that will be used in the application demonstration Chapters 8 and 9 for the evaluation of criteria and metric options related to product and performance

Table 5.4: Normalized Comparison Matrix for Thermal Performance

AM Process Metric Criteria	Print Speed	Nozzle Radius	Criteria Weight	Rank
Print Speed	$\frac{1}{4}$	$\frac{1}{4}$	$\frac{1}{4}$	2
Nozzle Radius	$\frac{3}{4}$	$\frac{3}{4}$	$\frac{3}{4}$	1
Total	1	1	1	

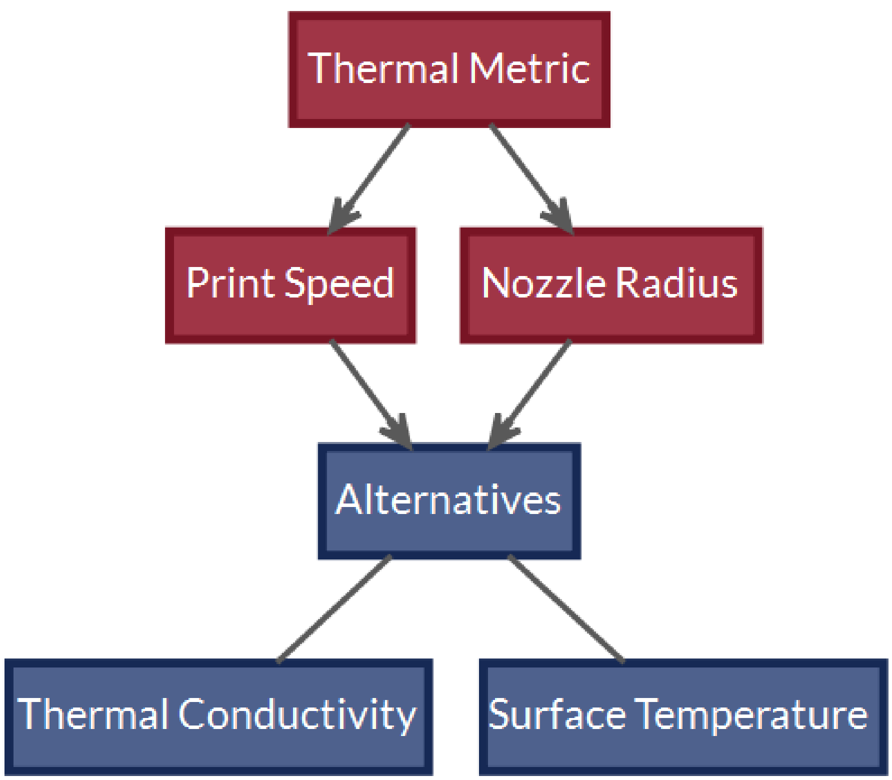


Figure 5.5: Object Tree for Performance Metric

	Weight	Surface Temperature	Thermal Conductivity	Inconsistency
Thermal Metric	100.0%	68.8%	31.3%	0.0%
Nozzle Radius	75.0%	50.0%	25.0%	0.0%
Print Speed	25.0%	18.7%	6.2%	0.0%

Figure 5.6: AHP Priority Table for Performance Metric

metrics. The design team must evaluate each criterion by the relative importance when compared to another criterion of the same type. Design teams are traditionally multidisciplinary and this methodology requires a traditional design team that has AM manufacturing expertise.

For this methodology there are only two types of criteria that are ranked, anthropometrics and the AM process metrics. The validation process used to assess the ratings assigned to each criterion is discussed in Section 5.4. Dieter and Schmidt [112] suggest the use of a higher point scale when information is more complete. Moreover, Saaty [113] provides insight into developing a fundamental scale incorporating reciprocals, Figure 5.7.

5.2.3 Alternate Selection Strategies and Techniques

Additional strategies can be applied to reduce metric options, related to product and performance metrics, in other trade-off analysis methods. The other strategies are explored to provide a comprehensive review of options for designers and researchers as they make decisions surrounding the most important factors for their de-

Importance	Definition	Explanation
1	Equal Importance	Two activities contribute equally to the objective
3	Weak importance of one over another	Experience and judgment slightly favor one activity over another
5	Essential or strong Importance	Experience and judgment strongly favor one activity over another
2, 4	Intermediate values between the two adjacent judgments	When compromise is needed
Reciprocals of above nonzero	If **i** has an above nonzero number assigned when compared with **j**, then **j** has the reciprocal value when compared with **i**.	

Figure 5.7: AHP Evaluation Scale for Metric Criterions

sign. Weighted decision matrices are an alternative approach to AHP. The weighted decision matrix methodology is discussed in this section along with two additional selection strategies including conservative and aggressive trade-off strategies.

The weighted decision matrix is a trade-off technique that can be used to determine (1) the best product metric given the anthropometric criteria and (2) the performance metric for the product given the AM process metrics. In the application of this method, two distinct weighted decision matrices would be developed. The weighted decision matrix allows for the rating of different metric options, given a set of criteria. This process relies on different evaluation schemes depending on the structure and ranking of the criteria. Objective trees measure the hierarchical nature of a construct, in our case criteria, allowing for equal or unequal rating options [111]. Based on the description of the weighted decision matrix discussed in Dieter and Schmidt [112], a valid set of weighting factors should sum to one. An objective tree for each matrix may be developed with the following weighting factor condition being considered, Equation 5.3, where $0 \leq w_i \leq 1$.

$$N = \sum_{i=1}^{n} w_i \tag{5.3}$$

After the weight values are generated from objective trees, the weighted decision matrix for criteria can be produced. The WDM consists of a criteria, weighting factor, and respective units for each criterion. The weight factor is obtained from the value determined by the objective tree. The magnitude is the unit of measurement associated with the criterion, which should be determined by the design team prior to the start of the evaluation process. The score is the value determined by the designers from an evaluation scheme or rating scale. The multiplication of the weight factor by the score establishes the rating value for each criterion. The total rating for each criterion is then added for a total value rating for each option given the criteria.

The correctness of the weighted decision matrixes can be determined through the adoption of the Consensus Model's evaluation parameters [115]. These processes have been validated in their own respective studies but they will need to be assessed for validity in the proposed applications.

The next set of trade-off strategies, conservative and aggressive, is discussed by Otto and Antonsson [116]. The conservative strategy is used to improve the lowest performing goal in terms of preference when selecting a design parameter set (DPS). Equation 5.4 shows the conservative formula being applied to determine the best design. The preferred design parameter solution set, $\overrightarrow{DP^*}$, is equal to the lowest performing goal with each goal, μ_i raised to its importance, ω_i. The number of performance parameters is depicted by q and n is the number of design parameters. In the equation min is used as the design metric because it improves the design's worst aspect (aspect with the lowest preference). Ideally improving the weakest aspect would improve the overall design.

$$\mu\overrightarrow{DP^*} = \max_{DPS}\left[\left(\min_{i\in[1,q+n]}[\mu_i^{\omega_i}]\right)^{\frac{1}{\max_{i\in[1,q+n]}[\omega_i]}}\right] \tag{5.4}$$

The second strategy presented in the Otto and Antonsson [116] paper was the aggressive trade-off strategy. This strategy attempts to maximize the overall performance regardless of the lowest performing goals. If lower performing goals increase the overall performance, then the lower performing goals will be maintained. Equation 5.5 represents the aggressive formula where the overall performance gains with each goal raised to its importance level. The formula is multiplicative.

$$\mu\overrightarrow{DP^{*}} = \max_{DPS}\left[\prod_{i=1}^{q+n}\mu_i^{\omega_i}\right] \tag{5.5}$$

These alternative strategies are not critical to the process but they provide insight into which trade-off strategies should be implemented conservatively or aggressively. They also provide validation for the weighted decision matrices' selections in cases where implementations of both strategies yield the same results.

5.2.4 Product Architecture and Subsystem Consideration

Product architecture and identified subsystems have a large influence on the organization of the Trade-off strategies presented in the preceding sections. Subsystems and dual functionalities define the number of AHP or alternative selection strategies that will need to be performed. In addition, product architecture influences the number of performance objective functions to consider for product optimization.

Product architecture is the arrangement of physical elements of a product to perform required functions [111]. The product structure and relevant interfaces are defined in the product architecture formation. There are two forms of product architectures that are commonly used modular and integral [111]. In this work, modular architectures are considered to enable product family design and subsequently mass customization. With the selection of different subsystems that have one or more functions, the problem can become increasingly complex.

As a general rule of thumb in engineering design function defines form for product development. What is missing is the functional consideration of products and subsequently product architectures is biomechanic functionality in consumer facing products. Table 5.5 presents the classification scheme for identifying static and dynamic product functionality based on interaction requirements from a biomechanic functionality perspective. In general, there is no product application that has a static initial interaction, unless the function of the product application is defined after the initial interaction occurs. These particular product classes, class I and IV, are addressed in the fields of ergonomics, which is driven by anthropometrics and biomechanics, and human variability. The goal of these fields is to apply methods that fit work to the person through adjustability in products or human parameters to maintain neutrality. In the present method, subsequent interactions define the functional classification. In the instances where the initial and subsequent interaction is static, class I, there is no adjustability in the design or adjustment is not necessary after it is initially set. In this case the functional application is defined after a previous interaction. Formal definitions of product classes II and III were presented in Chapter 3. The classes consider the initial interaction that a person has with a product, which has an impact on the user experience or biomechanical stress on human parameter. Class IV products have consider conditional dynamics which accounts for readjustment of product which require additional adjustments often times infrequently. This classification scheme for interaction variability is limited to physical interactions and excludes cognitive considerations of software design that do not also impact the physical limitations of human beings.

For example, the product architecture of a professional grade camera e.g. Nikon D3100, is both integral and modular. The interaction variability product classification of this camera is a Class III. The integral components should be considered in on trade-off analysis framework because the relative importance of integral subsystems is critical to the organization and optimization of the subsystem. On the other hand, modular components can be optimized independently or with other competing high-level objectives such as cost and quality. The camera frame and circuit board are integral, where the lens and flashcube are modular, which enable upgrades to your camera. These components also define the location of the modular components on the device, which impact interaction variability and assist in defining the accommodation design space. While each of the buttons of the camera frame represent a different subsystem with a focused function that would all need to be considered in a single optimization problem in the camera frame selected. This generates complexity in the problem and requires a MOO framework for a single subsystem; where as modular designs can be optimized separately with or without MOO depending on the number of competing subsystem functions.

Table 5.5: Interaction Variability Product Classification Scheme

Product Class	**Initial Interaction**	**Subsequent Interaction(s)**	**Functional Classification**	**Product Application**
I	Static	Static (no adjustment)	Static	Rear-view Mirror, Wooden Chair
II	Dynamic	Static	Static	Seat Belt, Shoes
III	Dynamic	Dynamic	Dynamic	Pen, Steering Wheel
IV	Static	Dynamic (adjustment)	Dynamic (Conditional)	Computer Monitor, Sit-Stand Desk

5.2.5 Conclusion

AHP was chosen over the three approaches discussed in this section because it fully encompasses the attributes of all three methods. AHP includes pairwise comparisons and provided weights based on normalized eigenvector values, which is done independently in the pairwise comparison examples presented in this section. Moreover, the inclusion of the option for evaluating multiple decision makers at the same time, discussed in Section 5.3, in AHP [114] allows for the summation of design decisions and consistency ratings amongst many evaluators. This accounts for some of the solutions provided in the aggressive and conservation strategies. While the three approaches discussed are all beneficial in the design decision-making process each of them would be required for a complete analysis of the design and validation, while AHP provides this in one method and includes elements of the other three methods but also allow for the evaluation of multiple decision makers for consistency. Thus, the AHP approach was selected for this methodology.

5.3 Product and Performance Metrics in Quality Function Deployment

QFD is a design method and tool for structured product planning and development among design teams. QFD enables design teams to identify "the voice of the customer" and evaluate proposed products or services systematically [112, 117]. There are four phases in the QFD method. The four phases include (1) product planning, (2) product design, (3) process planning, and (4) process control, shown in Figure 5.8 [1, 2]. The product-planning phase, which includes the House of Quality (HOQ) method, is the most commonly applied phase in the application of QFD. However, the other phases of QFD are rarely discussed or applied in most research [118].

The use of matrix diagrams is the basis of the QFD method and is utilized to extract and translate the "Whats" and "Hows" in this method. The "Whats" refer to the customer requirements and the "Hows" refer to the clarification of the "know-how" relationship between each phase of the QFD [1]. The "know-how" relationship can be interpreted as the process of understanding the customer or product requirements and developing a method or procedure for implementing the requirement into the conceptual framework of the design. For this work, addressing the "Hows" would be equivalent to addressing and clarifying the relationship between product and performance metrics. One question to consider is the impact of a performance requirement on the product design.

The product metric AHP assisted in developing a clear relationship between anthropometrics and product metrics. This represents the "Hows" for the product or parts design in the QFD. Moreover, the performance metric AHP assisted in connecting the AM process metrics and performance metrics. The performance metrics represent the "Hows" for the QFD. The application of the QFD has assisted in developing meaningful and clear relationships between the product and performance metrics for a targeted and impactful reduction in metrics for a feasible and concise optimization problem. While matrix diagrams are the heart of the QFD

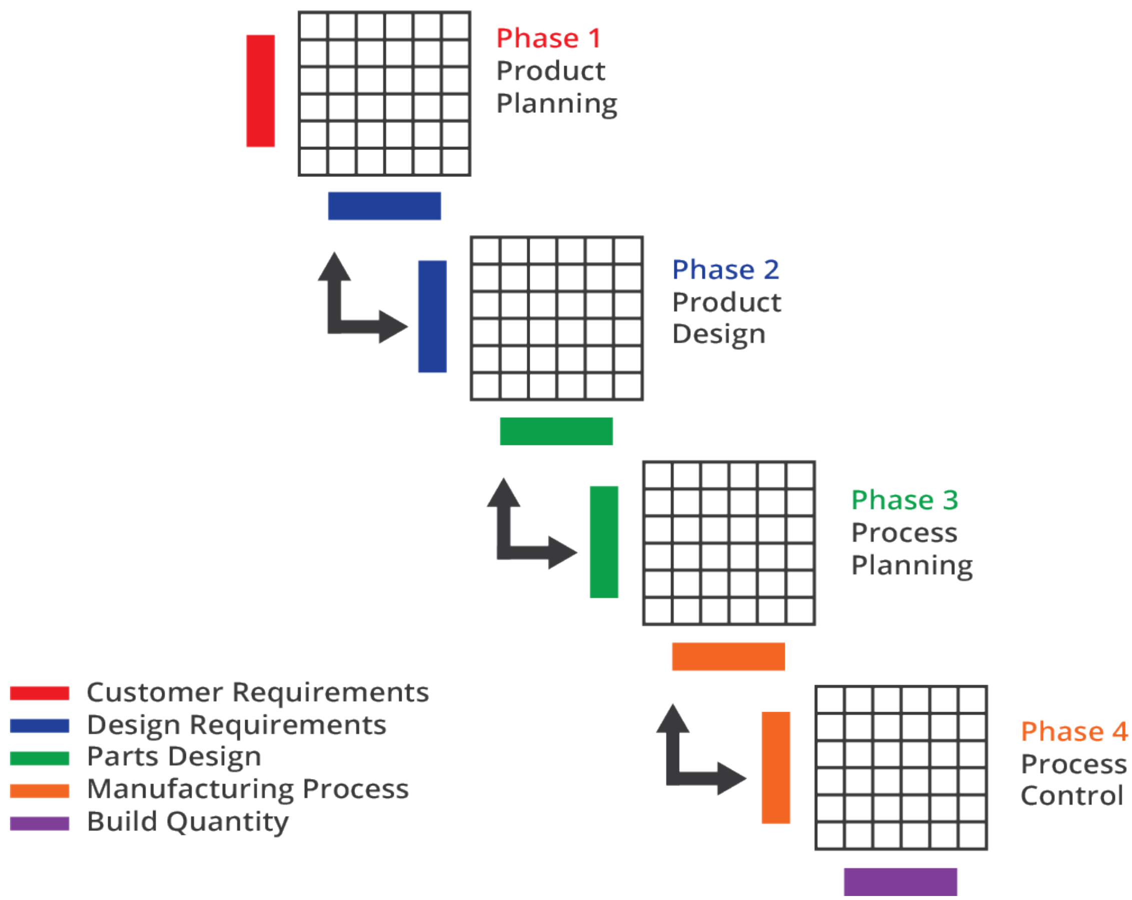


Figure 5.8: Four Phases of the Traditional QFD [1, 2]

method, the most commonly referenced tool or method in QFD is the HOQ. The HOQ, which was previously mentioned, is performed in the product planning phase of QFD and is the basis of the other matrices required for phases 2-4 of the QFD method [2, 117].

The new term presented in this work is called Analytic Quality Function Deployment(AQFD). AQFD symbolizes the integration of AHP and QFD for the reduction of product and performance metrics that influence the product design. The traditional QFD method suggests the use of AHP for integration into customer requirement development [1]. The AQFD method seeks to use AHP data generated from the product and performance metrics as the replacement for the HOQ utilized in the first phase of the traditional QFD method. The central focus of the AQFD method is the 2nd phase of the QFD method, which, as mentioned previously, is the product design phase. Recent research in ergonomic design has shifted the focus to the product design phase of the QFD method, for designing a spinal board [119]. In this application, the traditional QFD process was followed by generating the HOQ in the process planning phase, followed by the application of the product design phase for selecting a best spinal board design option [119, 120]. In the AQFD method, the performance metrics, ranked in the performance metric AHP, become the "Whats" derived from the HOQ in the product design phase, traditionally referred to as design requirements. Performance metrics are limited by some functional elements in the design that impacts the customer. Returning to our helmet example, the researchers want to ensure that the helmet does not get hotter than $35°C$ under the helmet so they must use materials with low conductivity and include a cooling mechanism. It is evident that there is a relationship between performance metrics in AQFD and design requirements in the traditional QFD. The helmet demonstrates a context where performance metrics will impact product metrics.

The "Hows" in the AQFD method are the product metrics, which are used to generate the dimensions of the product components. In the traditional QFD method, the 2nd set of "Hows is the parts design. The helmet example, discussed an approach to meet the performance metrics that directly impacts the product design. In AQFD, the product design is directly related to anthropometrics and accommodation so the product design metric must incorporate an approach that satisfies all requirements for performance, given the aforementioned consideration of anthropometrics. Lastly, the ranking order and weightings generated from the performance metric AHP become the "Hows" priorities in the AQFD method, Figure 5.9.

The present method identifies the customer requirements through the assessment of customer needs based on physical limitations. This is revealed in the anthropometrics being considered in the product design. The development of the AQFD method, addresses a limitation identified in the literature review regarding customers inability to identify their own preferences or needs [16, 20]. Other research in the application of QFD support the limitation in identifying customer needs, through the use of objective methods of data abstraction based on physical thresholds the customer needs can be attained [121]. However, addressing customer preferences requires additional methodological development. The demonstration of this trade-off process will be applied and discussed in Chapters 8 and 9.

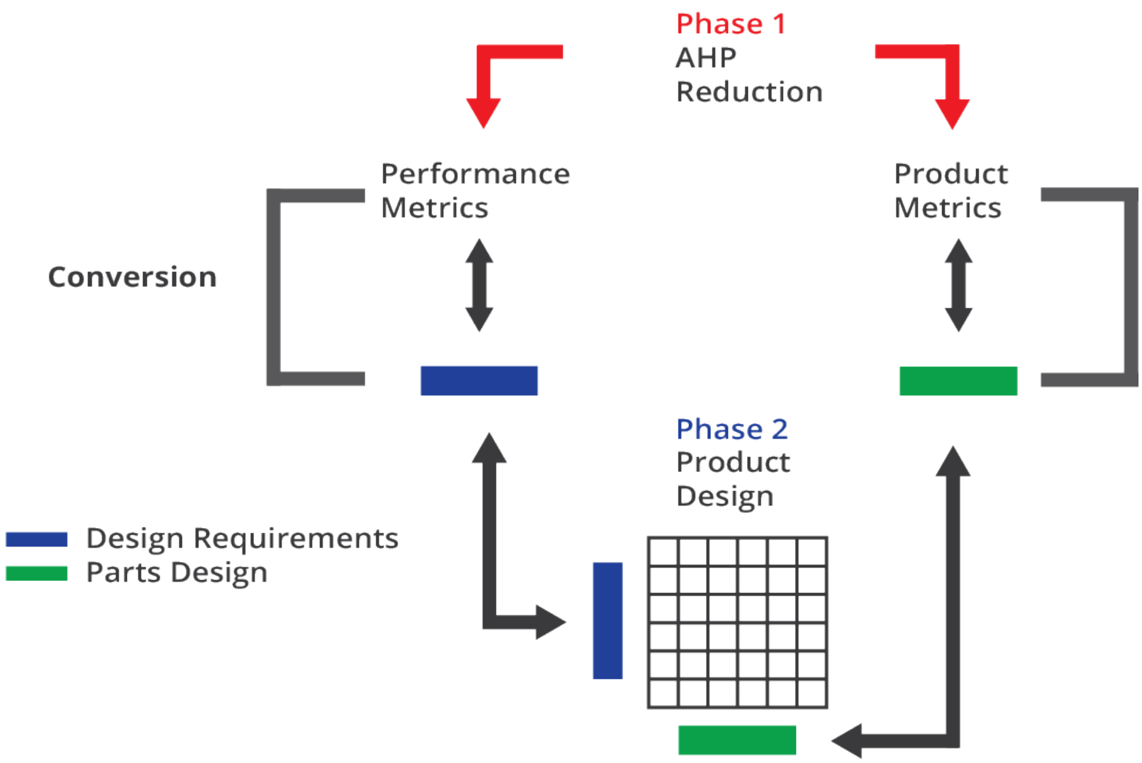


Figure 5.9: Two Phases of the AQFD Process

5.4 Validation of Trade-off Analysis Process

The constructs in the trade-off analysis process were identified through a literature review. A design study to assess the consistency amongst mechanical design engineering students for rating anatomical regions based on product interactions was also performed. However, the results of this study are limited in that they did not validate the entire AQFD method, only the anthropometric identification and consistency comparisons for the product metric AHP. Participants were asked to compare anatomical regions for the anthropometrics criteria of a water bottle and sunglasses application. The outcome of the validation procedure assisted in determining the consistency amongst evaluators for rating anthropometrics that were important for human product interactions. Table 5.6 provides insight into each construct and sources for validation of the AQFD method.

Research suggests that decision-making tools must be validated against the requirements and goals of the decision problem [123]. The construct references provide insight into procedures for validating the criterion for the AHP method and method procedures including the consistency index. The validation approaches presented below will measure internal validity. However, validity of decision outcomes is an open issue since "cardinal rankings of alternatives" are unknown [125]. Cardinal ranking have been determined to be superior to ordinal rankings due to the ability to provide refined information to reviewers but this information is often difficult to attain; moreover, cardinal rankings exposes methods to more bias due to evaluator "generosity" [126]. Evaluator "generosity" occurs when an evaluator administers a

Table 5.6: Identification of Constructs for Trade-off Analysis Process

Construct	Origination	Modification	Integration
Pairwise Comparison	[112, 122–124]	criteria importance ranking	No
AHP	[111–114]	consistency check for pairwise comparisons	Yes
QFD	[1, 2, 117, 119]	application of product design phase in QFD	Yes
Consensus Method	[115]	correction of judgments necessary for alternative selection	No

high score to every option high, which overvalues all designs even "bad designs" in a group ranking.

AHP is strongly connected to human judgment and cardinal rankings. However, the "generosity" bias in evaluators makes the comparison judgment matrix inconsistent [127]. The rough-APH was proposed as a method to reduce bias in AHP through conditional entropy and attribute significance concepts in rough sets theory [127]. Conditional entropy is the application of an algorithm that checks consistency in a rating system for the purpose of determining attribute significance, it is commonly referred to as Shannon's entropy and used in rough set theory [128]. Future work, should incorporate the rough set theory when consistency is sought for multiple evaluators of a product.

5.4.1 Validation Procedure for Anatomical Importance Rankings

The validation procedures for each construct will begin with the identification of a static and dynamic application including the sun glasses and a water bottle, respectively, discussed in validation of the human interaction factors in Chapter 4.

5.4.2 Details of Study Procedure

This study consisted of the validation of the AHP method focused on evaluation considering the anthropometrics for criteria attributes in the AHP. The evaluation was based on the demonstrated interactions for the water bottle and sunglasses applications.

1. *Task One:* Pairwise Comparison Ranking for Anthropometric AHP Criteria

    (a) **Part 1:** Participants were provided with a diagram of the selected applications, the primary function of the application, and the application requirements. The participant was then provided with a worksheet that described the anthropometrics that were relevant for each application (water bottle and sunglasses) and the relationship with the product components.

    (b) **Part 2:** Next, the participant was provided instructions on how to perform a pairwise comparison and asked to complete the tables provided. One table was provided for the water bottle application and the other was for the sunglasses. Each table listed the anthropometrics that were relevant for the human-product interaction to occur and participants were asked to rate each comparison set of anthropometric criteria. The rating results amongst participants were evaluated for consistency.

5.4.3 Summary of Study Outcome

For the water bottle interaction, participants achieved a majority consensus of $\geq 50\%$ for only 16 out of 28 of the anatomical pairwise comparisons for the interaction. On the other hand, for the sunglasses interaction participants achieved majority consensus of $\geq 50\%$ for 10 out of 28 of the anatomical pairwise comparisons. There were more ratings of consensus amongst the importance of the human interaction factors (musculoskeletal interfaces and functional classification) for the water bottle than the sunglasses application. The supports the theory complexity and magnitude of products limit the identification of human-component interactions. Appendix A presents the summary tables, reflecting consensus amongst designers for the relative importance of human interaction factors for the water bottle and sunglasses applications. Future work should develop extensive training of anatomical comparisons related to human-product interactions and measure anthropometrics and functional classification in separate pairwise comparisons for each interaction.

This information provided insight into the importance of the criteria in the selection of options, which indicates the success of the criteria for selecting product metric and performance metric options. Since prior knowledge of anthropometrics and human centered design had a huge impact of each designers ranking, there is a limited opportunity for the validation of participant ratings for accuracy [125]. Designers were selected for the study based on the requirement that they had taken an upper level undergraduate engineering design course and had a general understanding of the human anatomy. A more stringent exclusion criteria is required, specifically participants should have an understanding of anthropometric and biomechanical concepts in product design. There may be an option in future exploration of this work to find a method for obtaining external validity through testing of the same product in different populations in an effort to obtain significantly similar results. This information should be used for future investigation into rater consistency regarding the validation of any design matrix method.

Chapter 6: Optimization Process

Chapter 5 presented the methodological framework for Trade-off Analysis, step 4, and the application of the AQFD approach. The results of step 4 are critical to step 5, presented in the chapter, in order to frame the optimization problem. The process diagram for step 5 is presented in Figure 6.1. Section 6.1 discusses the framework for the optimization problem that was applied along with the problem parameters. Section 6.2 discusses the process used for the generation of the population and quantification the product build in static and dynamic products. The last section, 6.3, presents methods used for external validation, introduces research questions, and compares subjective and objective analysis approaches used in this work.

6.1 Objective Optimization

The selection of the applied optimization approach is justified in the developed model. The general form of the model including the objectives, constraints, and boundary conditions are described for application in demonstration chapters. The inputs, outputs, and objective functions are also defined with detailed descriptions that for additional insight into the functions that support the objective functions

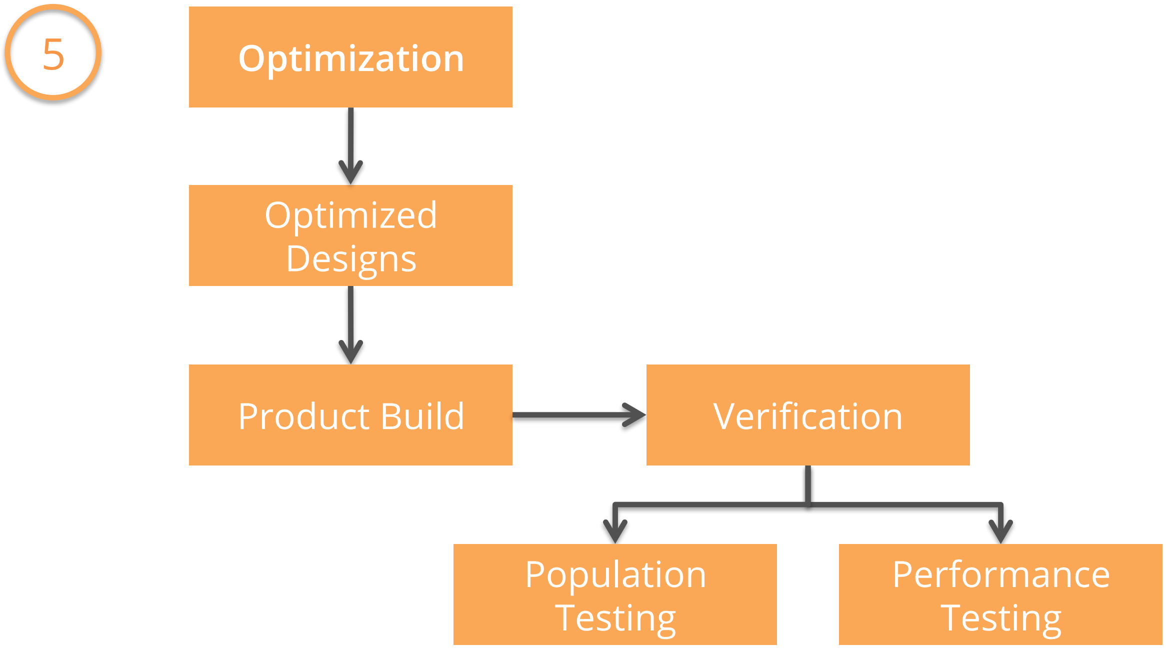


Figure 6.1: Process Diagram for Optimization Approach

including Monte Carlo sampling and Gaussian distribution functions. This framework provides insight into the general method for solving the optimization problem with any performance parameter and product. This section further describes the number of products required to accommodate the entire population, which informs the manufacturing approach for mass customization based on the performance objective. The products are then able to be designed, built, and tested in an actual or simulated population for performance; and the effectiveness of the optimization model is measured for its capacity to generated products that accommodate the population and maintain performance (e.g.,Temperature). The optimization process is represented in Figure 6.2 [3].

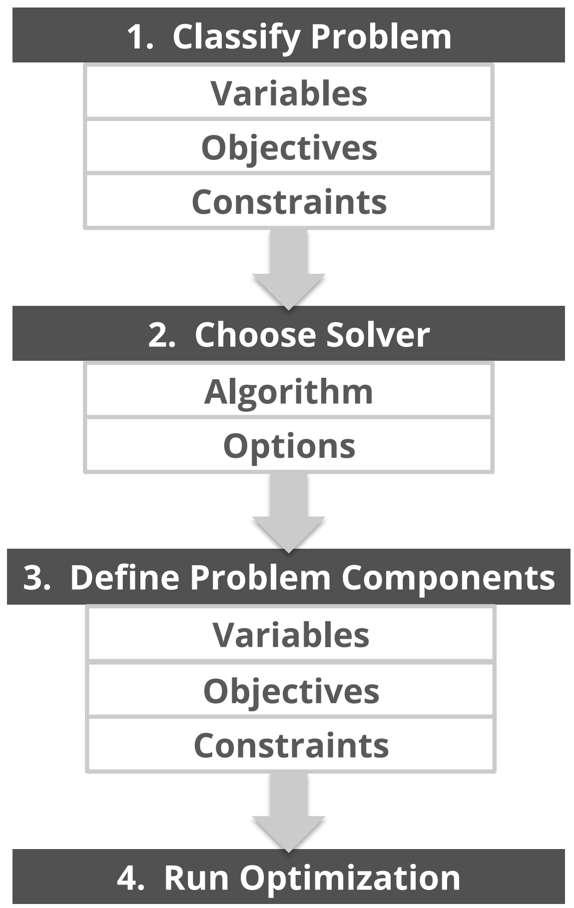


Figure 6.2: Optimization Process [3]

6.1.1 Selection of Optimization Algorithm

MOO techniques were considered to determine the framework for this method. Several studies discuss the effectiveness of robust optimization on obtaining an optimal solution with minimal sensitivity to uncertainty [129–132]. While uncertainty in the human parameters has been observed, it has not been quantified and incorporated into current public anthropometric databases. However, recent data provided insight on human comfort parameters in thermal, structural, etc. perspectives; this information provided optimal values for thermal modeling [133]. Methods that effectively access objective functions with optimal target points/values include the global criterion method (GCM). GCM assumes that an ideal value for the objective function is known [134]. In cases where an ideal value for the objective function is unknown, the Multi-objective Generic Algorithm may provide a better solution but is more computationally expensive that GCM [134]. The GCM provides two benefits (1) the ability to normalize objective functions prior to minimizing; and (2) the ability to maintain linearity given that the original problem is of linear form [135, 136].

This model framework seeks to maintain a performance requirement and penalize the design when the population is not accommodated. A surrogate model was used to integrate manufacturing parameters into the performance requirement for the application of this method, this model was analyzed to assess and visualize performance data in order to determine the modeling approach (linear, non-linear). The framework of this problem has two options (1) the optimal solution can be obtained in a MOO framework when there is more than one performance requirement (2) the solution can be obtained in the single or bi-level optimization problem with a penalty. The first option is directly applicable to solving a bi-level problem with multiple objectives [137]. The second option can utilize the global criterion method for solving a bi-level problem or a bi-level problem with a penalty function at the second level [138, 139].

The application of this method focused on implementing the bi-level problem or a single objective optimization with a penalty function on the constraints. The bi-level problem with the lower level penalty violation developed in 2007, addressed the complexity of the bi-level problem by reducing it to a single level problem with the penalty method [138, 140]. Linear programming was found to be the most efficient method to obtain the optimal solution for the bi-level problem [138]. A form of the linear bi-level problem that minimizes the performance objective function was selected with a focus on the penalty function for the accommodation non-linear constraint, Equation 6.1. The penalty function applies a large penalty to the objective when the constraint is violated. $f(x)$ is the objective function for performance, and $g_j(x)$ are constraints, and $F(x)$ is the objective function plus the penalty function with a penalty value, ϕ [138, 141, 142]. Equation 6.1 is a general approach that has application specific objective functions as demonstrated in Chapters 8 and 9, Equations 8.2 and 9.12, respectively.

$$
\begin{aligned}
\min_{x} \quad & f(x) & & \\
\text{s.t.} \quad & g_j(x) \leq 0 & & \forall j \in N \\
& x_j \geq 0 & & \forall j \in N \\
\min_{x} \quad & F(x) + \phi g_j(x) & &
\end{aligned}
\tag{6.1}
$$

6.1.1.1 Robust Optimization

Robust optimization would be useful for modeling the performance variation due to varying AM process parameters in additively manufactured parts. It would also be useful for measuring the anthropometric variability for human parameters, which would be beneficial in static applications. The current model accounts for the standard deviation of the anthropometric value, however, there is no additional error information for parameter values in anthropometric datasets. This means that when a randomly selected value from the distribution is determined, there is currently not enough knowledge to estimate accuracy of this guess to the true value. This problem is compounded because the datasets are older and not truly reflective of the current population. An alternative approach would be to collect current anthropometric data with automated measurement tools and let the error in the measurement tool account for the uncertainty in the parameter value.

In the current approach, a Gaussian mixture model was selected as an alternative to defining an uncertainty set under a robust optimization model. Under this approach, distribution and anthropometric variation information is captured and modeled enabling the random selection of people in the population based on their anthropometrics. In the robust optimization, the approach for modeling uncertainty is obvious and may vary. One could model the standard deviation of each anthropometric as the uncertainty set but also the difference in the dataset value to that actual value. It is not apparent which approach would provide the most pertinent additional information over the selected approach.

Moreover, robust optimization is a viable approach for modeling anthropometric parameter data, which takes on the form of static representations and is commonly associated with human variability. However, the problem becomes complicated when attempting to apply this to the new concept of *interaction variability* presented in this work. First, the interaction space is defined by the posture of the human parameter when interacting with the product component. In reality, the pose could be different every time the same interaction occurs. Second, this is a novel method and there is not enough data derived from the interaction space which varies within every interaction and amongst different interactions to model uncertainty.

6.1.2 Problem Parameters and Objective Functions

The problem goal is to optimize the performance of a product constrained by the end-user experiences during product interactions while maintaining accommodation. Examples include the fit of a device in a user's hand or the ease of pressing a button on a device and the performance of the design (surface roughness, thermal efficiency, etc.). The goals are (1) number of products required for accommodation

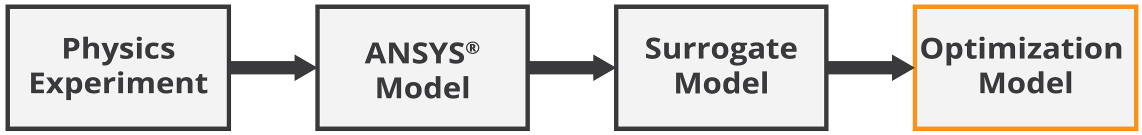


Figure 6.3: Process Flow Diagram for Objective Function Development

(fit), (2) performance (thermal performance, structural performance, etc.) and (3) product dimensions.

Surrogate model methods were necessary for building developing predictive models that contribute to the objective function. The predictive models were important for determining how different manufacturing metrics impact machine thermal performance. Validation of the function generated from the surrogate analysis was required to understand the functional behavior of the data collected to generate the model. Modeling of the experimental conditions of the additively manufactured component with ANSYS® 17.1 was necessary to replicate the conditions for future, more precise measurements. The process for experimentally testing the effect of AM process metrics on Performance metrics for development of the optimization objective function consisted of a 4-step process including 1) Experimental Testing, 2) Physics Modeling (ANSYS), 3) Surrogate Modeling, and 4) Optimization Objective Function, Figure 6.3.

The formal definition of accommodation and performance, the application will demonstrate thermal performance, that was investigated in this research is defined as the following:

1. *Accommodation:* a change in the spatial differences between the spatial-geometric

and interactive dimensionality of an application and the physical dimensions and capabilities of the human body, in order to attain fit. For example a shoe and a foot are spatially and geometrically unique, accommodation calculates the differences in the two elements and adjusts the values of the shoe in order to attain fit.

   (a) **Fit:** the alignment or minor overlap/underlay of the dimensions of an application and the human body.

2. *Thermal Performance:* the thermal energy change in an application related to the three modes of heat transfer (conduction, convection and radiation).

   (a) **Surface Temperature:** the temperature of the 1D conduction of additively manufactured parts.

Human interactions factors identified in Chapter 4 provided parameters for this optimization model. Thus, the variation of the human will be addressed in the product function through measurements, which include the mean and standard deviation of the musculoskeletal interfaces of interest and their functional classifications, associated with a normal distribution.

The input values or design variables for the product are dimensions of the design in terms of dimension (length, width, height) (mm), force and mass measurements (N, lbs), acceleration or vibration measurements (hertz), and distances and angles between product components (mm, degrees). The output for the product is the optimal product dimensions and the percent of the population accommodated by the product. The product function describes the dimension of the individual components and the relationship between each component with respect to the design variables. This is specific to the product being designed and based on the reduced set of product metrics, which consist of the shape and/or dimensions of product components, from Chapter 5. The accommodation function, Equation 6.2, is a constraint function based on the distribution of the population for each relevant anthropometric parameter relevant for the product interaction. The accommodation function is described by the sum of the change in Y_i for each person, i, in the population, N. Y_i is a binary variable that specifies whether a person has been accommodated, 1, or not accommodated, 0. The top portion of the equation is divided by the population, N, and multiplied by 100 to obtain population accommodation.

$$A = \frac{\sum_{i=1}^{N} Y_i}{N} \times 100 \tag{6.2}$$

Static and dynamic applications have distinct algorithms that describe the process for determining accommodation. For static applications, a "Fit Requirement" function that is product application specific is defined. In general, the "Fit Requirement" is related to the ratio of human parameters and product dimensions, Algorithm 1. On the other hand, accommodation for dynamic applications requires calculation of interactions for each active functional classification of the human parameter. Algorithm 2 provides an example of the accommodation function for the functional classification of reach, which requires you to use the interaction calculations to define and interaction space. After the interaction space is defined accommodation can be determined.

Algorithm 1: Static Accommodation

```
Data: people, product dimensions (pd), fit, FitsRequirement, number of
      products(N)
Result: Accommodation Constraint
begin
    fit = 0
    for person ∈ people do
        for product ∈ {1, ···, N} do
            if FitsRequirement(pd, person) then
                fit += 1
                break
    Accommodation = fit/|people|
    Accommodation Constraint = 100 × (0.95 − A)
```

The inputs for thermal performance are related to the controls on the additive manufacturing machine and the relationships between the variation of controls and performance. The machine controls and design variables for the thermal performance objective function may include layer thickness, nozzle diameter, temperature (bed, nozzle, and chamber), print speed, materials, fill density, etc. The performance outputs may generally include measures such as force, temperature, etc. but are dependent on the product application. Input and output values are subject to change depending of the importance of additional inputs or outputs that must be

Algorithm 2: Dynamic or Functional (Reach) Accommodation

Data: position, product dimensions (pd), people, fit, number of products (N)

Result: Accommodation Constraint

begin

  fit = 0

  for *person* $\in$ *people* **do**

    $ext_{max} \leftarrow$ **Calculate** maximum extension pose relative to product plane

    $flex_{max} \leftarrow$ **Calculate** maximum flexion pose relative to product plane

    for *product* $\in \{1, \cdots, N\}$ **do**

      if $pd - ext_{max} \geq 0$ *&* $position \geq flex_{max}$ *&* $position \leq ext_{max}$ **then**

        $fit += 1$

        break

  Accommodation = fit/$|people|$

  Accommodation Constraint = $100 \times (0.95 - A)$

evaluated prior to developing the optimization model. This is most pertinent to the performance objective as it is subject to change. Equation 6.3 represents the general structure of the bi-level or supporting function for the performance objective function, B, which is being applied to thermal performance. This function is centered on measuring the effects of manufacturing metrics on the outcome variable, which is a thermal performance objective such as surface temperature or conductivity. With the outcome variable being the objective function, B, the independent variables are represented by x_i. The effects of independent variables on the outcome variable impact the linear regression equation, Equation 6.3. The total number of independent variables will be based on the number of manufacturing parameters considered with relation to the performance metric. The regression equation, Equation 6.3 will actually act as the bi-level of the objective function, which will be a performance metric such as surface temperature or thermal conductivity.

$$B = \beta_o + \sum_{i=1}^{N} \beta_i x_i \tag{6.3}$$

Referring back to our optimization model presented in Equation 6.1, B represents $f(x)$. The design parameters along with the name and units for optimization are represented in Table 6.1. For example, the preference for force (amount of force necessary to interact with part build) and angle (degree of deviation or rotation required to interact with part build) should first be minimized to ensure that usability is maximized based on the minimal range identified for the population.

The performance parameters for the machine are depicted in Table 6.2. The

Table 6.1: Possible Design Variables for Product Metric

No.	**Design Variable**	**Name**	**Units**
1	Length	L	mm
2	Width	W	mm
3	Height	H	mm
4	Radius or Diameter	R	mm
5	Vibration	V	hz
6	Distance	D	mm
7	Angle	A	deg

parameters listed in Tables 6.1 and 6.2 are subject to increase or replacement with new important parameters that model performance metrics for specific applications, which may be deemed most important, by designers, for the population.

6.1.3 Objective Function Description and Solution Goal

The objectives for this problem are two-fold. The first objective is focused on providing the optimal accommodation in the design of the end product selected to the maximum spread of end users in the population. The second objective is to provide the highest performing end product given the AM approach selected due to the fact that poor performance could negatively impact accommodation through geometry inadequacies. The optimization problem presented will be solved by with the patternsearch algorithm in MATLAB®. The patternsearch function is better

Table 6.2: Possible Design Variables for Performance Metric

No.	**Design Variable**	**Name**	**Units**
1	Layer Height	LH	mm
2	Melting Temperature	T	C
3	Print Speed	P	mm/s
4	Nozzle Diameter	ND	mm
5	Material	M	ABS, etc.
6	Infill Density	FD	%

performing than the fmincon solver because the objective function in all cases either the objective or constraint function are non-convex. Thus the application of fmincon produces an error or fails to converge as it approaches a local minimum and the next set point is a larger value than the previous point. For multi-objective problem, the solver fgoalattain in MATLAB® may be utilized. fgoalattain is one way to solve for a minimum solution to a MOO problem. This method is most effective when you have an understanding of the ideal solution and a goal for the optimization problem. The framework for the basic objective functions are depicted in Equations 6.2 and 6.3, each general structure has been verified and will be customized for each application in this methodology.

The general algorithm developed to solve the optimization scheme presented in Algorithm 3. The algorithm has two goals:

1. To obtain optimal solution to performance objective(s).

2. To determine the number of product(s) required to accommodate the population.

The general optimization algorithm for obtaining the optimization goals is presented in pseudo code in Algorithm 3 with a random restart routine, to search the design space for the best possible optimal solution since a global optimization solver is used in this work. Moreover, the number of products increases with each solution until the population is accommodated and the best solution is obtained. The optimization solver used in this algorithm is called "patternsearch." The functionality of the patternsearch algorithm is centered on polling around an identified point, `https://www.mathworks.com/help/gads/patternsearch.html`.

6.2 Design Build

In this stage, the optimized design build is produced. After completing the part build it will be prepared for comparison testing in quality and thermal performance metrics. Due to open-ended questions regarding the impact of AM process metrics on thermal performance metrics i.e., surface temperature, preliminary experimental results fed into predictive surrogate models. Experimental validation of modified design builds (i.e. a flat helmet test) were conducted for the helmet demonstration but not verified and validated in the population. The following research questions are important and should be addressed when applying this method but only question 2 was addressed, from an optimization and experimental perspective,

Algorithm 3: Number of Products

```
Data: people, objective, product dimensions (pd), average product (ap), number of products (N), count,
      status, maximum number of products (Max), restarts
Result: Best Solution, Best Function Value, N
begin
    people = people (specify sample size)
    objective = @(x) objective (manufacturing parameters, pd, people)
    for N = count ∈ Max do
        Best Solution = 0
        Best Function Value = ∞
        for restart = 1 ∈ restarts do
            Manufacturing specifications
            solution_0 = initial solution
            lower bound = zeros
            upper bound = ∞
            for 1 ∈ N do
                Product specifications
                solution_0 = concatenate (2, solution_0, ap+random noise)
                lower bound = concatenate (1, lower bound, pd(lower bound)
                upper bound = concatenate (1, upper bound, pd(upper bound)
            nonlinear constraint = @(x) accommodation (people, pd)
            [Solution, Function Value, exitflag] = patternsearch (objective, solution_0, lower bound,
            upper bound, nonlinear constraint)
            if exitflag ≥ 0 & FunctionValue < BestFunctionValue then
                Best Function Value = Function Value
                Best Solution = Solution
                status = exitflag
                display restarts
        if status ≥ 0 then
            break
```

in this demonstration.

1. Does the end user experience comfort and satisfaction when interacting with a product that has been optimized for human variability and AM machine constraints?

2. Is the thermal performance of the product maintained when optimized for human variability and AM machine constraints?

The optimized design build was validated for thermal performance in a model validation procedure for thermal performance of one of the selected applications. The other application utilized validated measurements from anthropometric databases and range of motion (ROM) measurements for hand joints. Population simulation and validation in a computational tool such as Siemens ® Jack was considered. However, these computation tools rely on similar anthropometric databases as those used to construct the optimization models, which limits the insight to be gained from computation models. In this case, the computational tool acts a confirmation tool to check whether the optimized model actually produces the joint angles expected in the poses modeled for ROM of the anthropometric metric. Future work should attempt to validate the optimized models in the population. Tables 6.3 and 6.4 provide information on the general human interaction factors and the manufacturing characteristics, displaying direct and indirect relationships for each model. When applying this method, only metrics that directly impact human-component interaction or the product performance from a manufacturing perspective should be considered.

Table 6.3: General Human Interaction Factor Metrics for Optimized, Human, and Machine Models

Metric *Human*	**Optimized Model** *Direct*	**Human Model** *Direct*	**Machine Model** *Indirect*
Braincase	Braincase	Braincase	
Face	Face	Face	
Ear	Ear	Ear	
Throat	Throat	Throat	
Vertebral Column	Vertebral Column	Vertebral Column	
Thorax	Thorax	Thorax	
Pectoral Girdle	Pectoral Girdle	Pectoral Girdle	
Arm	Arm	Arm	
Hand and Wrist	Hand and Wrist	Hand and Wrist	
Pelvic Girdle	Pelvic Girdle	Pelvic Girdle	
Leg	Leg	Leg	
Foot	Foot	Foot	
Reach	Reach	Reach	Reach
Force	Force	Force	Force
Tactility	Tactility	Tactility	Tactility
Maneuverability	Maneuverability	Maneuverability	Maneuverability

Table 6.4: General AM Metrics for Optimized, Human, and Machine Models

Metric	**Optimized Model**	**Human Model**	**Machine Model**
Manufacturing	*Direct*	*Direct*	*Indirect*
Build Area	Build Area	Build Area	Build Area
Layer Thickness	Layer Thickness		Layer Thickness
Materials	Materials	Materials	Materials
Supports	Supports		Supports
Laser	Laser		Laser
Blade/Roller	Blade/Roller		Blade/Roller
Infill Density	Infill Density	Infill Density	
Print Head	Print Head		Print Head
Print Speed	Print Speed		Print Speed
Nozzle Radius	Nozzle Radius		Nozzle Radius
Temperature	Temperature		Temperature
Electron Beam	Electron Beam		Electron Beam
Vacuum Pressure	Vacuum Pressure		Vacuum Pressure
Ultrasonic Weld	Ultrasonic Weld		Ultrasonic Weld
Fusion	Fusion		Fusion
CNC Mill	CNC Mill		CNC Mill
Plasma Arc	Plasma Arc		Plasma Arc

6.3 Validation and Verification

Objective and subjective methods require evaluation in order to determine their appropriateness for addressing the aforementioned research questions through population and performance testing.

Objective statistical measures are more generally defined as parametric procedures. Parametric statistical procedures follow the assumptions that underlie the shape characteristics of distributions, i.e. the normal distribution [143, 144]. Examples of parametric tests include the Student's t-test and Z-tests. Subjective statistical measures, on the other hand, are generally defined as nonparametric procedures. Nonparametric statistical procedures may eliminate too much information and imply samples are "distribution free" [145]. Examples of nonparametric tests include the Sign and Kruskal Wallis tests. Objective data must be collected in a ratio or interval manner and satisfy parametric assumptions of normality in order to apply parametric statistical procedures; while subjective data must be collected in a nominal or ordinal manner for application in nonparametric statistical procedures [146].

Future research should validate the optimized model for the three outcome measures on comfort, satisfaction, and thermal performance. The population outcome has two measures, comfort and satisfaction. The comfort measure emphasizes neutral postures, small deviations and rotations, and low impact interactions (i.e., force applied) when interacting with the selected applications. The satisfaction measure is relative preference. This test can be conducted through subjective means with an A/B testing protocol and an ordinal ranking analysis.

The performance outcome has one measure, thermal performance of the optimal model compared to the alternative models (human, machine), which can be measured objectively in relation to surface temperature required to maintain human thermal comfort. Future work should validate the effectiveness of the optimized models in the population and experimentally validate the thermal performance in a fully functional helmet. The following subsections present approaches to population and performance testing but these approaches will not be demonstrated in this work due to the large scope and research funds necessary to acquire the participant pool for population testing and the thermal validation facilities for performance testing.

6.3.1 Population Testing

Population testing can be performed to validate the optimized design build against the human and machine design builds separately. A population sample is required to collected data and understand how well the design build meets the physical parameters of the human end user and their comfort expectations. This is a costly and expensive process because in order to obtain a representative population sample larger sample sizes are needed in various demographic populations. Random sampling is chosen as opposed to a stratification of the population or a virtual model approach because the human variability parameters used in the optimization model represent the US population. Thus, enrolled participants that meet parameter requirements will be able to effectively assess the models designed for their segment of the population. Inclusion/exclusion criteria will be utilized to measure the parameters of potential participants before enrollment. If the parameters fall outside of the normal distribution for the human dimensions (database values) then the participant will be excluded, otherwise they will be enrolled in the study.

An alternative approach would be to evaluate the 5th, 50th, and 95th percentiles separately, allowing the percentiles to determine the number of products required. Then the optimization model would be run three separate times for each percentile group range. This would produce three optimal parameter sets where components could be designed modularly or independently to reduce the amount of excluded users. This approach was not selected or necessary in this method because the entire distribution was modeled. A similar approach can be applied to smaller population distributions with limited data to address specialized or high-risk groups that may have parametric differences than the normal population.

6.3.2 Performance Testing

Thermal analysis only represents one AM performance measure and it is was selected as an important measure for pilot validation of the optimization model. Thermal properties are extremely important in AM; it is one of the top 10 issues or failures in AM [33]. Thermal testing provides performance evaluation of the optimized model, which will address the second research objective. In this instance the second research measure is surface roughness and/or part separation. The thermal testing of the selected application should occur in a closed thermal controlled chamber with internal and external sensors with the goal of ensuring that the application maintains thermal requirements under varying thermal conditions.

Chapter 7: Demonstration of Methodology

Implementation of the methodology involved satisfying a series of requirements, including the design of functionally complex products and identifying the method of production. This methodology focused on the AM approach as the manufacturing method of interest. Of the seven different AM approaches, the application chosen was the material extrusion process, specifically the FDM technique. FDM has several open source applications, which allow the researcher to control machine parameters and/or create new parameters. This type of environment is ideal for research and development because it enables exploration into experimental testing. AM techniques have the ability to produce highly differentiated components and products, with expedited turnover times, presenting a high value proposition for meeting the product requirements of an intended population.

The physical characteristics of the population are equally important as the manufacturing approach for the design of a product. The implementation of this methodology addresses variability in the population based on the extrapolation of anthropometric and biomechanical functions and limitations of the human being. In high-risk domains, the consideration of the physical parameters of highly variable populations is extremely valuable in the prevention of injuries and even death caused by device misuse. The five steps of the methodology are presented in Figure 7.1. The first step, which determines the selection of the applications/products with the high level requirements and components, is presented in Section 7.1. Chapters 8 and 9 will demonstrate this methodology for steps 2-4, including the Human Interaction Factors (2), Manufacturing Characteristics (3), and Trade-off Analysis (4), for the handheld device and helmet applications, respectively. Step 5, Optimization Process, for each application will be demonstrated in Chapter 10.

7.1 **Step 1:** Selection of Applications

This method has been demonstrated on two products including a handheld device and helmet application mentioned in the previous section. The selection of two different applications assists with determining external validity and generalizability of this method. The hardware associated with a handheld device and a helmet will be developed and modeled. This process is presented in the two applications is presented in Chapter 10 for the handheld device and helmet. Future work should test these models in the population to gather thermal performance data and thumb reach data in order to validate products. Siemens Jack$^{\text{TM}}$ Human Simulation Software is a computational tool that could also be useful for validation of specific product applications.

Handheld devices and objects are widely used across the globe. In 2014, reports showed that there were more mobile devices than people on the planet Earth. The actual number of mobile devices was 7.3 billion, which increased to 7.9 billion in

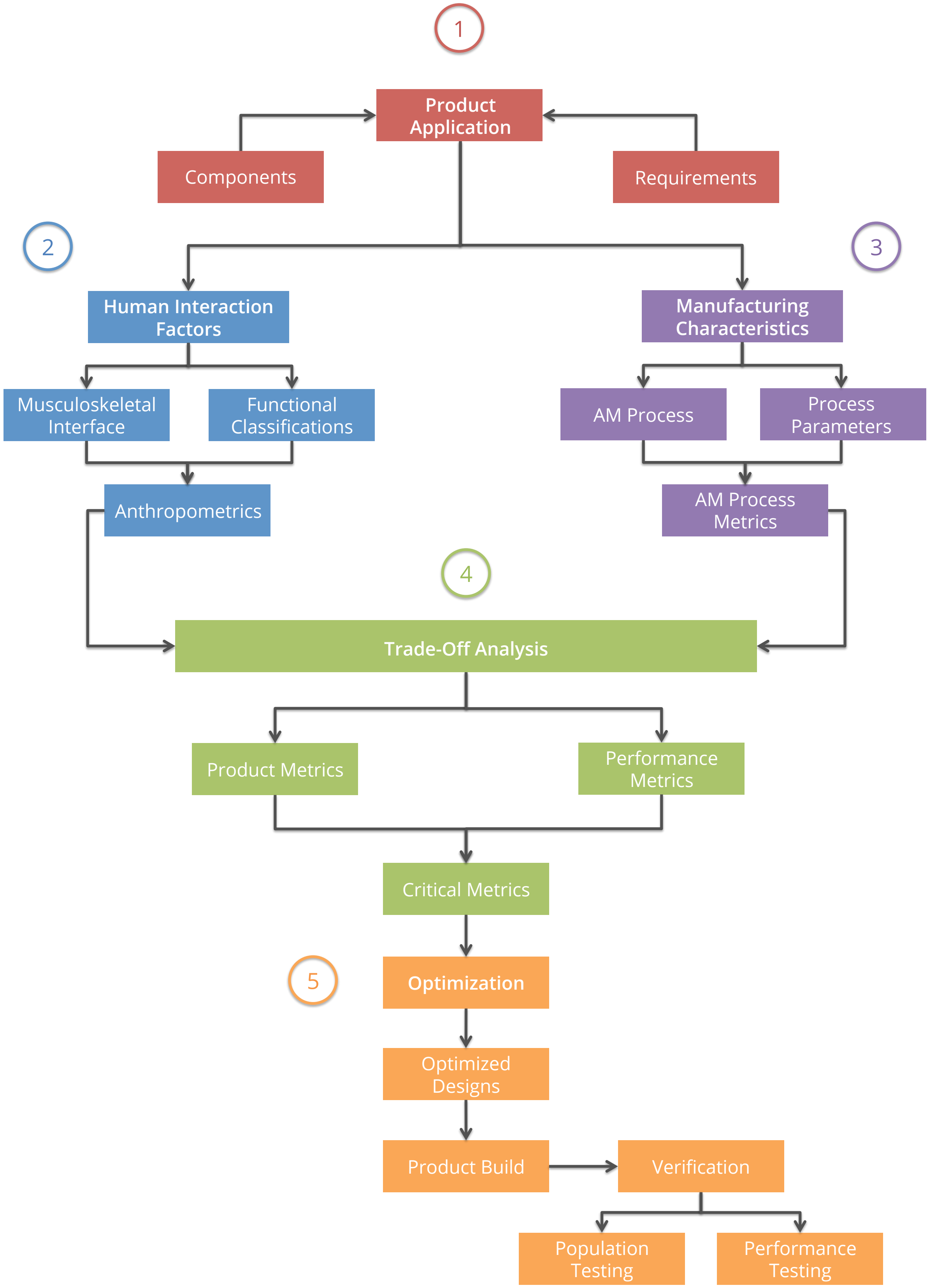


Figure 7.1: Diagram of Methodology, presented in Chapter 3

2015 [147]. By 2020, the number of handheld and personal mobile devices is expected to increase to 8.2 billion [147]. This is significant because a large portion of the identified population uses mobile devices and many mobile devices are also handheld devices. In addition to handheld devices and other handheld objects, such as writing mechanisms, utensils, containers, and tools that are used on a daily basis by majority of the human population; this emphasizes the importance of handheld objects in the global society and the necessity to demonstrate this methodology with a handheld device. The specific type of handheld device selected for this demonstration was a device that includes a button and casing. These are typical components found in most hand-held devices.

While the first application places emphasis on a type of application that is widely used by the global population, the second application is focused on a safety critical application. Helmets are used in uncontrolled environments to protect the human head, which contains the brain, braincase, and skull from injury [148]. Helmets are considered protective gear and have been proven to be effective in reducing head injuries [149]. Testing a helmet in the population is signification because it identifies the limitations with regard to head protection prior to mark release. This application is not used by everyone or used as consistently as other forms of headwear and common applications. However, helmets are required to be worn by law for certain activities in the United States and need to be worn as specified to reduce the risk of head injury, which in many instances can lead to death [150].

The handheld device and helmet applications were selected for the external validation of this methodology and provided two vastly distinct perspectives for assessing its effectiveness. Each application assesses different areas of the musculoskeletal system. The focal areas of the handheld device are the hand and wrist. The handheld device application represents our dynamic application first defined in Chapter 3. A dynamic application requires additional interaction, after an initial interaction, to carry out the primary function of the application. The primary function of the handheld device is to receive inputs and provide output for the end user. The input types are limited to physical inputs and outputs (i.e., tactile feedback). With the function defined the two requirements are set, (1) the handheld device must receive physical inputs from the end user, (2) the handheld device must provide output. The handheld device has components such as button, screens, device architecture and frame, and insertion mechanisms that interface with the human end user. The focus of this demonstration will be on the interactions associated with the buttons. The primary physical components being tested include inputs of buttons, frame and architecture (casing). In this demonstration, outputs will not be explored due to the limitations of the computational testing methods.

The helmet application assessed the braincase of the musculoskeletal system. The helmet represents our static application also defined in Chapter 3. A static application does not require any additional interactions, after an initial interaction, to carry out the primary function of the application. The primary function of the helmet is to protect the human head. The important measures included in the primary function include protection from outside objects and thermal regulation inside the helmet. The requirements of the helmet include the following: (1) helmet must protect the human head and (2) helmet must maintain a constant temperature.

The helmet has components such as the shell, straps, and padding. The shell and padding are the focus of this demonstration. Chapter 10 will highlight the internal and external validation of this method.

Chapter 8: Demonstration of Handheld Device Application

In this chapter, steps 2-5 of the methodology are discussed. Step 2 presents the *human interaction factors*, Section 8.1. Step 3 discusses absence of the *manufacturing characteristics* for the handheld device demonstration due to computational focus on dynamic modeling, Section 8.2. Step 4 presents the *trade-off analysis* for the handheld device components for the AQFD method, Section 8.3. In the final step, Step 5, the product metrics selected for the handheld device are formulated, designed, and optimized for the interaction defined by the functional classification for the target population, Section 8.4. The handheld device results were demonstrated in an output diagram that showed the optimal button placement in the reach zone for the population. Preliminary conclusions and limitations are discussed in the final section of the chapter, Section 8.5. As mentioned in Chapter 7, the components of the device that interface with the human end user include buttons, a screen, device architecture and frame, and insertion mechanisms. Although the end user interacts with the aforementioned components at different points within the device lifecycle, this application is focused on the components with the most frequent human interactions. These components include a button and the device frame or casing.

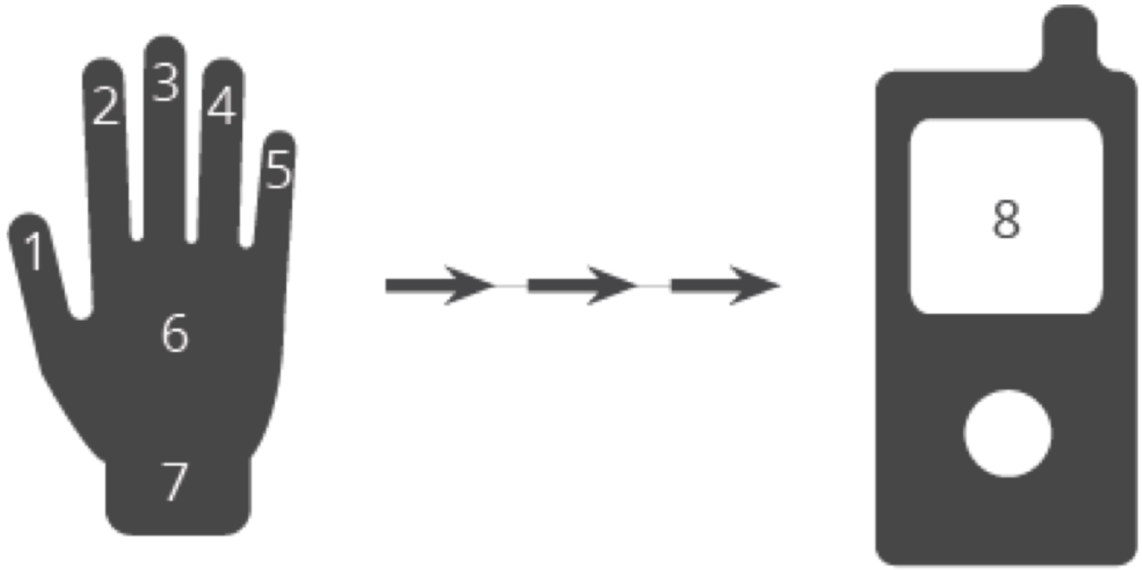


Figure 8.1: Hand and Wrist System and Handheld Device

8.1 **Step 2:** Identification of Human Interaction Factors

8.1.1 Musculoskeletal Interfaces

The human interfaces that will interact with the device are described based on the musculoskeletal interfaces discussed in the Chapter 3. The musculoskeletal interfaces that are relevant for the handheld device application include the hand and wrist system, Figure 8.1. The elements of the hand and wrist that interact with the handheld device, 8 (screen), include the phalanges (fingers, 1-5), metacarpals (palm, 6), and the carpal system (wrist, 7). The hand and wrist system consists of 54 bones.

The identification of the hand and wrist system elements allowed mapping of the relationship between elements and design or product components to be determined, Table 8.1. The linkages between the element and product component mappings and the ranges of the intended interactions also determined. For example, humans were expected to use their hand and wrist to interact with 8, Figure 8.1. The product components of the handheld device that captured the thumb and hand interactions were the button and casing, respectively. Thus, one of the mappings is the thumb $\rightarrow$ button and this interaction is *thumb presses button*. A comprehensive representation of the musculoskeletal interfaces, elements, product components, and interactions for the handheld device is presented in Table 8.1. From the musculoskeletal system and product design perspectives, the interactions require a very specific level of detail to capture and comprehend the levels of interaction that occur between the human being and the handheld device. Two of these interactions were modeled in the demonstration of this application, (1) pressing buttons on device and (2) griping the device.

8.1.2 Functional Classifications

In the handheld device application, the interactions between the human being and the device have been identified. The functional classifications that are relevant include reach (flexion, extension, adduction, and abduction), force (grip, push), tactility (sense), and maneuverability (deviation). While the musculoskeletal interfaces cannot be altered since they are static characteristics of the human being, functional classifications represent the interactions between the human being and the device.

Table 8.1: Musculoskeletal Interface Mapping and Product Interaction

Musculoskeletal Interface	**Element**	**Translation**	**Product Component**	**Interaction**
Hand and Wrist	Phalanges	Fingers	Button	Pressing button to control Pressing button to navigate **Pressing buttons on device (1)** Pressing and holding power button
			Casing	**Griping the device (2)** Inserting external components
	Metacarpals	Palm	Casing	Holding the device
	Carpal System	Wrist	Casing	Positioning the device

Functional classifications can be controlled and adjusted for the population to reduce extreme stress or stain on the body. The functional classifications identified in Section 4.1, are presented for the handheld device application. The mappings of the active functional classifications, the classifications levels, and the product components, are described by interactions, Table 8.2. The interactions provide a general scope of the functional classifications that are active for different interactions that occur between the classification level and the product component for the handheld device application.

The relationship between the interactions identified in the musculoskeletal interface and functional classification mapping are represented in Figure 8.2. A visual demonstration of the active musculoskeletal interfaces and functional classifications identified are mapped with red and green arrows, respectively. The active interfaces or classifications relevant to the interactions are outlined in blue. The relationship between the interactions listed under the musculoskeletal interface and functional classification mappings are represented by the mappings that share the same interactions. An example of a shared interaction is presented in the interaction "pressing button on device, which is shared, by the "reach" and "force" functional classifications as well as the "hand and wrist" musculoskeletal interface. The activated interface elements are fingers, palm, and wrist for "hand and wrist" system. Likewise, the active classification levels are extension, flexion, adduction and abduction for "reach" and grip and push for "force." For the reach level, the actions are expected to occur during an initial starting point and continue to the ending point of the stated interaction: "pressing button on device", Figure 8.2. The specific items

Table 8.2: Functional Classification Mapping and Interactions

Functional Classification	**Classification Level**	**Product Component**	**Interaction**
Reach	Extension Flexion Adduction Abduction	Casing, Button	Selection of items on device
Force	Grip	Casing	Holding the device
	Push	Button Casing	Pressing button on device
Tactility	Sense	Display	Vibration feedback after item selection on device
Maneuverability	Deviation Rotation	Casing	Pressing button on device

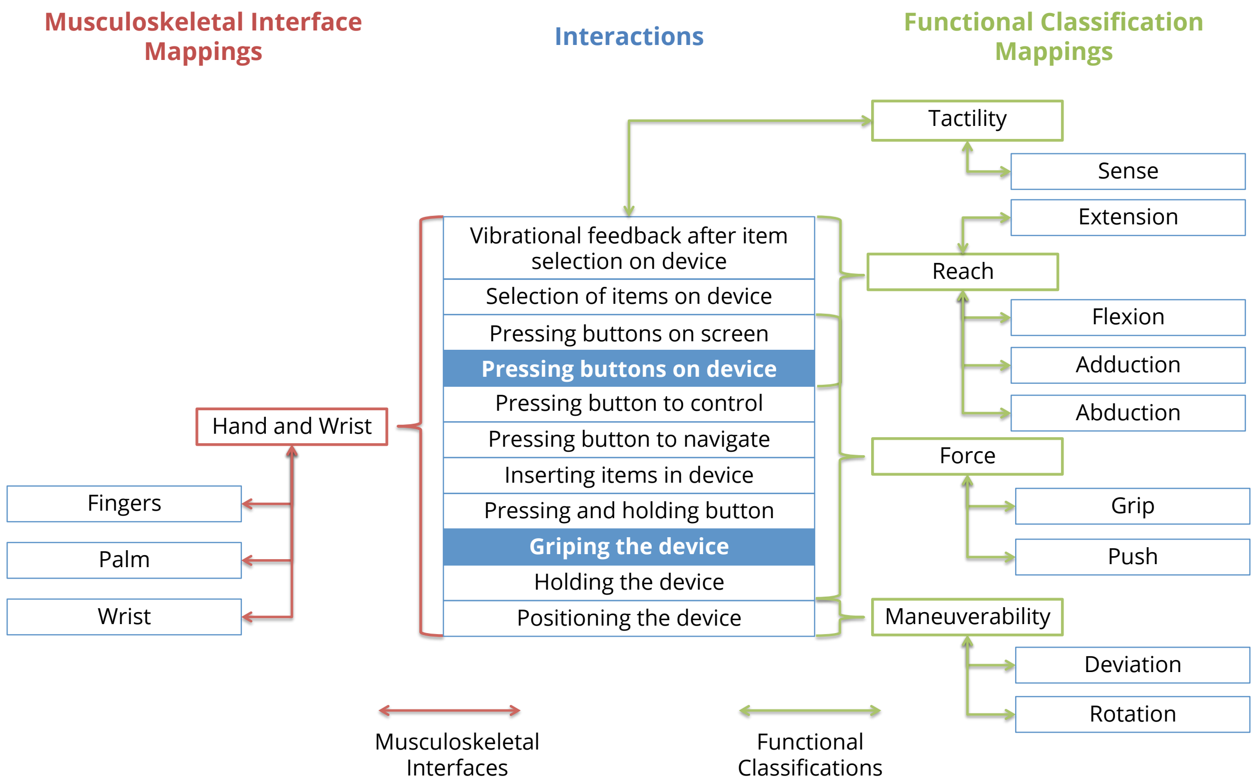


Figure 8.2: Interaction Mappings for Handheld Device

that were modeled include the hand and wrist system for the musculoskeletal interface and reach for the functional classification. Force could not be modeled due to the limitations in the selection of a computation model validation approach for this research method.

Because the functional classification interactions are more general and wider in scope, all functional classifications are active for the one relevant musculoskeletal interface and the common interactions, Figure 8.2. The interactions identified aided in the selection of a parameter range for the musculoskeletal interface elements and functional classification levels. They also provided a portion of the requirements for the design of the button and casing for the handheld device application that was applied in the build and testing phase of the product design. The other requirements were derived from the population and/or additional product specifications but not heavily emphasized as the focus of the demonstration was to validate the technical aspects of this methodology.

8.1.3 Anthropometrics

The target population encompasses adults, ages 18-65 years old, and aging adults, ages 65 years and older. Measurements for these populations were collected from anthropometric databases. The average and standard deviation for men and women in the two target age groups for the relevant musculoskeletal interfaces, *static anthropometrics* and functional classifications, *dynamic anthropometrics* are presented in Tables 8.3 and 8.4, respectively. All values are presented in millimeters and derived from several different databases including the *Bioastronautics Data Book and Anthropometric Data for Domestic and Industrial Standards*, compiled by Pheasant, with some values predating 1983 [51]. Comprehensive anthropometric values for the human variability measures of interest for people 65 and older, in the US, were not available in current anthropometric databases. Moreover, these databases do not truly reflect the physical changes in the US population due to the increase in the size of the average citizen. Thus, the most appropriate measurements from current databases were used in this demonstration with the expectation that, in future work, human measurements and measurement distributions will be obtained and seamlessly integrated into this research methodology.

Table 8.3: Static Anthropometrics: Mean and Standard Deviation for US Adult Population

Musculoskeletal Interface	Element	Measure	US Adult Population			
			Men		Women	
			μ (mm)	σ (mm)	μ (mm)	σ (mm)
Hand and Wrist	Fingers	Thumb Length	51	4	47	4
		Thumb Breadth	23	2	19	2
		Thumb Thickness	22	2	18	2
		Index Finger Length	72	5	67	4
		Index Finger Breadth	21	1	18	1
		Index Finger Thickness	19	1	16	1
		Middle Finder Length	83	5	77	5
		Ring Finger Length	72	4	66	4
		Little Finger Length	55	4	50	4
	Palm	Hand Length	189	10	174	9
		Palm Length	107	6	97	5
		Hand Thickness	51	4	45	3
		Hand Breadth	105	5	92	5
	Wrist	Wrist Thickness	55	4	51	3
		Wrist Length	169	11	151	10

Table 8.4: Dynamic Anthropometrics: Mean and Standard Deviation of US Adult Population

Functional Classification	**Level**	**Measure**	**US Adult Population**			
			Men		**Women**	
			μ (deg)	σ (deg)	μ (deg)	σ (deg)
Reach	Flexion	Wrist Flexion	90	12	62.5	7.1
		Thumb Flexion - **MCP**	68	-	71	-
		Thumb Flexion - **IP**	81	-	81	-
		Index Finger Flexion - **MCP**	97	6.2	97	6.2
		Index Finger Flexion - **PIP**	109.9	8.1	109.9	8.1
		Index Finger Flexion - **DIP**	56.5	15.5	56.5	15.5
	Extension	Wrist Extension	99	13	61	9.6
		Thumb Extension - **MCP**	19	-	28	-
		Thumb Extension - **IP**	33	-	33	-
		Index Finger Extension - **MCP**	72.6	5.7	72.6	5.7
		Index Finger Extension - **PIP**	0	0	0	0
		Index Finger Extension - **DIP**	49.1	9.7	49.1	9.7
	Adduction	Wrist Radial Deviation	27	9	-	-
		Thumb Radial Deviation	62.9	-	62.9	-
		Index Finger Radial Deviation - **MCP**	20.5	6.2	20.5	6.2
		Index Finger Radial Deviation - **PIP**	0	0	0	0
		Index Finger Radial Deviation - **DIP**	3.1	3.8	3.1	3.8
	Abduction	Wrist Ulnar Deviation	47	7	-	-
		Thumb Ulnar Deviation	10.2	4	10.2	4
		Index Finger Ulnar Deviation - **MCP**	27.3	4.9	27.3	4.9
		Index Finger Ulnar Deviation - **PIP**	3	3.8	3	3.8
		Index Finger Ulnar Deviation - **DIP**	5.2	2.9	5.2	2.9

8.1.3.1 Limitations of Existing Data

The collected values assisted in determining the variation of different averages for the adult and the older populations. The presented measurements of joint ranges in the hand and wrist system were only collected for the male population [51]. The dash marks represent information that was not currently available in databases, Tables 8.3 and 8.4. Additional research was conducted to estimate the missing values in Tables 8.3 and 8.4 however the distribution information could not be determined.

There are more missing values present in Table 8.5 due to the fact that many of the measurements for these values were not collected or considered in traditional databases. It is important to remember that the original data collected from the referenced databases are only estimates and it is recommended to conduct user trials in safety-critical applications [51].

The information represented in current anthropometric tables based on the measurements of the human body is referred to as static human variability. The information related to the human interacting with device components is referred to as dynamic human variability data, which is not widely available in literature. However, some researchers have recently explored dynamic/functional anthropometrics to define thumb reach envelopes, postures, and touch interactions for handheld devices [151–154]. The aforementioned research studies provide critical information for handheld device design but do not comprehensively explore the limits of the human both statically and dynamically for optimal hand held device design. All researchers use preference as a decision-making factor in small populations, which in many instances will render the dynamic/functional anthropometric data useless in different populations [152]. This is primarily due to population variation. In smaller samples, the variation captured is not necessarily reflective of the variation in the larger population. Thus, it is extremely difficult to extrapolate or generalize the information derived from smaller samples to the larger population. The present research utilized objective methods based on human biomechanical limits and static and functional anthropometrics to understand the impact of interacting at different interface regions of hand-held devices based on an optimal region. The optimal regions were determined through the concepts of inverse kinematics. The information generated will inform designers of the accommodation impact of their design. Since this method emphasizes optimal regions based on human limits and anthropometric datasets it is expected to be useful in many applications outside of the present demonstration.

Many additional data values related to dynamic or functional anthropometrics are found in independent research studies. Estimates were provided for the missing values through other research studies that may have additional limitations in the optimization values determined due to the limited scope of these studies. For example the vibrotactile feedback value for the functional classification tactility and level sense is derived from current frequencies used in mobile devices based on a study where researchers assess the perceived intensity and roughness of the haptic feedback for 20 (10 male, 10 female) subjects under age 32 [155]. Computational validity limitations associated with measuring force, tactile feedback, and feasible dynamic displacement (active joint metrics during an interaction) with a human model limit the robustness of this demonstration and render population validation for these specific metrics useless. Since these aspects of the functional classifications are not being modeled in this application due to computational validity limitations, future research in this area is encouraged to expand and validate databases for these classification levels. All variables included were collected for the optimization model in lieu of "Population Testing" in step 5 of this methodology, in order to obtain accurate information for future studies.

8.1.4 Summary of Critical Anthropometrics

Based on the musculoskeletal interfaces and functional classifications identified, the anthropometrics that were critical to the trade-off analysis and subsequent optimization model for a handheld device are represented in Table 8.5. The musculoskeletal interfaces and functional classifications are represented in Table 8.5 as a comprehensive representation of the high-level human interaction factors. Along with the human interaction factors that are relevant for the development of the handheld device is the unit of measure for each factor set.

8.2 **Step 3:** Identification of Manufacturing Characteristics

The handheld device design was computationally modeled in the optimization output. The dissertation committee suggested a computation model validation as feedback, so the demonstration of the dynamic application,*i.e. handheld device*

Table 8.5: Anthropometrics for Handheld Device

Interaction Factor	**Units**
Musculoskeletal Interface	
Hand and Wrist	*mm*
Functional Classification	
Reach	*deg*

was not manufactured. In addition, a general performance metric, as defined in this method, was not considered for the handheld device. Instead the performance metric considered was relative distance between product components. This means that the manufacturing characteristics were not linked to the objective function. The performance metric is this instance refers to an engineering performance goal such as stress, strain, force, etc. that would be optimized to ensure the functionality of the product satisfied specified requirements. Due to the dynamic nature of the handheld device application, the complexity was centered in modeling the reach zone of the interactions between the product components. Specifically, the reach zone for the thumb on the phone surface was modeled and the location of the button relative to the handheld device casing was optimized. Thus the full demonstration of the Manufacturing Characteristics, step 3, is presented for the Helmet, static application, in Chapter 9.

8.3 **Step 4:** Trade-off Analysis for Handheld Device Application

The trade-off analysis process described in Chapter 5 is demonstrated in this section. An AHP analysis was performed for each product component in the handheld device application. The first AHP was performed to evaluate the product metrics for the button component based on *anthropometrics* obtained in Section 8.1. The second AHP was performed to evaluate the product metrics for the casing component. The process for conducting the AHP analyses is described in the proceeding subsections. The application of the AQFD method for integrating the product and performance metrics will be demonstrated in the Helmet application since performance metrics were not considered in handheld device demonstration due to the focus on product component interaction. Thus, the proceeding sections focus on phase 1 of the trade-off analysis, specifically the product metrics step with more than one component subsystem, Figure 8.3

8.3.1 Product Metric - Button Component

The anthropometrics obtained in Section 8.1 were mapped to product components based on the interaction between the musculoskeletal interface and functional classification and the product component. For the button the interaction of focus was on *pressing buttons on device*. The button could have several distinct features that impact the interaction between the button and the musculoskeletal interface, which in our case could be a thumb or finger. The features may include the shape, surface, displacement, and resistance. The modeling capacity is limited in reference

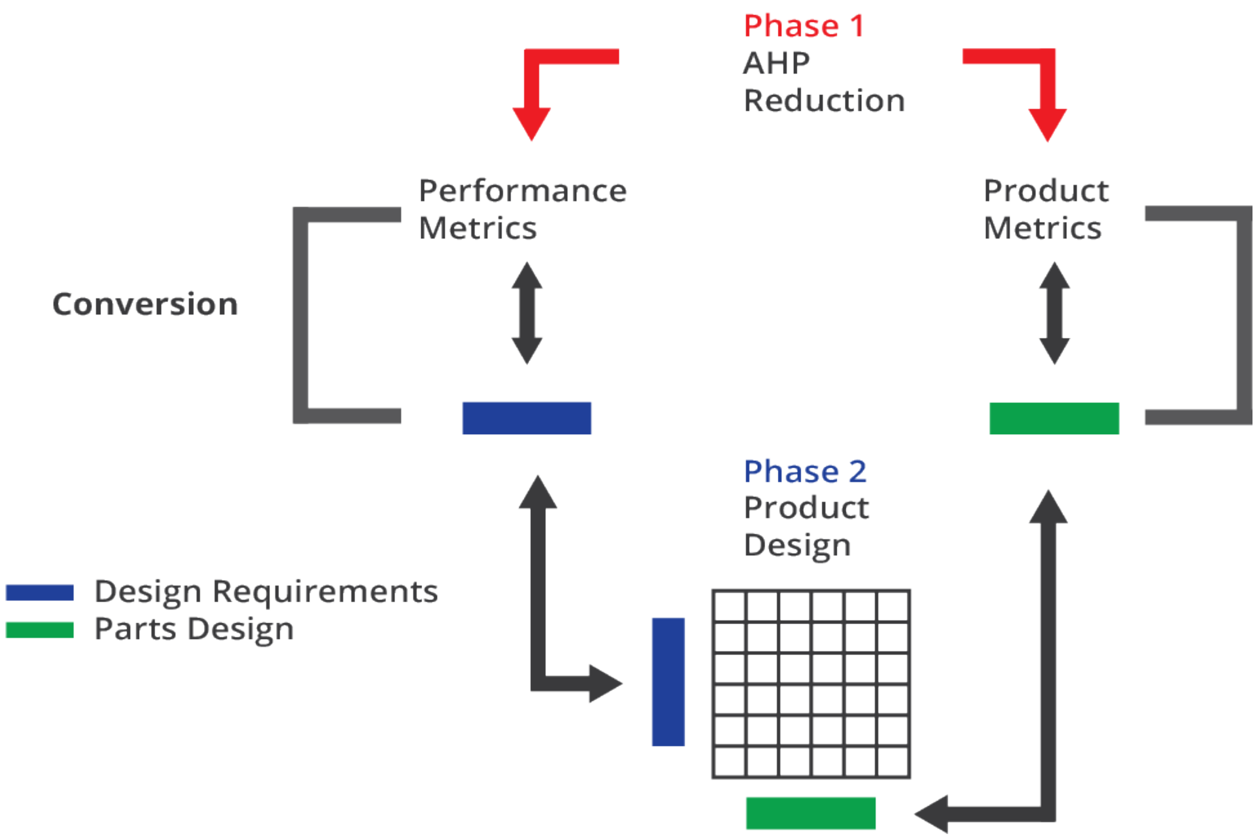


Figure 8.3: AQFD Process, Presented in Chapter 5

to the latter two features. Thus, the focus of feature consideration will be on the shape and the surface.

The shape of a button could be square, triangle, circular, elliptical, rectangle, other polygons, rhombuses, or any combination of shapes. The product metric AHP for the button will evaluate four shapes including: (1) circle, (2) ellipse, (3) triangle, and (4) rectangle. The surface of a button could be convex, concave, flush, or a combination of surfaces. For this demonstration, the button will have the same surface for consistency in the comparison. Based on a pilot study that measured different button features in a small sample population, convex buttons were preferred the most amongst participants, thus this will be the surface of our button. The button shape is determined based on the proceeding AHP analysis, Section 8.3.3.1. After the button shape is determined the button dimensions will be determined in the optimization process, *step 5*, in Chapter 10.

8.3.2 Product Metric - Casing Component

The anthropometrics mapped to the casing product component include the fingers, palm, and the wrist. The finger and palm are examples of primary interactions, which are direct interactions between the musculoskeletal interface and product component. While the wrist is a secondary interaction, which is an indirect interaction where the interface and component do not have direct contact. The measures considered for the musculoskeletal interfaces are the length and breadth while the measures for the functional classifications are the distal interphalangeal

(DIP), proximal interphalangeal (PIP), and metacarpophalangeal (MCP) joints as well as the extension, flexion, and ulnar deviation for each finger. The interaction of focus was on *griping the device*.

The shape of the casing can range in the number of shapes and combinations of shapes. These shapes could include elliptical, circular, square, rectangular, etc. in nature. The AHP for the casing will evaluate three different shape options including: (1) ellipse, (2) rounded square, and (3) rectangle. The dimensions of the casing are also optimized in Chapter 10.

8.3.3 AHP for Product Metrics Selection

The AHP processes for the button and casing product metrics are presented in the subsequent subsections. Each section will visualize the hierarchical tree with the comparison criteria and the alternative shape options. The results of each AHP is presented in a summated results table as initially displayed in Chapter 5 with insight into the consistency amongst comparisons of alternative shape options.

8.3.3.1 AHP for Button

The criterion for the button consists of the anthropometric values observed in Section 8.1. The functional classifications are merged into a single reach category and were evaluated based on the effect that each shape is expected to have on extension, flexion ulnar, and radial deviation, given the anthropometric value for the musculoskeletal interfaces identified. The relevant criteria for the selection of the casing shape are presented in the following list. These criteria apply to both the button and casing components.

1. Thumb Length

2. Hand Length

3. Hand Breadth

4. Palm Length

5. Reach

The hierarchical tree is presented in Figure 8.4. The first step of the AHP process consisted of completing the pairwise comparison for each of the criteria listed. While the criterion does not vary from the button to casing components, the importance for each criteria is altered. The most important criteria for the button component was determined to be *Reach* followed by *Thumb Length*, Figure 8.5. After comparing each of the anthropometric criteria in a pairwise comparison, the shape alternatives are compared for each anthropometric criteria.

The summary of the AHP for the button component is presented in Figure 8.5. The overall inconsistency in the rating was low, however the rating for the palm length criteria was high at 9%. The results reveal that the best button option is the *rectangular shape*. The rectangle and circle shape options were close in comparison with first choice, rectangular shape, having a 33.4% score and the second choice, circular shape, having a score of 33.8%. Thus, the shape that will be considered for the button option is the rectangle.

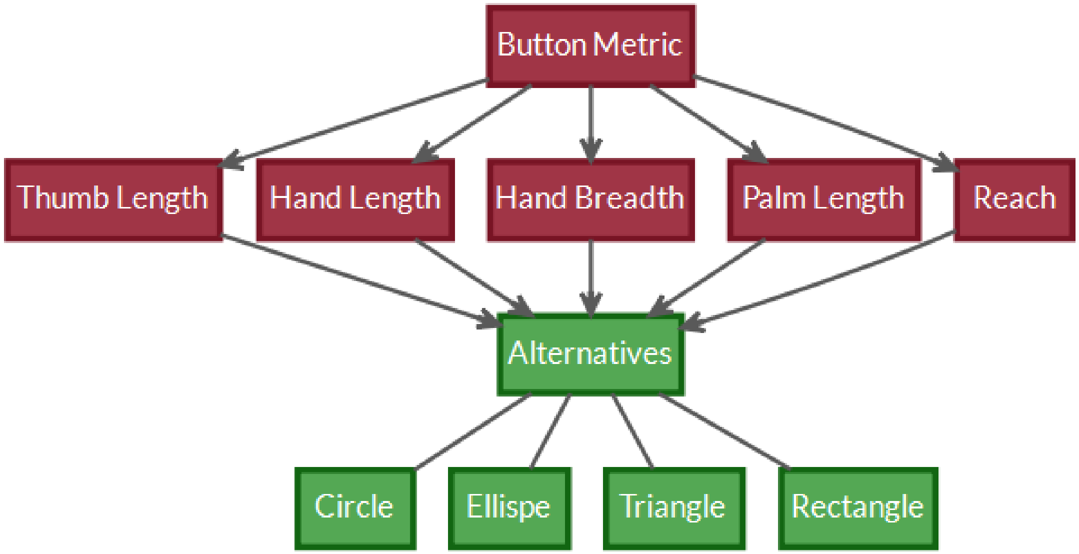


Figure 8.4: AHP Hierarchical Tree for Button Metric

	Weight	Rectangle	Circle	Ellispe	Triangle	Inconsistency
Button Metric	100.0%	34.2%	33.8%	20.0%	11.9%	1.8%
Reach	33.4%	12.6%	9.9%	7.5%	3.4%	1.7%
Thumb Length	29.3%	10.0%	11.2%	4.9%	3.1%	1.7%
Hand Length	15.6%	5.5%	5.1%	3.0%	1.9%	1.7%
Hand Breadth	11.5%	3.2%	3.9%	2.7%	1.6%	2.2%
Palm Length	10.3%	2.9%	3.8%	1.8%	1.9%	9.0%

Figure 8.5: AHP Analysis Results for Button Metric

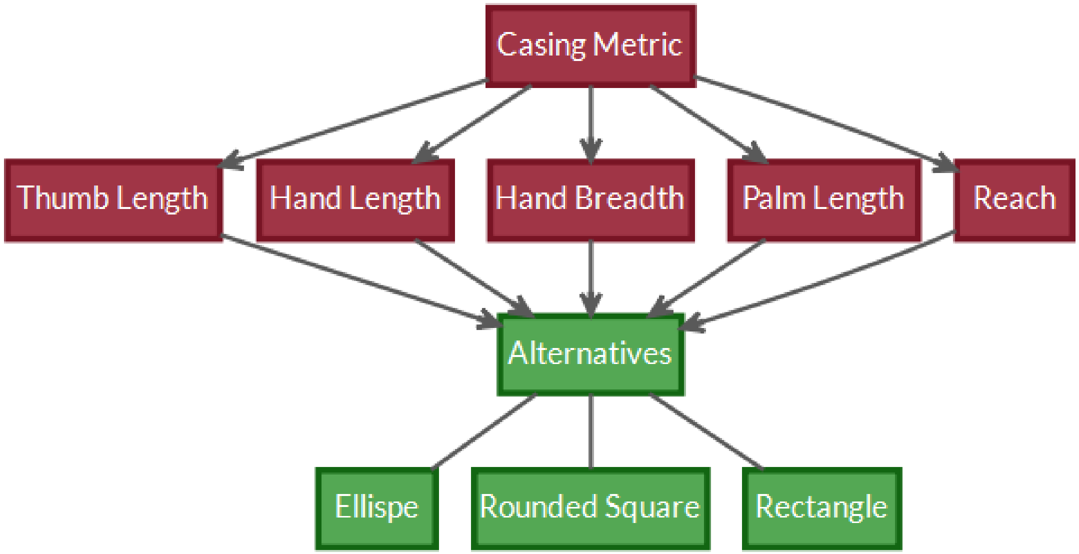


Figure 8.6: AHP Hierarchical Tree for Casing Metric

8.3.3.2 AHP for Casing

The anthropometric criterion for the casing product metric was the same as the button metric. However, in the casing metric the most important anthropometric criteria included the *Hand Length* and *Hand Breadth* followed by *Reach*. The hierarchical tree is presented in Figure 8.6. The results of the AHP are presented in Figure 8.7. The results show that the *ellipse shape* is the best option for the casing. The inconsistency in the rating was relatively low with 4.6 % as the highest value observed for the Hand Breadth criteria.

	Weight	Ellispe	Rectangle	Rounded Square	Inconsistency
Casing Metric	100.0%	50.5%	34.1%	15.4%	1.7%
Hand Length	27.1%	10.8%	10.8%	5.4%	0.0%
Hand Breadth	24.8%	13.1%	8.3%	3.5%	4.6%
Reach	22.0%	12.3%	7.0%	2.7%	1.6%
Thumb Length	14.6%	7.9%	4.3%	2.4%	0.8%
Palm Length	11.5%	6.4%	3.7%	1.4%	1.6%

Figure 8.7: AHP Analysis Results for Casing Metric

8.4 **Step 5:** Optimization

In this section, the product metrics including the square shaped button and the ellipse shaped casing selected for the handheld device are formulated, designed, and optimized for the interaction defined by the functional classification for the target population, Subsection 8.4.1. The handheld device results were validated in an output diagram that showed the optimal button placement in the reach zone for the population.

8.4.1 Optimization Framework for Handheld Device

The optimization framework for the handheld device consists of two main functions, which follow a non-convex optimization framework. This is important and requires careful attention in the selection of the solver algorithm. The goal of this optimization problem was to minimize the relative displacement and parameterize the device components that decrease the extension and flexion of the thumb as it interacts with the handheld device. The objective function is constrained by the lengths and breadths of the population hand sizes and the relative dimensions of the metacarpal, proximal phalangeal, distal phalangeal of the thumb in a Gaussian distribution of hands. The formal definitions of the objective (relative displacement) and constraint (accommodation) are defined:

1. Relative Displacement

    - the comparative orientation of handheld device components while interacting with the hand through varying the spatial-geometric dimensions of the handheld device components and producing the number of devices needed to satisfy population constraint given interaction constraints for the human and device.

2. Accommodation

    - fitting the handheld device components to the dimension of the relevant human parameters, including the thumb breadth and length for the handheld device application.

8.4.2 Handheld Device Application

The components of the handheld device application that were modeled for this optimization problem include a button and casing. The goal of the optimization problem is to minimize the relative displacement between the button and the reach

Figure 8.8: Reach Envelope for Thumb on Device Surface

zone of the casing. The reach zone of the casing is defined by the reach envelope trajectory along the frontal plane. In this demonstration, the axis of motion is the anteroposterior axis. In addition, the range of thumb flexion defines the reach envelope or interaction design space, Figure 8.8, across the frontal plane of the device surface [152, 156].

The human body is split into three planes the coronal (frontal), sagittal, and traverse, Figure 8.9. The respective axes of the planes are mediolateral, anteroposterior, and craniocaudal. For the handheld device, the flexion of the thumb occurs in the frontal plane with the possible range of motion is along the anteroposterior or sagittal axis. In general, the frontal plane captures the range of motion referred to as adduction and abduction, along the anteroposterior axis. The traverse plane captures the range of motion referred to as twist and rotation, about the craniocaudal axis. The sagittal plane captures flexion and extension of all other body parts, along the mediolateral axis. The interest of this problem is limited to the reach envelop defined by the active and functional range of motion (AROM and FROM) for thumb flexion, 42.5° and 35°, respectively [157,158]. The reason for this focus on thumb flexion is due to the fact that interaction between the hand and the thumb is defined by the flexion in the metacarpophalangeal joint (MCP), interaction does not occur when the thumb is in a extended state at this joint. On the other hand, the proximal and distal phalangeal joints, PIP and DIP respectively, assist in defining the lower limit of the reach zone for each individual with flexion and extension of the distal phalangeal joint. The FROM for the PIP and DIP joints are 55 and 80, respectively, in terms of flexion [158]. The extension for the DIP, PIP, and MCP are 15°, 10°, and 25°, respectively [158].

Comfort is defined in ergonomics by changing positions often and maintaining neutral postures [159]. Thus, the placement of components is optimized when they fall within the reach zone closer to the lower limits of the angle ROM. The thumb reach envelope was calculated based on the extension and flexion of the thumb in 2 poses. The first posture includes an initial extension state of the thumb on the surface edge of the device, Figure 8.10. The second posture slightly flexes the MCP and PIP joints in initial extension position and fully flexes the DIP joint on the

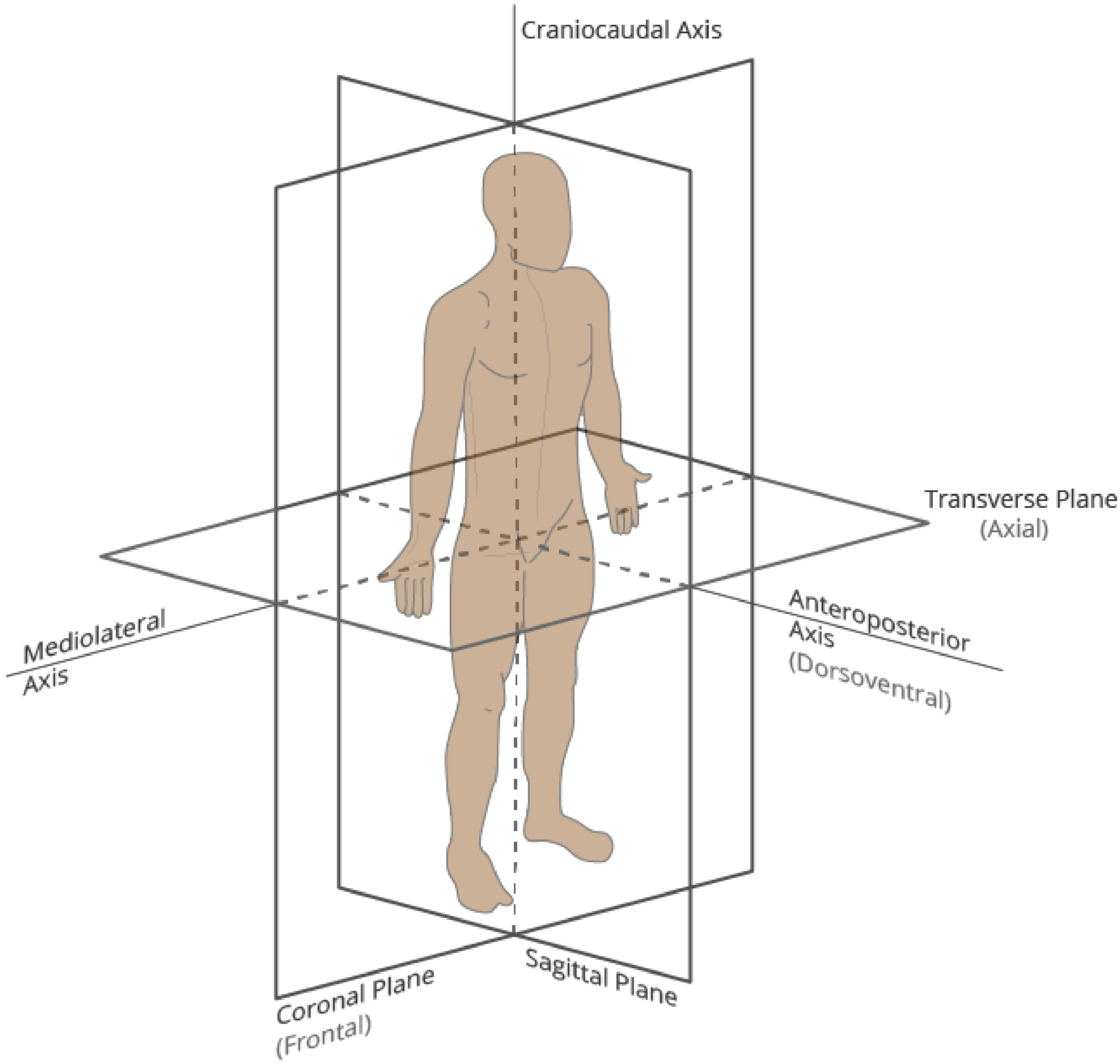


Figure 8.9: Anatomical Planes and Movement Axes

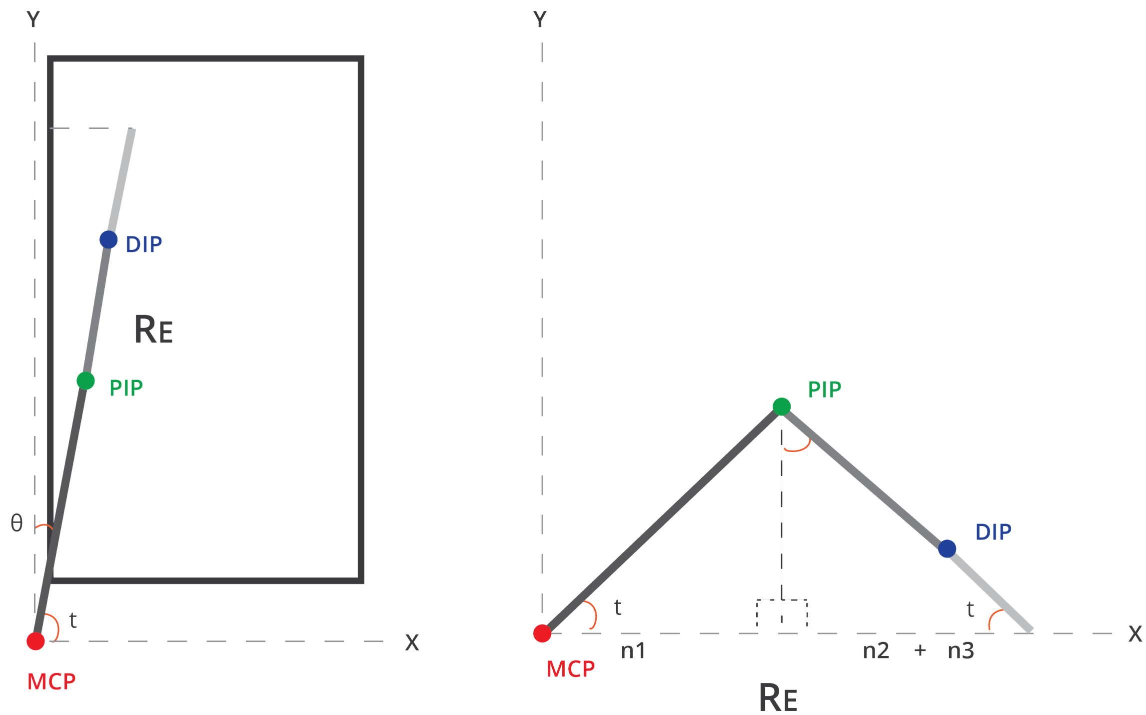


Figure 8.10: Thumb Reach Zone Joint Orientations: Extension (Position 1)

top surface of the device, Figure 8.11. These postures are referred to as R_E for the first position which is considered the extension position and R_F for the flexion state. These positions are used to calculate the reach zone of the device at the MCP angle of 35°. A detailed view of the two positions provides more insight into the calculation of R_E and R_F, Figures 8.10 and 8.11. Theta values for the angles of DIP, PIP, and MCP values at each position are represented in Table 8.6.

Each position of Thumb relative to the device, generates a point that creates the reach zone space. The x-y point generated at each position is parameterized to a circle which correlates range of space available between the radius, R, of the Thumb on the device surface with the distal phalanx in flexion and extension. Thus, the x and y coordinates are parameterized by theta (t in extension and flexion poses),

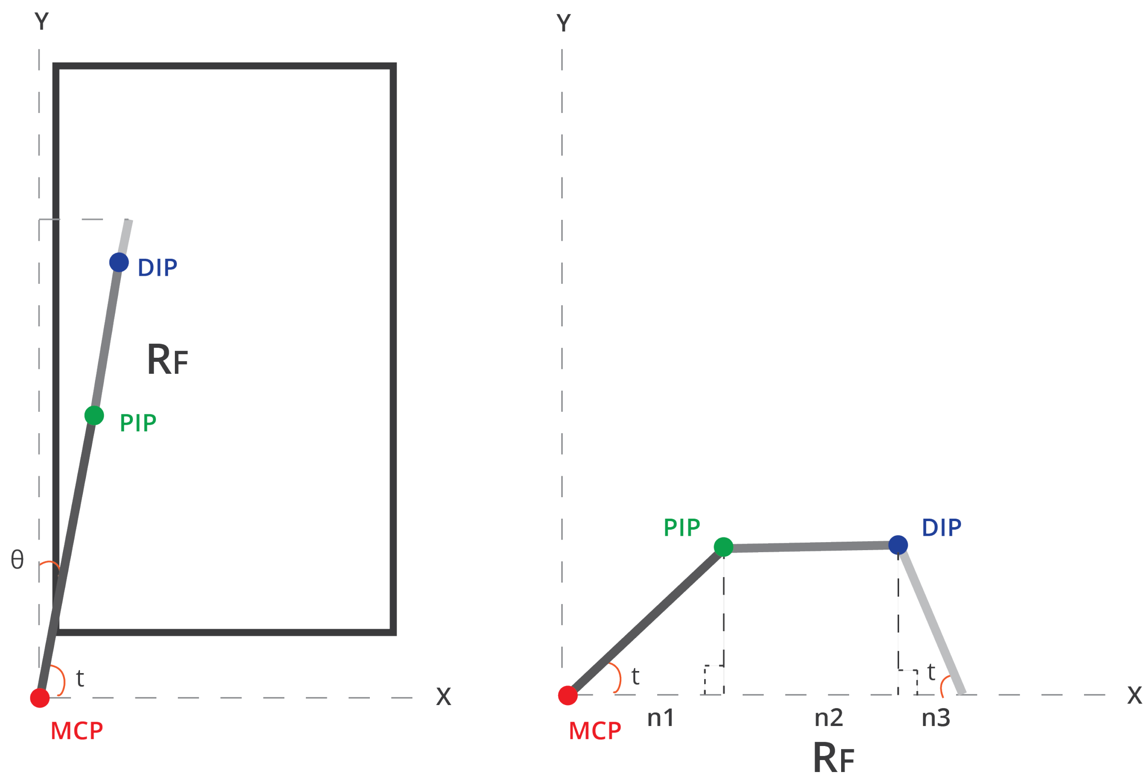


Figure 8.11: Thumb Reach Zone Joint Orientations: Flexion (Position 2)

Table 8.6: Thumb Angles for Reach Zone Positions

Thumb	**Position 1 (°)**	**Position 2 (°)**
Distal Interphalangeal	8.0	72.0
Proximal Interphalangeal		49.5
Metacarpophalangeal	3.5	31.5

which ranges from 0 to 62.9° for the abduction across the phone surface of the metacarpophalanx, which is the bone where the thumb and device interaction at the surface of the device begins, Equation 8.1

$$\begin{aligned}
&(X_N, Y_N) = F(\theta) \\
&where \\
&\theta = 0...62.9 \\
&X_{1...N} = R_{1...N} \times cos(\theta) \\
&Y_{1...N} = R_{1...N} \times sin(\theta)
\end{aligned} \tag{8.1}$$

8.4.3 Formation of Problem

The results of the AQFD, Chapter 8, provided the shape of the button and casing components. The shapes include a square and ellipse, respectively. The design variables for the optimization model include the button length, casing length, and casing width. The constraints are defined by the hand length and hand breadth, Table 8.7, and include the parametric lengths, Table 8.8 of the thumb digits, which define the reach envelope for each individual in the sample [158,160]. The parametric lengths of the thumb were very important for determining the reach envelope for each person in the sampled population.

The formation of the handheld device optimization problem is defined by the design variables, constraints, and objective(s). Due to the fact that both the objective and constraint function are non-linear, it was important to observe and validate the correct mathematical model that best fits the data in order to accurately calcu-

Table 8.7: Constraint Variables for Population Accommodation

Variable	US Adult Population			
	Men		Women	
	μ (mm)	σ (mm)	μ (mm)	σ (mm)
Hand Length	189	10	174	9
Hand Breadth	105	5	92	5

Table 8.8: Parameterized Thumb Lengths Based on Overall Hand Length

Bone Name	Length (mm)
Distal Interphalangeal	$0.158 \times$ Hand Length
Proximal Interphalangeal	$0.196 \times$ Hand Length
Metacarpophalangeal	$0.251 \times$ Hand Length

late the optimal solution. The correct model selection is also important for giving the model a precise initial guess for the solver algorithm.

The design variables for the handheld device design include button length, casing length, casing width. Button length equals button width since the AQFD results presented a square for the button shape. The objective function is the distance equation, which minimizes the relative distance between the button and casing. The distance should not exceed the length of the casing in a space where the components no longer interact. The constraint function follows a Gaussian distribution and constrains the space by the hand lengths and breadths for men and woman in the population. Due to the fact that men and women must be modeled, the constraint function follows a multimodal distribution, which creates a non-convex problem. The selection of the solver algorithm was important because depending on the path or method that a particular solver takes it can either fail to solve or take extremely long as it approaches local minima or maxima. Fmincon was initially selected but the algorithm became continuously confused finding minima close to the initial value or failing to solve because the non-convex nature of the function. Thus, the algorithm could never find a minimum point without the subsequent points increasing. On the other hand, the Patternsearch function released in the global optimization package of MATLAB®, provides a more robust solver that completes 4 time steps and at 4 points around the given point at each step and makes a decision based on the location of the lowest point. This allows one to model non-linear constraints similar to Fmincon but obtaining a better solution for a single objective problem. Figure 8.12 provides the details of the optimization considerations in this problem.

8.4.4 Optimization Design

The objective function calculates the relative distance, D, between two points, one point is at the center of the button of the other at a point in the x-y coordinate of the casing. Equation 8.2 represents the objective function where x_1 is the x-position of the button, x_2 is the y-position of the button, x_3 is the length of the button, x_4 is the width of the casing, and x_5 is the length of the casing. The goal of the objective function is to minimize the distance between the button and the casing within the thumb reach zone defined by the accommodation constraint. The accommodation

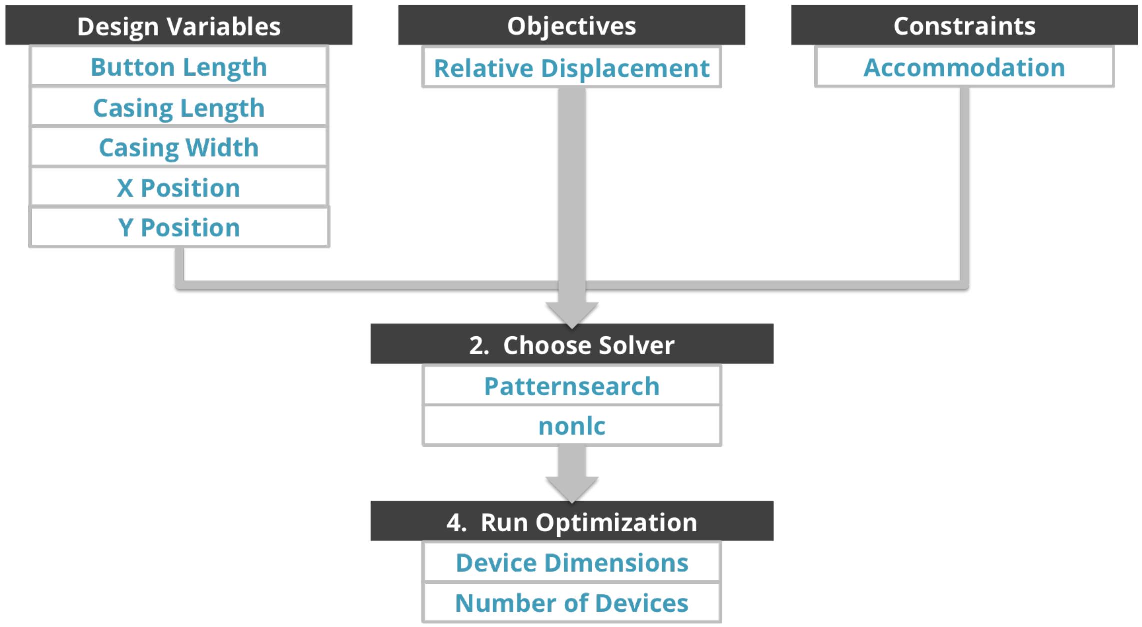


Figure 8.12: Optimal Design Plan

function, A, calculates a reach zone of the device interface based on the maximum extension and flexion of the thumb, Equation 8.3. It subsequently creates a reach region for possible interactions on the x-y plane of the device surface. The lower limits of casing length and width are limited by the size by the hand breadth and length dimensions and based off a previous pilot study that determined the preferred measurements of a device based on literature for component dimensions.

$$
\begin{aligned}
\min_{x} \quad & D(x) = \sqrt{\sum_{i=1}^{n} (\mathbf{c_n} - \mathbf{x_n})^2} \\
\text{s.t.} \quad & A(Y) \geq 95 \\
0 \leq & \; x_1 \leq 100 \\
0 \leq & \; x_2 \leq 125 \\
8 \leq & \; x_3 \leq 14 \\
35 \leq & \; x_4 \leq 200 \\
105 \leq & \; x_5 \leq 400
\end{aligned}
\tag{8.2}
$$

where

x_1 : is x-position of button.

x_2 : is y-position of button.

x_3 : is button length.

x_4 : is casing width.

x_5 : is casing length.

$\mathbf{x_n} = [x_1, x_2]$

$\mathbf{c_n} = [x_4, x_5]$

$$
A(Y) = \frac{\sum_{i=1}^{N} Y_i}{N} \times 100 \tag{8.3}
$$

where

$Y_i)$: is a binary variable for accommodation.

N : is the population sample.

A Monte Carlo approximation is also applied at this point to the norm or relative distance, $D(\hat{x})$, objective function, Equation 8.4. The application of Monte Carlo allows for the summation of the relative distance(s) among the population in an effort to obtain an accurate estimate of the population sample size. This is important because insight can be drawn regarding the impact of the solutions in the actual population through understanding the relationship between population sample and accommodation.

$$D(\hat{x}) = \frac{1}{N}\sum_{i=1}^{N} D(x_i) \tag{8.4}$$

where

$D(x_i)$: is relative distance between button and casing component for each person

$D(\hat{x})$: is relative distance estimate for the total population

N : is population sample size

8.4.5 Optimized Handheld Device Design Results

The results of the optimization solution reveal that 1 device is required to accommodate the population. In addition, the optimum solution set for the handheld device is presented, Figure 9.11. Based on the results, one device accommodates both the male and female population, Figure 9.12. The relative position of the button in the thumb reach zone, Figure 9.13, for the optimal solution is presented. This

Figure 8.13: Population Distribution of Hands

reach zone contour depicts total population accommodation when alpha is shaded and no accommodation when alpha is translucent or unshaded in the reach zone. The x and y axes represent the maximum extension length along casing and casing width, respectively.

8.5 Conclusion

The product metrics, including the button and casing components of the hand-held device, were analyzed in this demonstration of the human interaction factors (step 2), trade-off analysis process (step 4), and optimization model (step 5) in

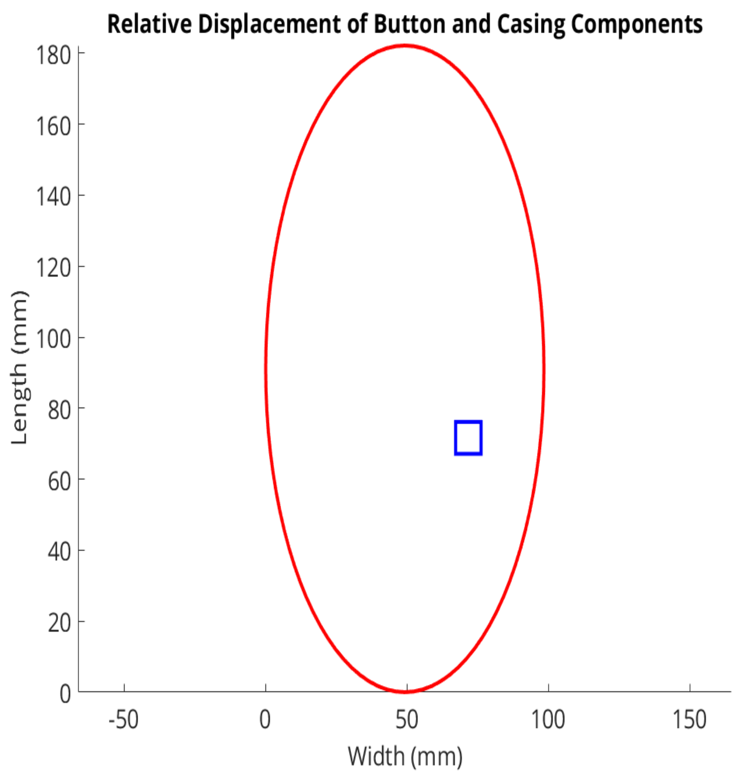


Figure 8.14: Relative Displacement of Components

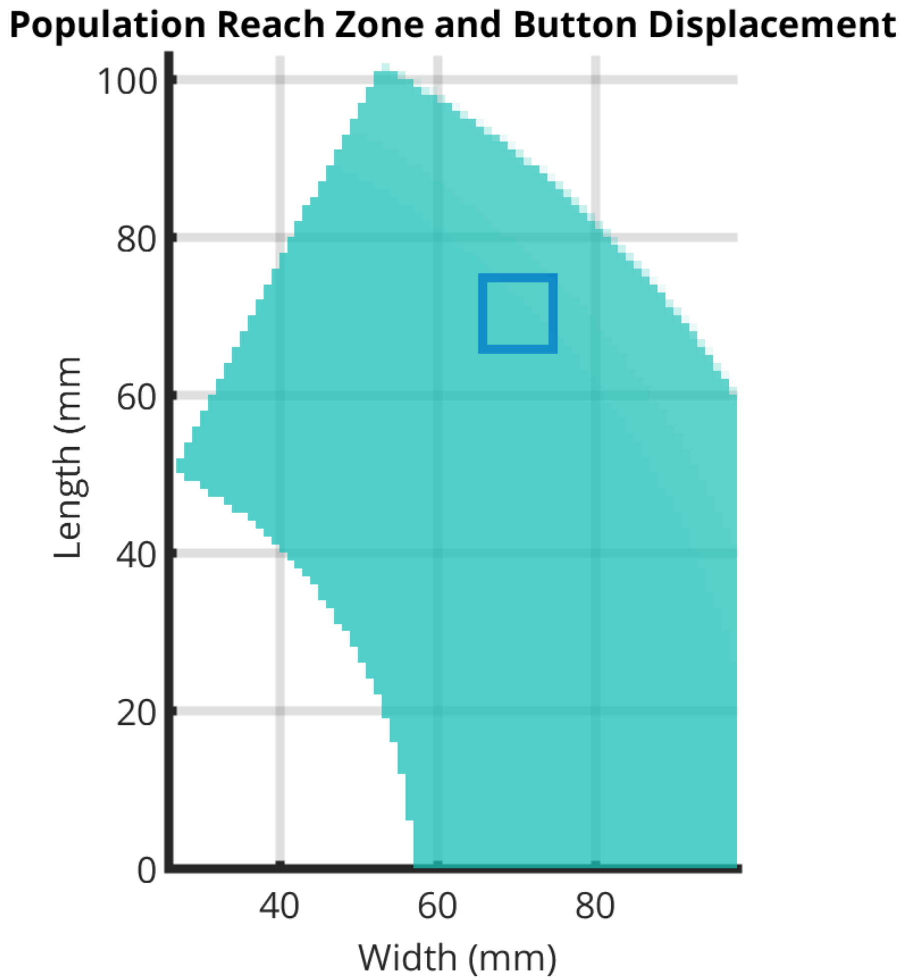


Figure 8.15: Button Component Placement in Thumb Reach Zone w.r.t Casing Width

Sections 8.1, 8.3, and 8.4 respectively. As discussed previously in this chapter, the manufacturing characteristics were not observed for the demonstration. The focus of the dynamic demonstration was on optimization model for the dynamic application modeling the interaction space. The best component shapes for the handheld device were revealed to be a rectangle for the button and an ellipse for the casing. The dimensions and relative placement of these components was optimized in the optimization model.

Chapter 9: Demonstration of Helmet Application

The demonstration of the helmet application mimics the structure of the handheld device application. For the handheld device application, the focus was on demonstrating the process for optimizing the primary functional classifications of the musculoskeletal regions, which requires a process of identifying and defining interactions. The helmet application also identifies the musculoskeletal interface but there is no functional classification associated with the braincase, which is the musculoskeletal interface identified for interaction, thus the helmet is a static application, which focused on fit as a form of interaction variability in the optimization model. The helmet application had a two-fold goal and required detailed and distinct investigations of helmet fit and the helmet heat exchanger. The helmet fit was determined with investigations of gap and comfort along with head dimensions, while the helmet heat exchanger was the performance metric, which had a thermal-driven goal of cooling the human head in hot, dry climates. Since portions of the HX were additively manufactured additional research was required on the impacts of AM process parameter on thermal performance. The helmet application focuses on optimizing the performance metric, which was not considered in the handheld device application. The addition of the performance metric is explored with a structured

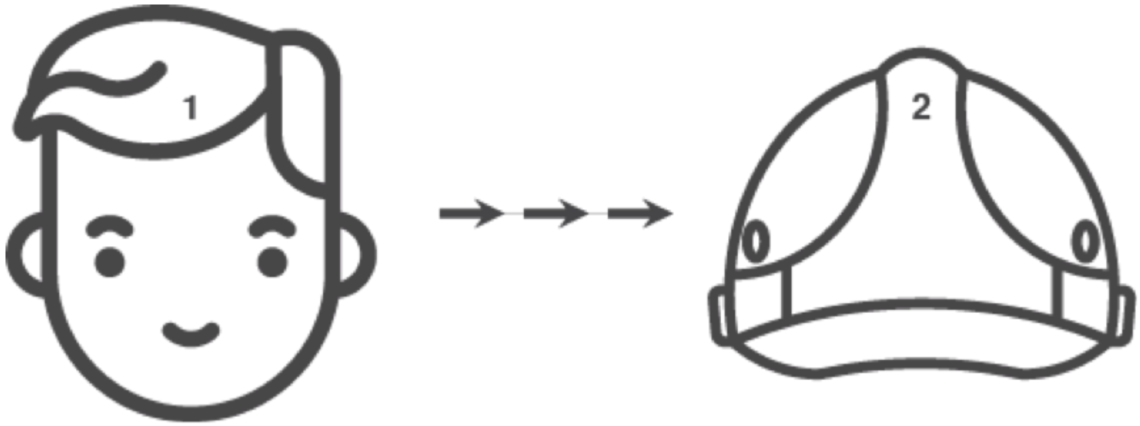


Figure 9.1: Braincase System and Helmet

focus on thermal performance. Chapter 9 details steps 2-5 of the methodology for the helmet application. Section 9.1 provides human interaction factors. Section 9.2 provides manufacturing characteristics for AM. The AQFD full method is applied in Section 9.3, which provides the product and performance metrics for the optimization model. The optimization model for the helmet is presented along with the surrogate and thermal models, which describe the relationship between AM process parameters and thermal performance, Section 9.4. The design focus of the helmet design is for use in a dry hot climate in a military application. The specification and requirements are discussed in the proceeding sections.

9.1 **Step 2:** Identification of Human Interaction Factors

9.1.1 Musculoskeletal Interfaces

The musculoskeletal interfaces that are relevant for the helmet include the braincase, face, and ears. The elements of the braincase that interact with the helmet include the neurocranium (skull). The braincase system consists of 8 bones; all of which are important for the helmet application [94]. The face and ear system consists of 22 bones [94]. The helmet will not have direct contact with the ear, the design provides additional space that is intended to house headphones underneath the helmet. However, when helmet is fully utilized it may apply additional pressure to the ear, which may impact the internal bones in the ear. This is unlikely to occur without heavy impacts that damage outer layer bones first. The relevant bones in the face consist of the zygomatic. Other important bones that are possibly relevant include: maxilla, mandible, nasal, and vomer. For the purpose of this demonstration, the specific musculoskeletal interface of focus will be the braincase labeled at 1 in Figure 9.1. Since the design of interest is a Kevlar military helmet, the emphasis of the design is based on the surface area of the head because the sides of the helmet are not meant to fit the ears and the face is not covered, Figure 9.2.

The mapping of the relationship between elements and product components for the helmet application are depicted in Table 9.1. The product components of the helmet are surface area of the helmet shell and padding which includes a gap metric, Table 9.1. The interaction will occur between the surface area of the human head and the padding, which is required for the head to hold the helmet on the head. Padding is the only component the directly interacts with the braincase.

Figure 9.2: Ballistic Kevlar Military Helmet

Table 9.1: Musculoskeletal Interface Mapping and Product Interaction

Musculoskeletal Interface	**Element**	**Translation**	**Product Component**	**Interaction**
Braincase	Ethmoid Frontal Occipital Parietales Sphenoid Temporals	Head(Skull)	Padding	**Pressure feedback into padding**

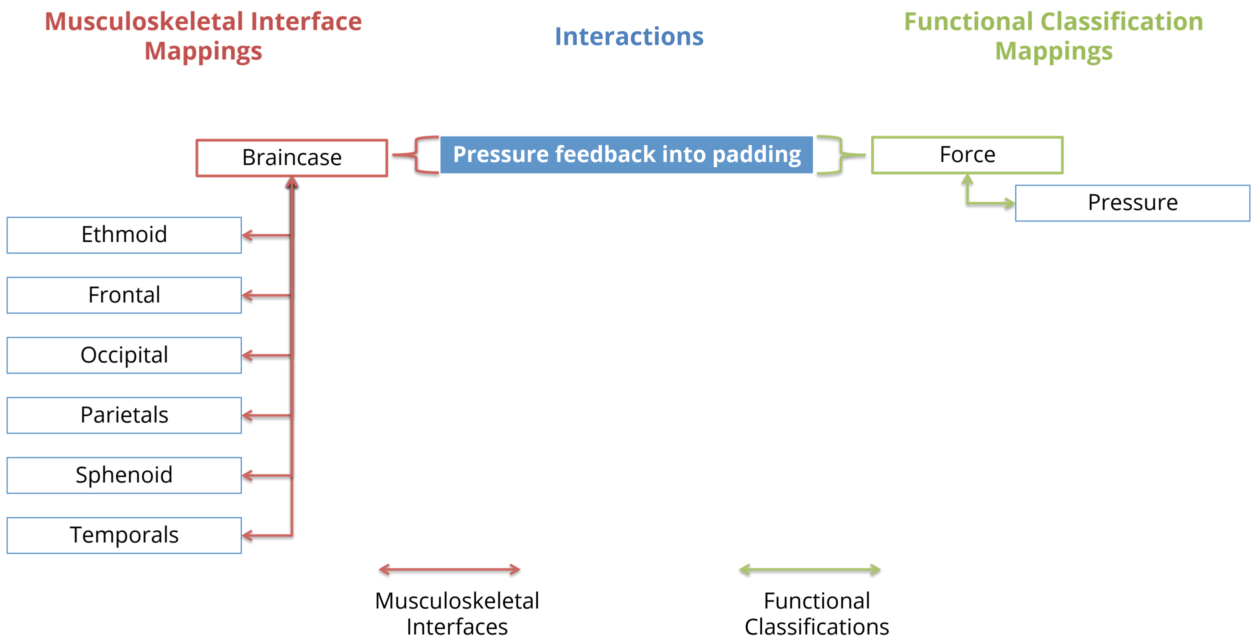


Figure 9.3: Mapping Interaction for Helmet

9.1.2 Functional Classifications

The helmet is a static application, thus the relevant interactions that occur after the initial interaction are present in the form of pressure applied to the braincase musculoskeletal interface. Table 9.2 shows the mapping relationship between the function classifications that result in applied pressure. The interaction mappings for the musculoskeletal interface and functional classification interaction reveal just one interaction, Figure 9.3.

9.1.3 Anthropometrics

Tables 9.3 and 9.4 represent the anthropometric data necessary to determine the measurements that are needed to capture the variability of the relevant mus-

Table 9.2: Musculoskeletal Interface Mapping and Product Interaction

Functional Classification	Classification Level	Product Component	Interaction
Force	Pressure	Padding	**Pressure feedback into padding**

culoskeletal interfaces and functional classifications in the population. Specific anthropometric measurements of interest include the head circumference, head breadth (width), and head length [51].

In assessing helmet accommodation, researchers examined the effectiveness of three-dimensional (3D) scanners. Experimentation with a 3D scanner and probe revealed that 3D systems were more conservative in measuring standoff (SOD) distances for assessing helmet accommodation [161]. Researchers also confirm the selected anthropometric measures, as they found head length and breadth to be more robust for measuring SOD distances for fit than head circumference [161]. There is limited information on head circumference but is can be calculated from the head length and breadth values. Another option that is considered is a supplemental data set for a study conducted at the department of defense, which collected head and face anthropometric data including head circumference data on a population of 367 (195 female, 172 male) US civilians ages 17-69 [162]. The pressure data is also missing but due to the computation method of analysis the application of force to the head will not measured. In future work, an actual helmet will be developed and tested on a manikin head at this point the pressure will be calculated based on maximum force data for skull fractures with applied compression force [163]. This data provides an ideal of the maximum compression that can be applied to the skull before injury occurs [163].

Table 9.3: Static Anthropometrics: Mean and Standard Deviation for US Adult Population

Musculoskeletal Interface	**Element**	**Measure**	**US Adult Population**			
			Men		**Women**	
			μ (mm)	σ (mm)	μ (mm)	σ (mm)
Braincase	Skull	Head Circumference	574.54	16.22	549.84	20.48
		Head Length	195	8	180	8
		Head Breadth	155	6	145	6

Table 9.4: Dynamic Anthropometrics: Mean and Standard Deviation of US Adult Population

Functional Classification	**Level**	**Measure**	**US Adult Population**			
			Men		**Women**	
			μ (N)	σ (N)	μ (N)	σ (N)
Force	Pressure	Maximum Skull Compression	622.8	-	622.8	-

9.2 **Step 3:** Identification of Manufacturing Characteristics

AM was selected as the manufacturing process for the demonstration of the helmet application. The specific AM process selected was FDM, which is categorized under material extrusion. FDM provided flexible material and rapid prototyping options for the helmet heat exchanger design. More specifically, the heat exchanger was designed passively therefore low thermal conductivity materials that serve the dual purpose of helmet padding and heat piper holders were needed. FDM applications allowed for the heat pipe holders to be designed and swiftly prototyped with flexible material for thermal performance evaluation.

The FDM application is most commonly associated with 3D printing and many researchers, makers, and designers have contributed to an open source community that supports research and development. The FDM printers on the market in many instances are developed to work with open source software allowing the user to control more parameters on the printer. This was specifically useful for this demonstration because it was important to understand the impact that machine controls have on thermal performance. The characteristics associated with the material extrusion process in general as well as those related to a fused deposition modeling process, such as the Lulzbot TAZ 5, are depicted in Table 9.5. The specific characteristics that are inherent to the Lulzbot TAZ 5 and other FDM printers, Figure 9.4, include: all material extrusion characteristics, material color variations, fill pattern (i.e. grid, lines, etc.), fill density (i.e. 40%), print head, and print speed Table 9.5.

This machine is relatively sophisticated and provides open-sourced programs

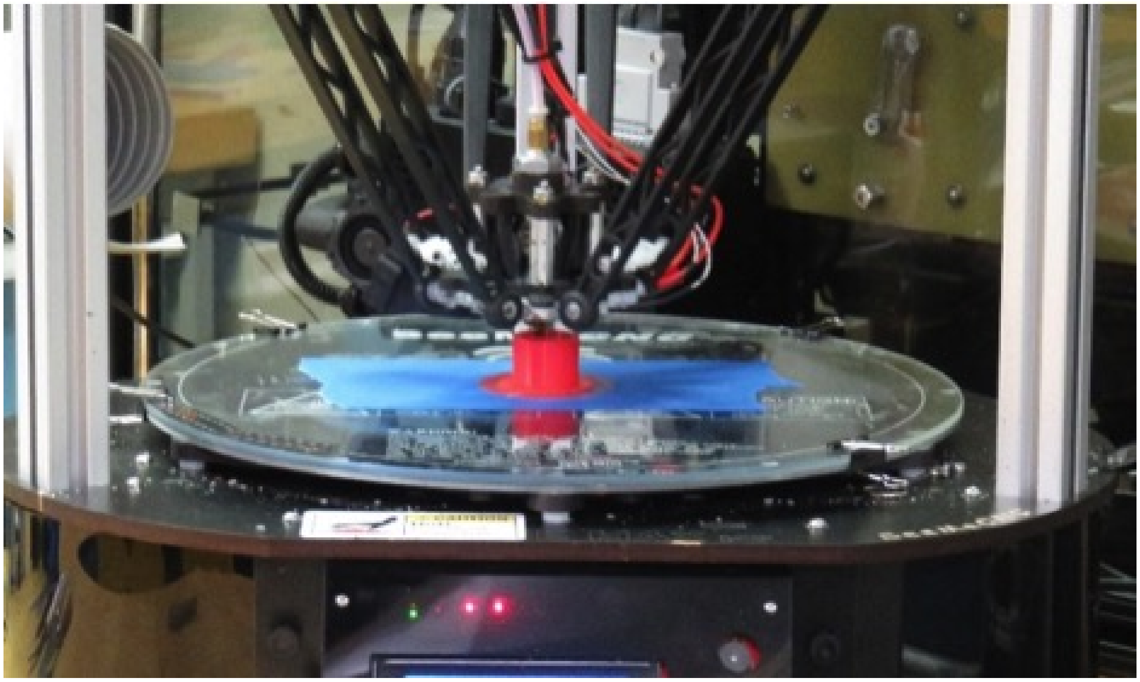


Figure 9.4: FDM Application for a 3D Printer

that allow for advanced control options. Since there was limited knowledge of the impact that different control-settings have on thermal performance, experimental research was required to obtain this information. A study to obtain the required information was conducted at Los Alamos National Laboratory in the Thermal and Mechanical Engineering Additive Manufacturing Research and Development Group.

A design of experiments (DOE) was performed to understand the impact of the manufacturing characteristics on thermal performance (i.e. Surface Temperature and Thermal Conductivity). These characteristics included material, layer height, and infill density. This study had limitations in the amount of heat loss from the power supply to the heater. However, it provided great insight for the development of an ANSYS thermal model to predict the thermal behavior as the

Table 9.5: Manufacturing Characteristics for the Material Extrusion Process and Lulzbot TAZ 5

Manufacturing Characteristics	**Material Extrusion Process**	Lulzbot TAZ 5
Build Area	○	
Layer Height	○	
Material	○	
Support Material	○	
Polymer Color		○
Fill Pattern		○
Part Density		○
Print Head		○
Print Speed		○
Nozzle Radius	○	

product changes. The process for the selection of the manufacturing characteristics and relevant thermal performance metrics will be discussed in the next section.

The selection of the AM process, Material Extrusion, and the machine type, Lulzbot TAZ 5, allowed for the identification of all relevant manufacturing characteristics. The manufacturing characteristics along with the number of levels, types of levels, and units of measure are represented in Table 9.6. The manufacturing characteristics will be further investigated in step 4 as they inform the development

Table 9.6: AM Process Metrics for Helmet

Characteristic	**Units**
Material Extrusion	
Layer Height	*mm*
Material	*kg*
Lulzbot TAZ 5	
Part Density	%

of the thermal performance objective function.

9.3 **Step 4:** Trade-off Analysis for Helmet Application

The trade-off analysis process for the *Anthropometrics* and *AM Process Metrics* generated in Sections 9.1 and 9.2, respectively, is presented here. The first AHP was performed to evaluate the product metrics based on Anthropometrics observed in Section 9.1. The second AHP was performed to evaluate the performance metric based on the AM Process metrics obtained in Section 9.2. Similar to the handheld device application, the proceeding section outline to process for obtaining the product and performance metrics though the application of the AQFD methodology presented in Chapter 5, Figure 9.5.

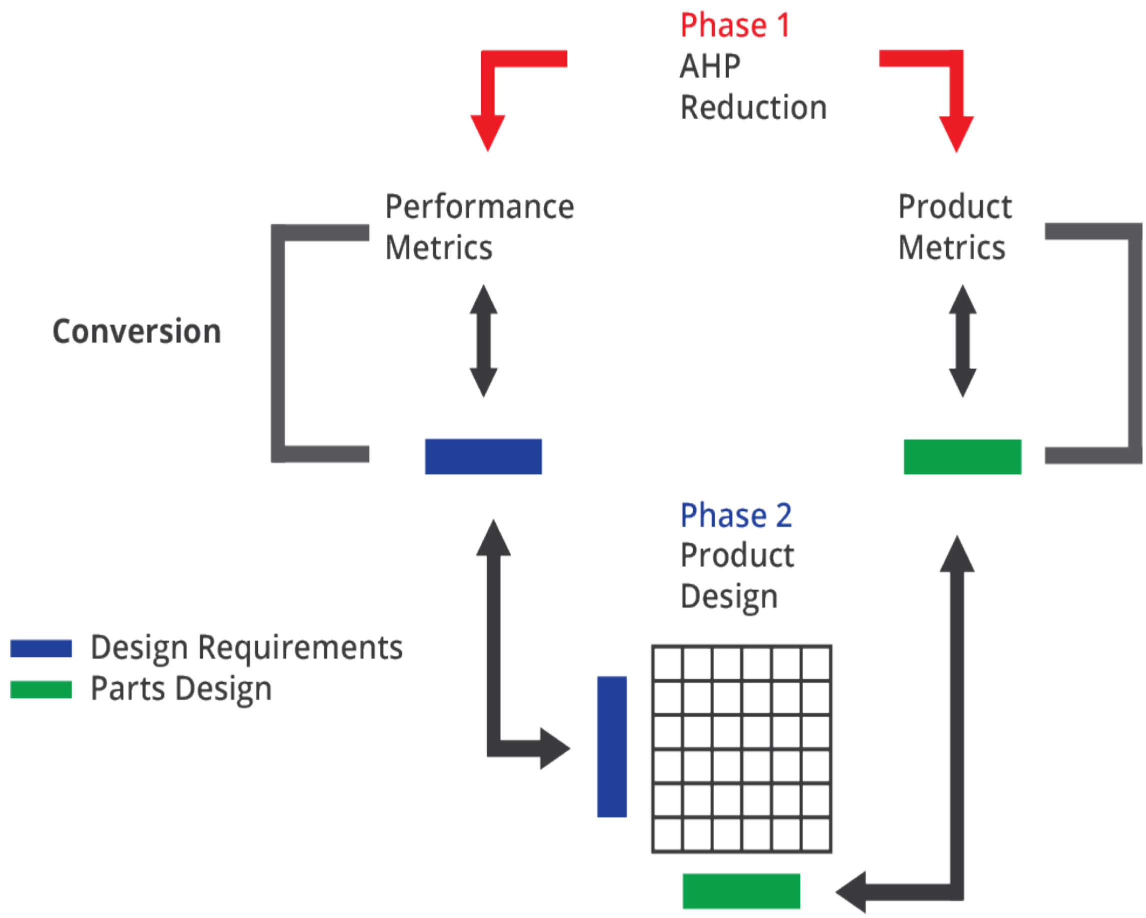


Figure 9.5: AQFD Process, Presented in Chapter 5

9.3.1 Product Metrics

The Anthropometrics obtained in Section 9.1 were mapped to product components based on the interaction between the musculoskeletal interface and functional classification and the product component. For the helmet the interaction of focus was on *pressure feedback into padding*. The helmet is a static application, so the only expected interaction is a continuous application of pressure to the head. The product metrics are important for determining the best approach for modeling the helmet so that it will fit the head.

A shape that captures the dimensionality of the head will provide the best helmet fit. The product metric options include: (1) Helmet Surface Area, (2) Helmet Circumference, (3) Hemisphere Surface Area, (4) Body Surface Area, (5) Ellipsoidal Cap Surface Area, and (6) Spherical Cap Surface Area. Many of the listed product metrics are self-explanatory and they focus on the variables that match the measured dimensionality of the head. For example, a two variable equation can capture more information about the variability of the human head than a one variable equation. The metric that requires further explanation is the body surface area metric, which given a weight of the body part can calculate the surface area of that body part [164]. The body surface area is calculated using the *Mosteller Formula*, which is named after the physician that created the estimate.

9.3.2 Performance Metrics

The AM Process metrics obtained in Section 9.2 provide the input for the performance metric. The performance metrics options for measuring thermal performance include: (1) Outer Surface Temperature, (2) Internal Temperature, (3) Thermal Conductivity, (4) Heat Flux, (5) Thermal Resistance, (6) Heat Transfer Efficiency, and (7) Power Dissipation. The metrics were evaluated based on their experimental rectitude and design application of a military helmet worn in hot climates.

9.3.3 AHP for Product Metrics

The AHP plot for the helmet product metric options is presented in Figure 9.6. The relevant criteria for the selection of the helmet product metric are presented in the following list.

1. Head Length
2. Head Breadth
3. Head Circumference

The results of the AHP analysis are presented in Figure 9.7. The overall consistency of the AHP is high with the highest percent inconsistency being 4.8% for the head length. The most important criteria were the *head breadth* followed by the *head length*. The top rated product metric option was *helmet surface area*.

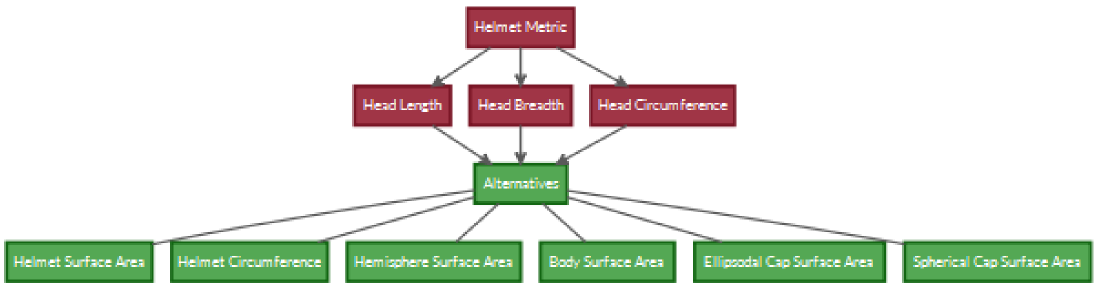


Figure 9.6: AHP Hierarchical Tree for Helmet Metric

	Weight	Helmet Surface Area	Ellipsodal Cap Surface Area	Body Surface Area	Spherical Cap Surface Area	Helmet Circumference	Hemisphere Surface Area	Inconsistency
Helmet Metric	93.8%	24.6%	21.2%	20.0%	12.8%	7.8%	7.3%	0.0%
Head Length	33.8%	8.7%	6.9%	7.5%	4.7%	3.0%	3.0%	4.8%
Head Breadth	40.0%	10.8%	9.3%	8.9%	5.1%	2.8%	3.0%	1.4%
Head Circumference	20.0%	5.1%	5.0%	3.6%	3.0%	2.0%	1.3%	1.8%

Figure 9.7: AHP Analysis Results for Helmet Metric

9.3.4 AHP for Performance Metric

The AHP plot for the thermal performance metric options is presented in Figure 9.8. The criteria for the selection of the performance metric were based on the AM process metrics and are presented in the following list.

1. Layer Height
2. Part Density (Infill Density)
3. Material
4. Print Speed
5. Extrusion Temperature
6. Print Bed Temperature

The results of the AHP analysis for the thermal metric, Figure 9.9, revealed that the most important criteria was the part density also called the *infill density* in open source software. The *material* criteria was ranked second. *Surface temperature, thermal conductivity, and thermal resistance* were ranked first, second, and third, respectively for the thermal metric. The results for the thermal metric identified are experimentally tested and validated in a surrogate model. The experimental process will be discussed in Section 9.4 along the corrective modeling efforts.

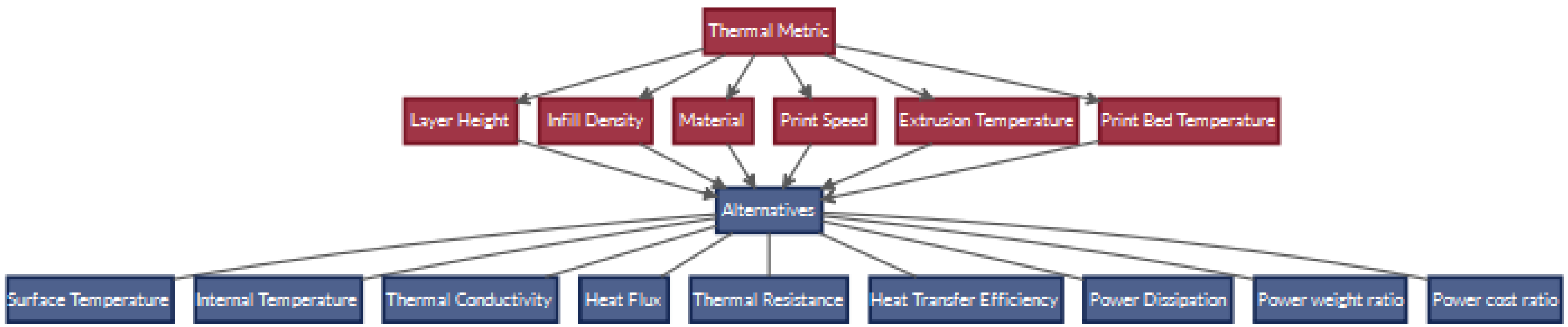


Figure 9.8: AHP Hierarchical Tree for Thermal Metric

	Weight	Surface Temperature	Thermal Conductivity	Thermal Resistance	Heat Transfer Efficiency	Power Dissipation	Heat Flux	Power cost ratio	Power weight ratio	Internal Temperature	Inconsistency
Thermal Metric	100.0%	20.2%	19.5%	17.6%	11.2%	8.7%	6.2%	6.1%	5.6%	4.9%	4.8%
Infill Density	33.6%	6.9%	6.5%	5.4%	3.9%	3.1%	2.2%	2.1%	1.9%	1.6%	5.3%
Material	26.5%	4.5%	6.4%	5.6%	2.5%	2.0%	1.5%	1.3%	1.4%	1.3%	6.2%
Layer Height	21.3%	5.1%	3.0%	3.2%	2.7%	2.0%	1.3%	1.6%	1.2%	1.1%	4.5%
Extrusion Temperature	7.7%	1.4%	1.5%	1.5%	0.9%	0.7%	0.4%	0.5%	0.5%	0.3%	6.7%
Print Bed Temperature	5.8%	1.2%	1.2%	1.1%	0.5%	0.4%	0.4%	0.4%	0.3%	0.3%	3.2%
Print Speed	5.2%	1.1%	0.8%	0.9%	0.7%	0.5%	0.4%	0.3%	0.3%	0.2%	8.0%

Figure 9.9: AHP Analysis Results for Thermal Metric

9.3.5 AQFD for Product and Performance Metrics

The final process in the AQFD methodology is to apply the AQFD all product metrics and performance metrics generated in the previous subsections are compared at once with the application of the QFD method. As mentioned in Chapter 5, the product design phase, Phase 2, of the QFD is applied for the comparison. The helmet metrics become the parts design values and the performance metrics become the design requirements.

The AQFD from the AHP results is presented in Figure 9.10. The weights generated from the thermal metric AHP provided the weights for the design requirements. The product metric with the highest score is helmet surface area. Each part design is rated for importance based on the design requirement. The "+" indicated a high importance, "*o*" indicates moderate importance, and "$\wedge$" indicates low importance. The weighted sum is calculated for each column, which represent each product metric or part design. Thus, the product metric that will determine the product dimensions for the helmet(s) produced will be the helmet surface area, this metric considers the anthropometric values that we must fit in to accommodate a population of people.

9.4 **Step 5:** Optimization

The AQFD results were integrated into the helmet design and the thermal performance goal of minimizing helmet surface temperature constrained population head dimensions. A two-phase process was developed as a basis to the development

Key		
+	-	9
o	-	3
^	-	1

		Parts Design (Product Metrics)					
Design Requirements (Thermal Metrics)	Weight	Helmet Surface Area	Helmet Circumference	Hemisphere Surface Area	Ellipsoidal Cap	Body Surface Area	Spherical Cap
Surface Temperature	20.2	+	+	o	o		o
Thermal Conductivity	19.5	o	^	^	+	o	+
Thermal Resistance	17.6	+	^	^		o	+
Heat Transfer Efficiency	11.2	^		o	^		^
Power Dissipation	8.7	+	+		o		o
Heat Flux	6.2	^		^	^		
Power - Cost Ratio	6.1	o	^		^	+	
Power - Weight Ratio	5.6			o		+	o
Internal Temperature	4.9	^		^	o		^
Priority Value		5.2	3	1.6	3	2	4.5
% Priority		27	16	8	16	10	23

Figure 9.10: Phase 2 - AQFD Results

of the optimization problem. Phase 1, consisted of experimentally measuring the influence of AM characteristics or process parameters on thermal conductivity and surface temperature, which is a contribution of this dissertation. Additional ANSYS® numerical models were developed to complement experimental result. Phase 2, consisted of the helmet thermal model development and experimental validation on flat demonstration of passive heat exchanger design in a Kevlar military helmet. Phase 2 mathematical models were provide courtesy of Los Alamos National Laboratory (LANL) staff [165, 166].

The optimization process for the helmet began with a design of experiments for the selected thermal metrics including surface temperature and conductivity for the FDM process in Phase 1. This initial research was necessary because parts that are additively manufactured generally have altered material characteristics due to the manufacturing process [6, 29, 30, 32, 109, 167]. Thus, in order to design the helmet optimization problem there was a need to observe and adjust for the differences in thermal performance due to AM. The results of Phase 1 was integrated into the equations generated in Phase 2 for determining the objective function for the helmet surface temperature also identified at the as the performance metric, which is minimized in this optimization problem. The helmet was validated through the testing of a flat helmet design with all components of the curved helmet to determine whether temperature could be maintained at 35° in a passive heat exchange system that utilized additively manufactured material based on an updated surrogate model.

The optimization framework for the helmet is also a non-convex optimization problem. In both demonstrations the problem is non-convex due to the fact that the constraint follows a bimodal Gaussian distribution to account for the variation of male and female anthropometric sizes in the population. When either an objective function or constraint function is non-convex the entire optimization problem becomes non-convex and must meet certain conditions to observe an optimum [168]. The goal of the helmet optimization problem is to minimize the helmet surface temperature. The objective function is constrained by the lengths and breadths of the adult human head in a population of heads, which follow a Gaussian distribution for men and woman in the US population. The formal definitions for the objection (thermal performance) and constraint (accommodation) functions are defined for the helmet application.

1. Thermal Performance

    - the thermal energy change required to dissipate enough heat to maintain a specified temperature underneath the helmet. For this application the specified temperature should be minimized to a value less than or equal to the thermal comfort temperature for human heads, 35°C [133]. In addition, the number of helmets that can maintain thermal comfort for the population is also identified with the consideration of thermal performance.

2. Accommodation

    - the fit of the helmet to the human head through varying the spatial-geometric dimensions of the helmet including the AM components of passive heat exchanger (HX), given the static physical dimensions of human heads. The accommodation function also assists with determining the percentage of accommodation each helmet provides for the population.

9.4.1 Helmet Application

The helmet application contains a passive HX, which was experimentally tested for cooling the head to ensure that a temperature below the maximum head temperature of 35°C was maintained in a hot, dry climate. The components of the helmet include the wick, shell, AM holder(s), and heat pipe(s), Figure 9.11. The objective function calculates the surface temperature of the helmet that is required to maintain head temperature below 35°C. The surface temperature increases with ambient relative humidity and temperature. The function is set to maintain a head temperature below 25°C, with the HX system acting as an air conditioner. The objective function includes a surrogate model which estimates the surface temperature of the AM material given variable infill densities ($D = x_2$) and layer heights ($L = x_1$), Equation 9.1. A Monte Carlo sampling approach, Equation 9.2 was also applied to the objective function, in order to calculate the number of samples required.

$$Y(x) = 19.62 - 0.64 - 4.28 \times x_1 - 1.75 \times x_2 \tag{9.1}$$

where

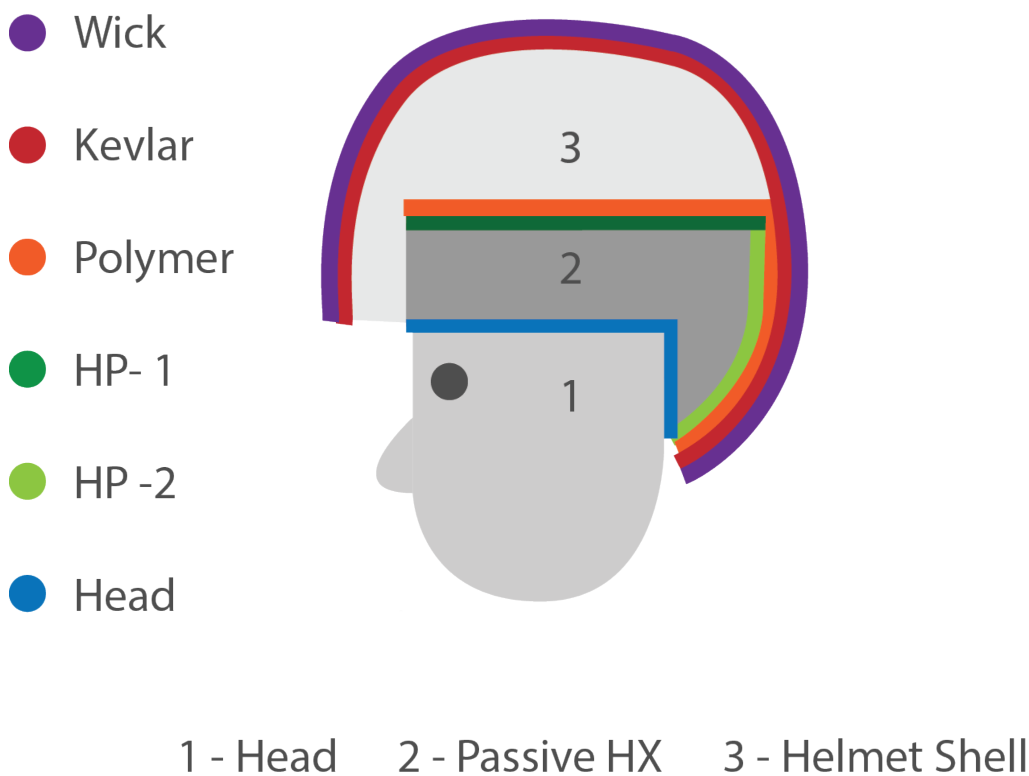


Figure 9.11: Helmet Diagram with HX Components

L: is x_1

D: is x_2

$$T(\hat{x}) = \tfrac{1}{N}\sum_{i=1}^{N} T(x_i) \tag{9.2}$$

All three modes of heat transfer (conduction, convection, and radiation) were considered with evaporation in the systems of equations extracted from the a thermal model developed at LANL. The solution for the systems of equations provides a values for θ_s and q_{cond} which can then be used to build the objective function for this model. The solution of θ_s solves for the surface temperature at the wick of the helmet surface, Figure 9.12. In addition, q_{cond}, Equation 9.3, models the overall conduction of the model, including materials interfacing with the helmet. With the modification of a previously developed thermal model which solves the systems of equations for maintaining a helmet surface temperature that will guarantee thermal comfort to the wearer of under 25°C, the conduction equation was adapted from the model to solve for surface temperature given the incorporation of the surrogate model that accounts for AM characteristics in R_{total}, which included the thermal resistivity for the FDM heat pipe holders/padding. The development of the thermal, surrogate model integration is discussed in the thermal and surrogate modeling section.

$$q_{cond} = \frac{\theta_{head} - \theta_s}{R_{total}} \tag{9.3}$$

9.4.2 Design of Experiments

The DOE work for this experiment was two-fold. The first goal was to understand the impact of AM manufacturing characteristics on surface temperature and subsequently thermal conductivity, which were determined, based on the AQFD results in Chapter 9. The second goal was to identify a material with low thermal conductivity that could also provide comfort to the human wearer.

The initial work was used to calculate the thermal conductivity variation based on 1D conduction through polymer $2'' \times 1''$ cylinders with surface affixed thermocouples. These experiments enabled the assessment of surface temperature variation and the conductivities derived from each cylinder. Thermal conductivity was measured through a heat input with thermocouples to capture the temperature change, the cylinder was fully insulated to measure conduction through the part. The cylinders varied in manufacturing characteristics including infill density (20%, 80%) and layer height (0.1mm, 0.4mm), for materials Polylactic Acid (PLA), Acrylonitrile Butadiene Styrene (ABS), and Polyurethane (PUR) for a complete 2^3 DOE with dummy variables, Table 9.7. Two FDM machines, Lulzbot TAZ® and Rostock MAX™, were initially tested yielding comparable results amongst ABS and PLA materials. The Lulzbot TAZ® FDM printer was selected and the third material, PUR - Ninja Flex by Ninja Tek, was analyzed to observe variability in thermal conductivity compared to ABS and PLA. The results of the comparison of all materials in terms of thermal conductivity are presented, Figure 9.12.

Due to limitations regarding the power input and the need to collect and

Table 9.7: 2^3 DOE for AM

Level	Material ($\frac{W}{m \times C}$)	Layer Height (mm)	Infill Density (%)
0	ABS	0.1	20
1	PUR (Ninja Flex)	0.4	80
	Dummy (PLA)		

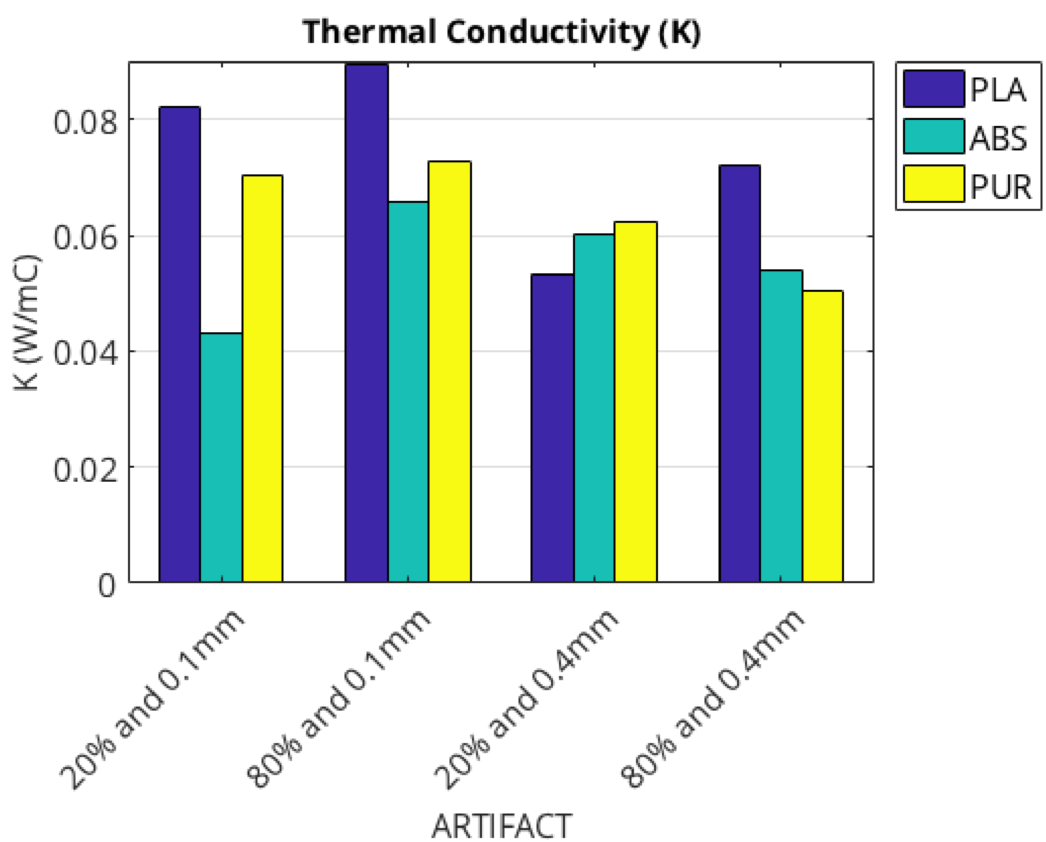


Figure 9.12: Thermal Conductivity Results for DOE

analyze different shaped data and multiple level for a new DOE and thermal model was developed in Solidworks Simulation™ and ANSYS®. This model was used to standardize an accurate estimate of the power input based on a comparative analysis of the experimental results with the model results for the cylinder experiments based on surface temperature. The next section details the thermal and surrogate modeling for integration into the R_{total} resistive equations.

9.4.3 Thermal and Surrogate Modeling

Thermal and surrogate modeling for the experimental design consisted of a three-step process. The steps included 1D conduction laboratory experiments, ANSYS® model development to evaluate alternative shaped designs with faster results and additional design levels, surrogate modeling to predict the effects of AM characteristics on surface temperature in order to optimize the entire design. The next immediate step after surrogate modeling is optimization and it is discussed in the sections proceeding this section.

1. AM Experiment and Thermal Model

2. Surrogate Model

3. Helmet Thermal Model

9.4.3.1 AM Heat Pipe Holder Thermal Model

The cylinder experiment consisted of an experimental design, where 7 thermal couples were applied to the surface of a cylinder, which varied in infill density and

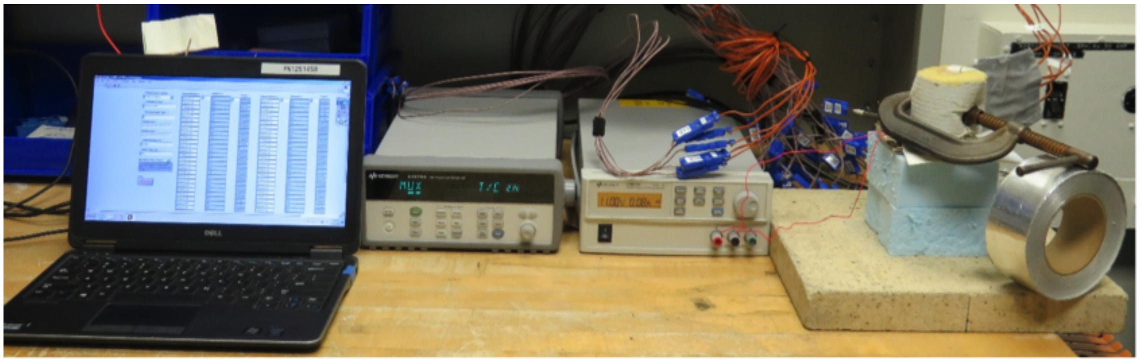


Figure 9.13: Thermal Experimental Design for AM Cylinders

layer height AM characteristics according to the DOE described previously, Figure 9.13. The experimental set-up included a data acquisition system (DAQ) connected to a LabVIEW™ program on the pictured laptop that calculates the temperature of the 7 thermocouples applied to the AM cylinder. The power supply was connected to the heater, which is placed on the bottom of the AM cylinder, Figure 9.14. Four thermocouples, $T1 - T4$, are placed on the surface body of the test artifact, one is place on the top surface, $T5$, another is placed on the heat patch and taped with fiberglass tape to secure, $T6$, and the final one observes the temperature of the environment or laboratory, Figure 9.14. Polyglass™ is then placed around the AM cylinder and secured with a clamp. The system is then placed a top of several insulation layers in order from top to bottom, woven titanium tape, Plexiglas, Styrofoam, and Concrete. Each experiment required a 6-hour ramp time and 30-minute dwell time, followed by a 30-minute break down and set-up for the proceeding experiment.

Due to the long experimental run times required for thermal equilibrium and

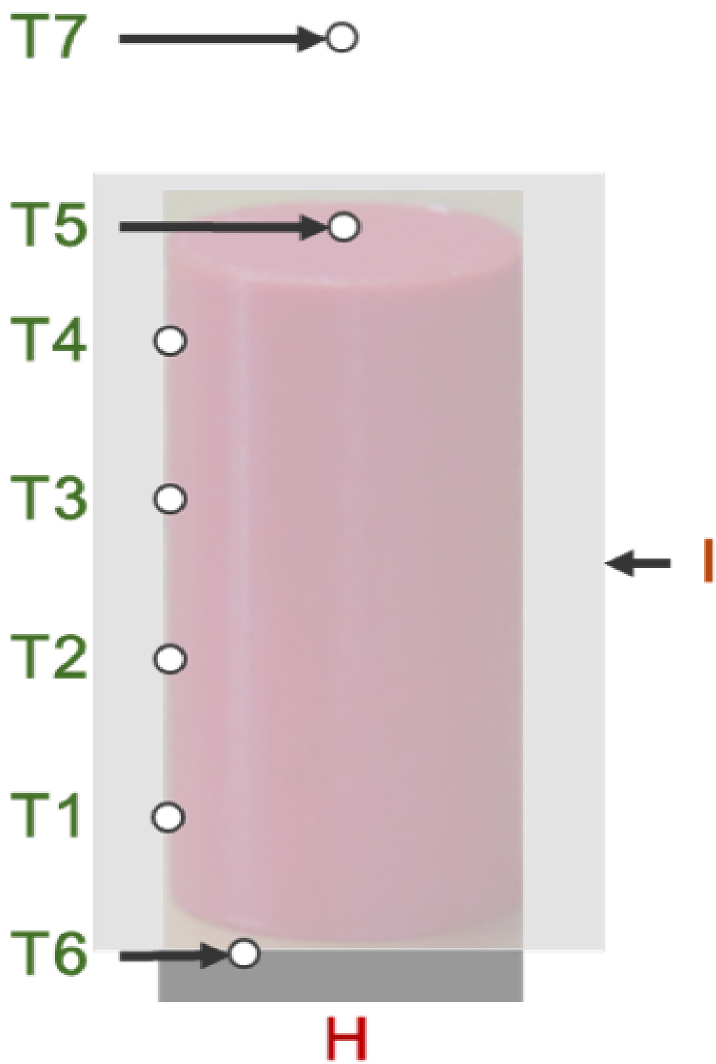


Figure 9.14: Thermocouple Layout on AM Cylinder with Heater and Insulation

identified heat losses in the power applied to the experimental design, two thermal simulation models were created to preform additional levels of experiments from the initial DOE, Table 9.7. ANSYS® was effective in modeling the infill density AM characteristic but not for layer height. The simulated cylinder experiment produced similar surface temperature results as the experimental design for 20% and 80% infill density analyses with ABS, PLA, and PUR materials, Table(s) 9.8 and 9.9. Experimental results at layer heights of $0.1mm$ and $0.4mm$ were compared at the modeled infill density with the simulated model results which do not include layer height. The location of surface temperatures was taken at $T4$ and $T6$, Figure 9.14. The model versus experimental data shows that PUR generally does not dissipate the heat as well as ABS and PLA but has more consistency amongst the experimental and model results and lower temperatures at the heat source. More specifically at the 80% infill density, the PUR material consistently has lower overall surface temperature ratios compared to ABS meaning it dissipated heat more efficiently. Figure 9.15 depicts the ANSYS® model developed to capture the model temperatures based on thermal conductivities of materials derived from databases, Table 9.10.

The ANSYS® model was then used to model the AM heat pipe holders for infill densities ranging from 20% to 80%. A grid infill pattern was used to duplicated experimental characteristics and distances between grid lines were interpolated based on the actual printed holders at 20% and 80% to get an accurate estimation of the distances between grid lines, Table 9.11. The results were used as input data for the surrogate model development, Table 9.12. The surrogate model data for the AM

Table 9.8: Surface Temperature Validation for Cylinder Experiment @ 20% Infill Density

Material	T4°C	T6°C	T4°C	T6°C	T4°C	T6°C
	(0.1mm)	(0.1mm)	(0.4mm)	(0.4mm)	(Model-20%)	(Model-20%)
ABS	21.194	40.300	19.735	33.686	20.710	34.520
PLA	20.835	31.402	23.597	39.232	20.521	37.220
PUR	22.318	35.098	22.317	36.250	21.047	31.530

Table 9.9: Surface Temperature Validation for Cylinder Experiments @ 80% Infill Density

Material	T4°C	T6°C	T4°C	T6°C	T4°C	T6°C
	(0.1mm)	(0.1mm)	(0.4mm)	(0.4mm)	(Model-80%)	(Model-80%)
ABS	23.913	37.177	26.704	42.374	27.133	50.540
PLA	21.563	33.911	20.299	32.573	26.833	57.954
PUR	19.473	31.998	24.553	41.080	27.177	48.737

Table 9.10: Thermal Conductivities for Material in Cylinder ANSYS® model

Material °C	Thermal Conductivity ($\frac{W}{m \times C}$)	Specific Heat ($\frac{K}{kg \times K}$)	Reference
ABS @ 23	0.17	2093	[169]
PLA @ 25	0.13	1800	[170]
PUR @ 25	0.19	1760	[171]
AIR @ 20	0.0257	1.009	[172]
Glass Cloth	0.0354	0.8	[173]

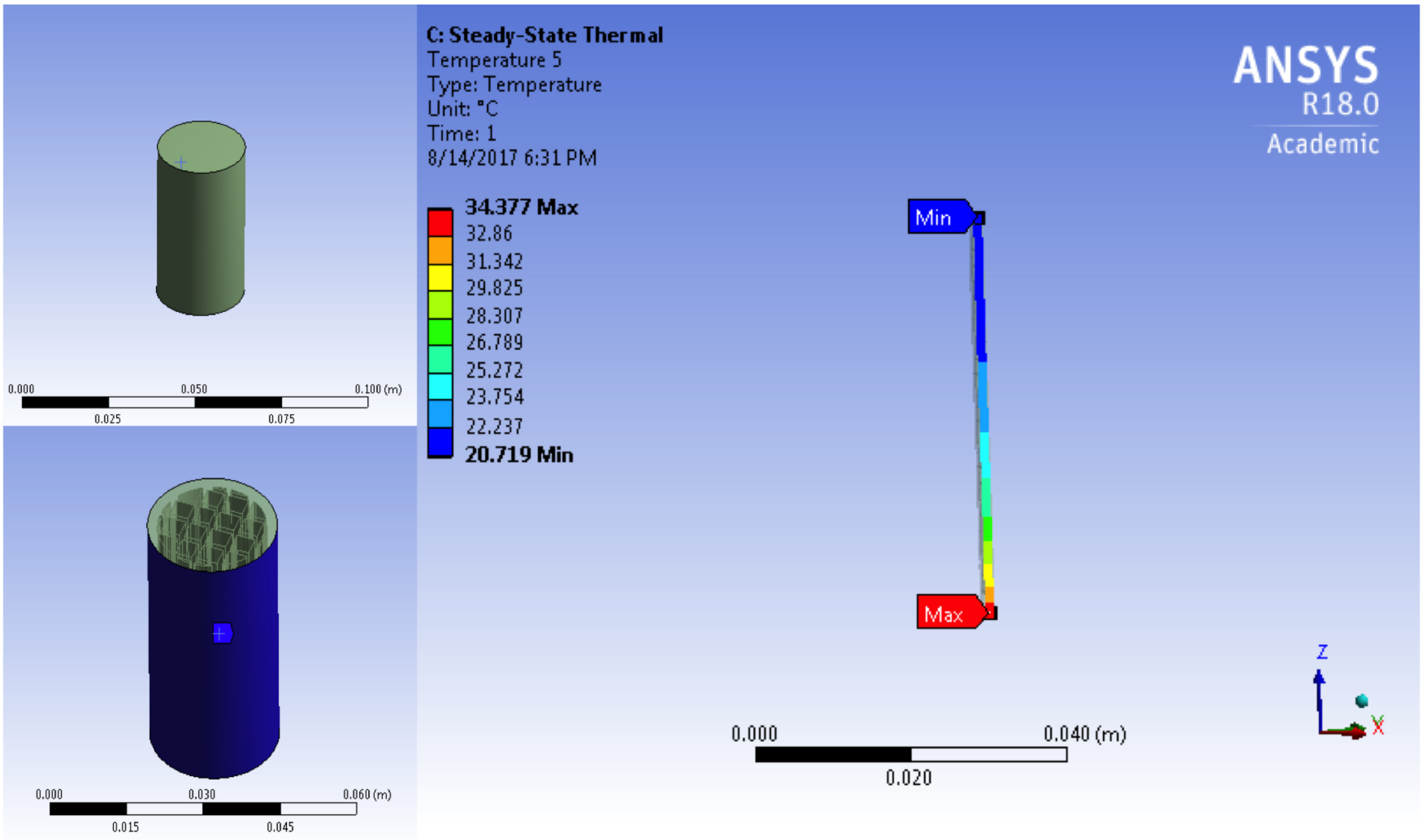


Figure 9.15: ANSYS® Model for Cylinder Experiments

Table 9.11: Linear Interpolation for Grid Pattern Infill Densities

Infill Density (%)	**Wall Distance** (mm)	**Wall Thickness** (mm)
20	5	1
30	4.36	0.938
40	3.72	0.875
50	3.09	0.813
60	2.45	0.750
70	1.82	0.688
80	1.18	0.625

heat pipe holders represents a single variable multi-level DOE, with the expected most important variable infill density. A surrogate model based on the initial 2^3 DOE was also generated to show the impact of layer height on surface temperature based on experimental data, Table 9.13. However, it is important to note that the surrogate model was never experimentally validated. The final section discusses the development of the surrogate models based on the data generated experimentally and from the thermal models presented in this section.

9.4.3.2 Surrogate Model

Two surrogate models were developed based on the data presented in the previous subsection. The first model discussed considered both layer height and infill density in the model and was based on the AM cylinder experiments. The cylinder surrogate model revealed a negative association with both layer height (strongest) and infill density as related to surface temperature, Figure 9.16. The model consisted

Table 9.12: Surrogate Model Data: AM Heat Pipe Holders (PUR)

Observation	**Infill Density (%)**	**Surface Temperature (°C)**
1	20	24.191
2	30	24.136
3	40	24.587
4	50	24.582
5	60	24.598
6	70	24.602
7	80	24.608

Table 9.13: Surrogate Model Data: AM Cylinder Test Artifacts

Material ($\frac{W}{m \times C}$)	**Layer Height** (mm)	**Infill Density (%)**	**Surface Temperature (°C)**
0.13	0.1	20	20.835
0.17	0.1	20	21.194
0.19	0.1	20	22.518
0.13	0.4	20	23.596
0.17	0.4	20	19.735
0.19	0.4	20	22.316
0.13	0.1	80	21.563
0.17	0.1	80	23.913
0.19	0.1	80	19.473
0.13	0.4	80	20.299
0.17	0.4	80	26.704
0.19	0.4	80	24.553

of a 2^3 DOE where variables included material, infill density, and layer height. Material had three levels and was a categorical variable, thus it was treated as a dummy variable in the model. The results of the AM cylinder surrogate model reveal that the residuals appear to be randomly distributed about zero, suggesting a linear relationship, Figure 9.17. Moreover, the residuals do not form a horizontal band around zero and appear to be uneven. Lastly, there are residuals that seem to be outliers suggesting that a linear model it is actually not the best fit. Figure 9.17 also presents another regression model for the thermal model results of the heat pipe holders at seven different percentiles ranging from $20-80\%$ for ABS, PLA, and PUR. The fitted versus residuals model is this case clearly depicts a non-linear relationship between dependent (surface temperature) and independent variables (material and infill density) because residuals are not equally distributed about zero. It is also key to note that additional levels and data are required to make a true conclusion in regard to the appropriateness of a linear model to describe the relationship between AM characteristics and surface temperature.

The next model attempts to gain additional insight into the impact of infill density and material on surface temperature, Figure 9.18. Infill density revealed what appears to be a logarithmic or cubic relationship with surface temperature as infill density increased. This model can be used to estimate additional points between 20% and 40% to estimate exactly where the behavior of the model changes. This fitted versus residuals plot for infill density and surface temperature also support the observation of a non-linear relationship, Figure 9.19. Upon initial further investigation of material and surface temperature, it appears that PLA can achieve

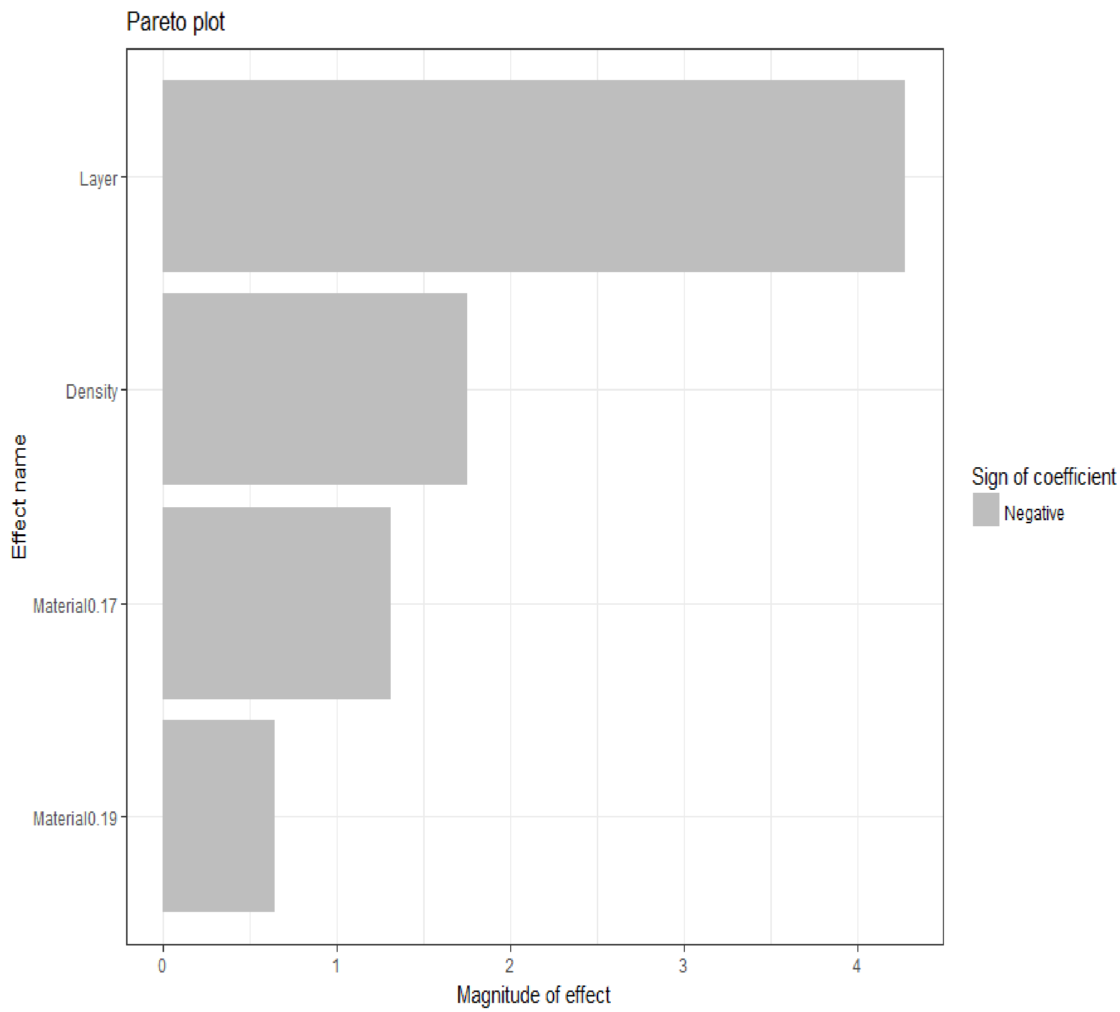


Figure 9.16: Pareto Plot for Effects of AM Characteristics in Cylinder Experiment

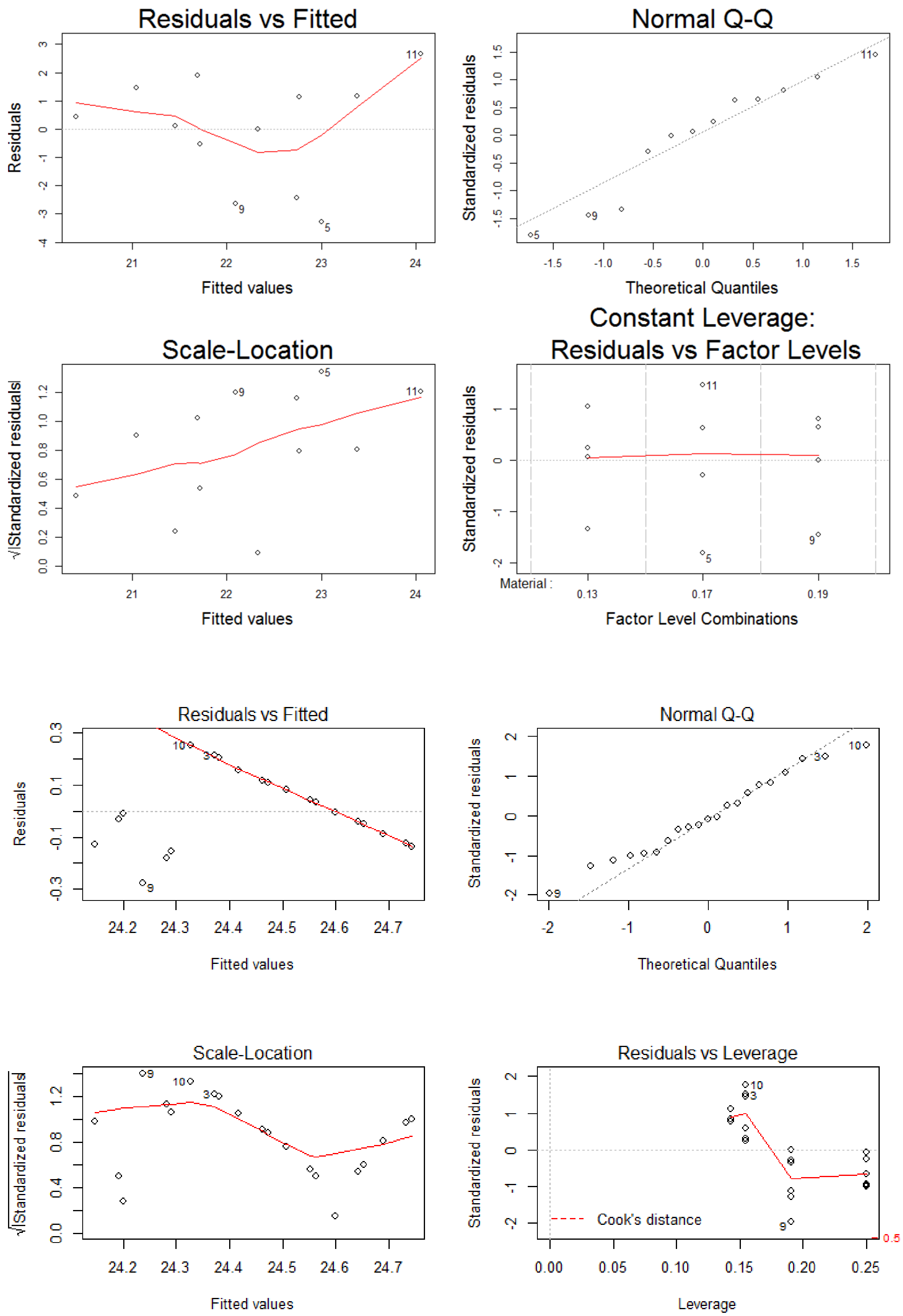


Figure 9.17: Cylinders (Top) and Heat Pipe Holders (Bottom) Plots for 1-D Conduction Tests

the lowest temperatures but the majority of surface temperatures for all three materials stabilize around 24.6 C°, Figure 9.18. This means the any of these materials because of their low conductivities could perform well for the helmet application and PUR has the extra benefit of being flexible which serves dual purposes of fit and thermal performance. Although insight was gained in this model, it is limited because it does not account for interactions and other AM process controls that may have a relationship with surface temperature. The PUR infill densities and surface temperatures are presented in Table 9.12. Figure 9.20 presents the results of 20% infill density of the AM heat pipe holder. With additional insight on the effects that AM characteristics have on surface temperature, the helmet thermal model is discussed in the next section.

9.4.3.3 Helmet Thermal Model

The thermal model for the helmet, Figure 9.11, included the calculation of conduction along the vertical and horizontal axes of the helmet. The resistive calculation R_{total} was modified to include the thermal conductivity value for PUR. R_{total} is a variable in the conduction equation, Equation 9.3, of the helmet thermal model developed at LANL, [165, 166]. The selection of PUR, discussed in the previous section, was due to flexible nature of the material and the consistency in heat dissipation under different power loads and manufacturing characteristics. The helmet thermal model conduction equations in the $X(horizontal) = A$, Equation 9.4, and $Y(vertical) = B$, Equation 9.5, directions provide the total conduction through the

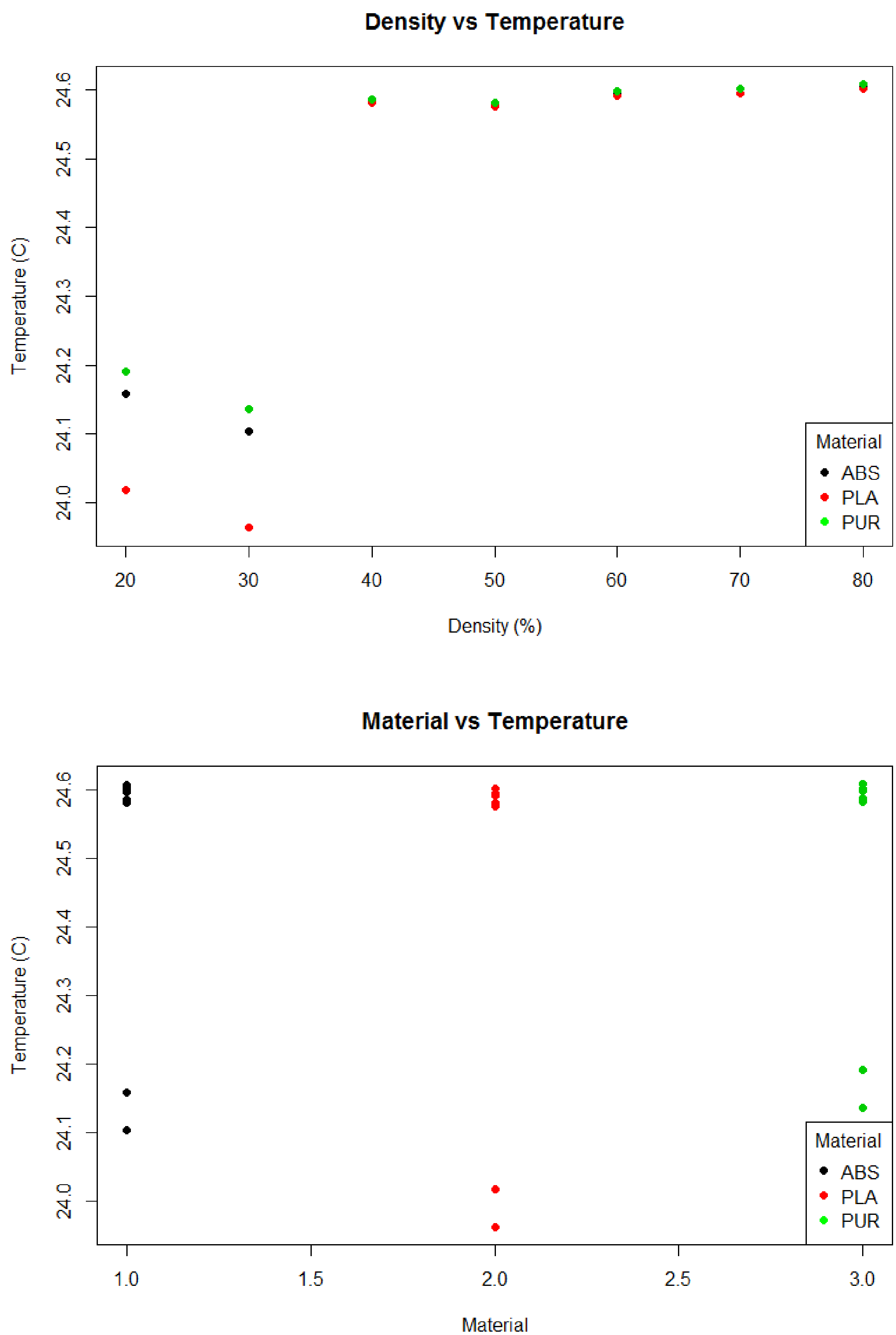
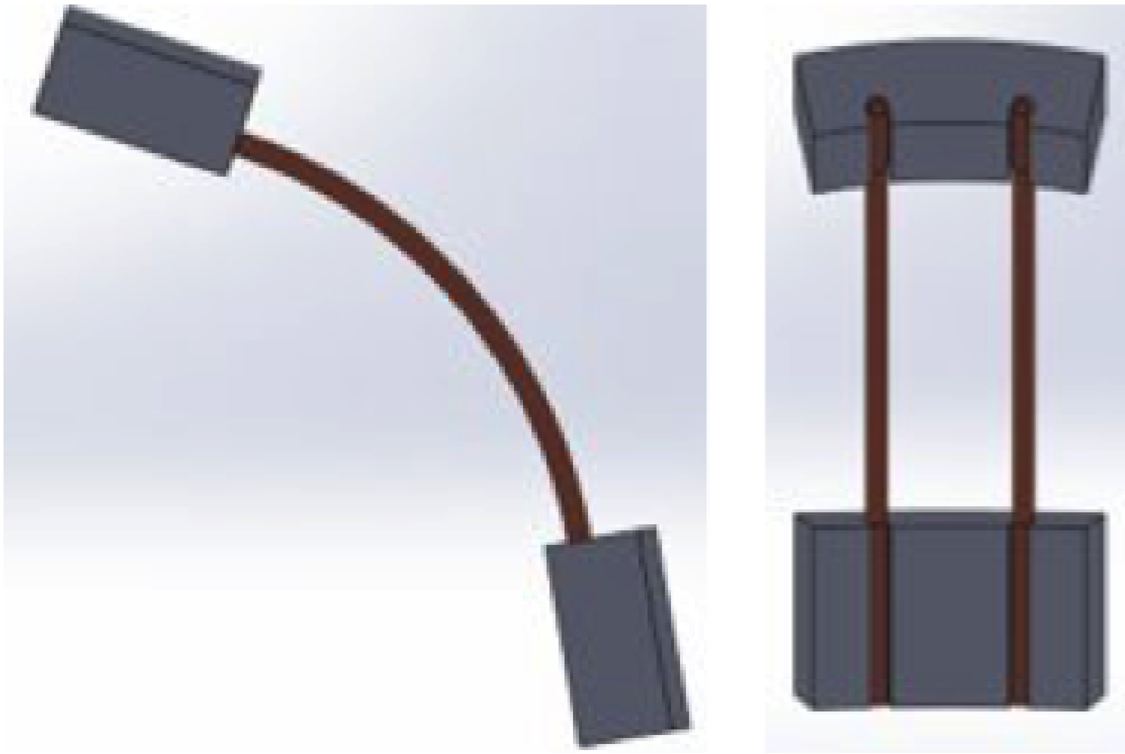


Figure 9.18: 1-D Conduction Heat Pipe Holder Model Results



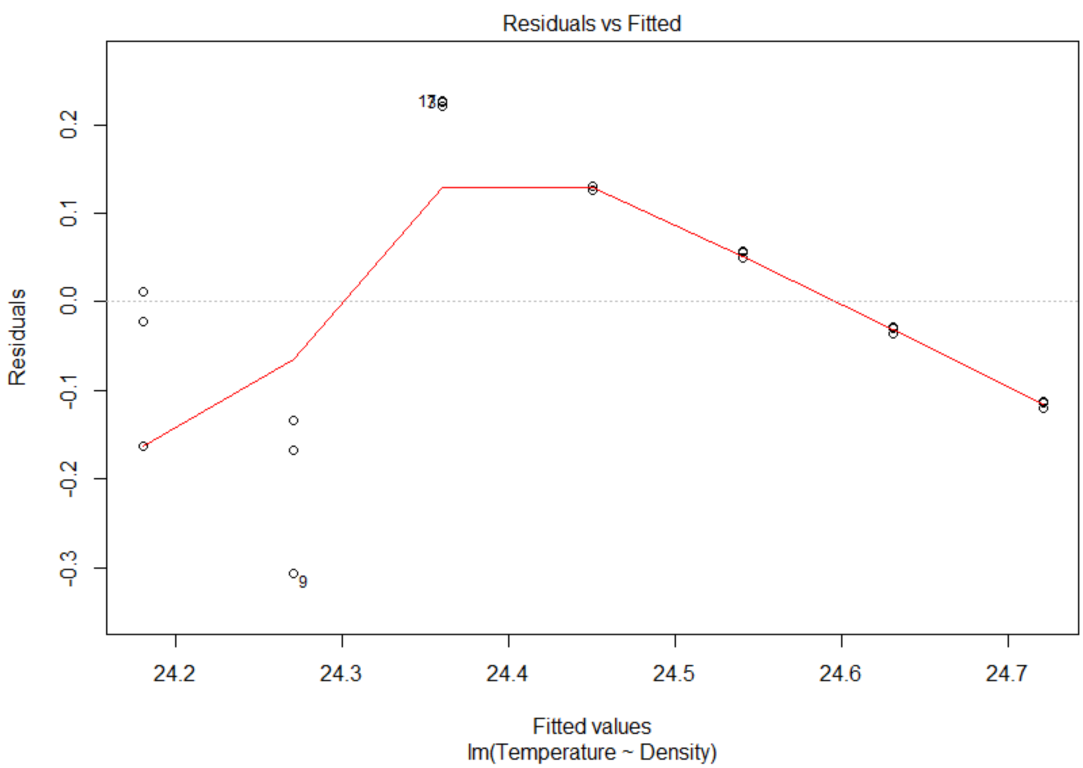


Figure 9.19: Regression Plot for Infill Density and Surface Temperature for Heat Pipe Holders (Top)

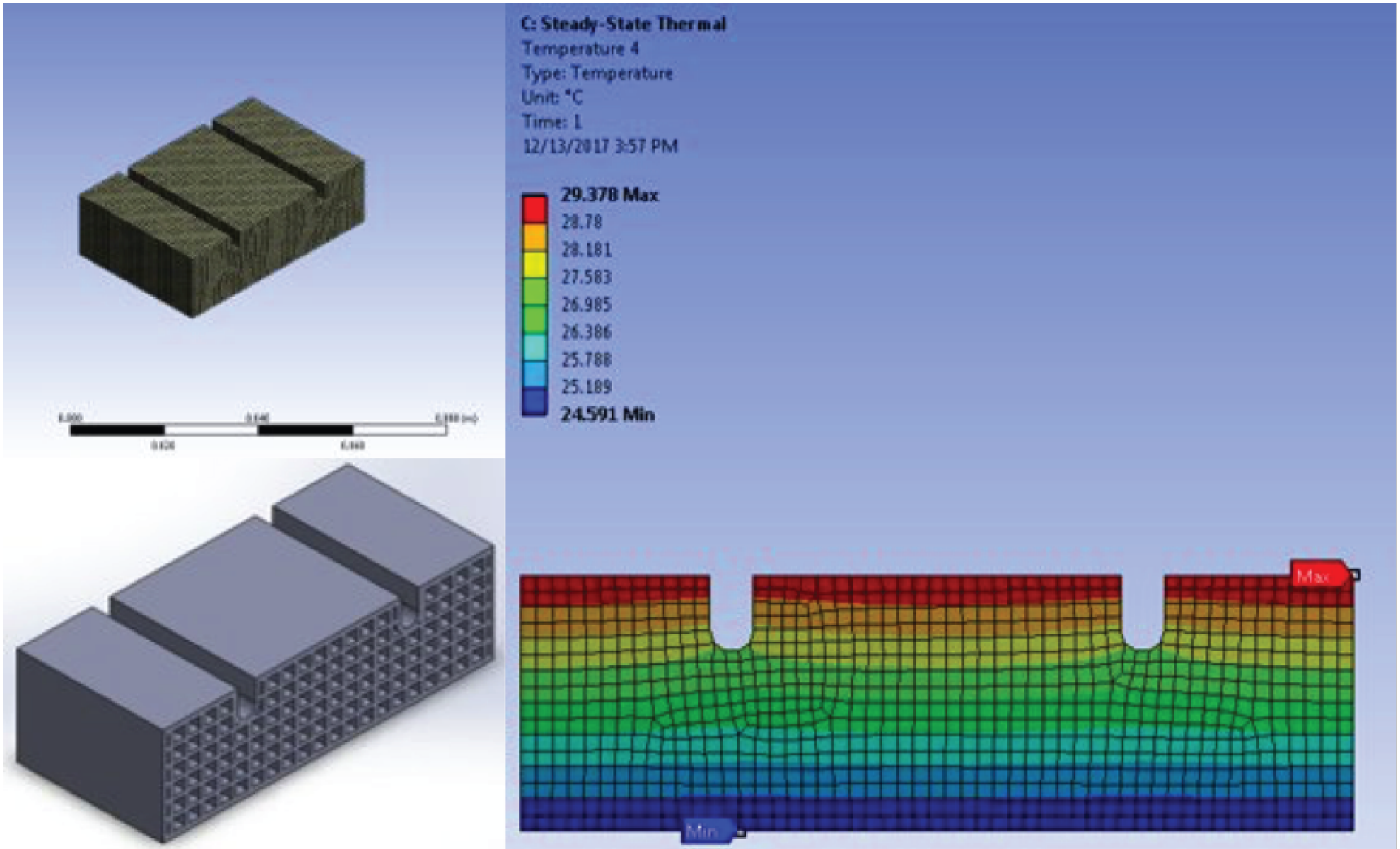


Figure 9.20: ANSYS® Model of 20% Heat Pipe Holder

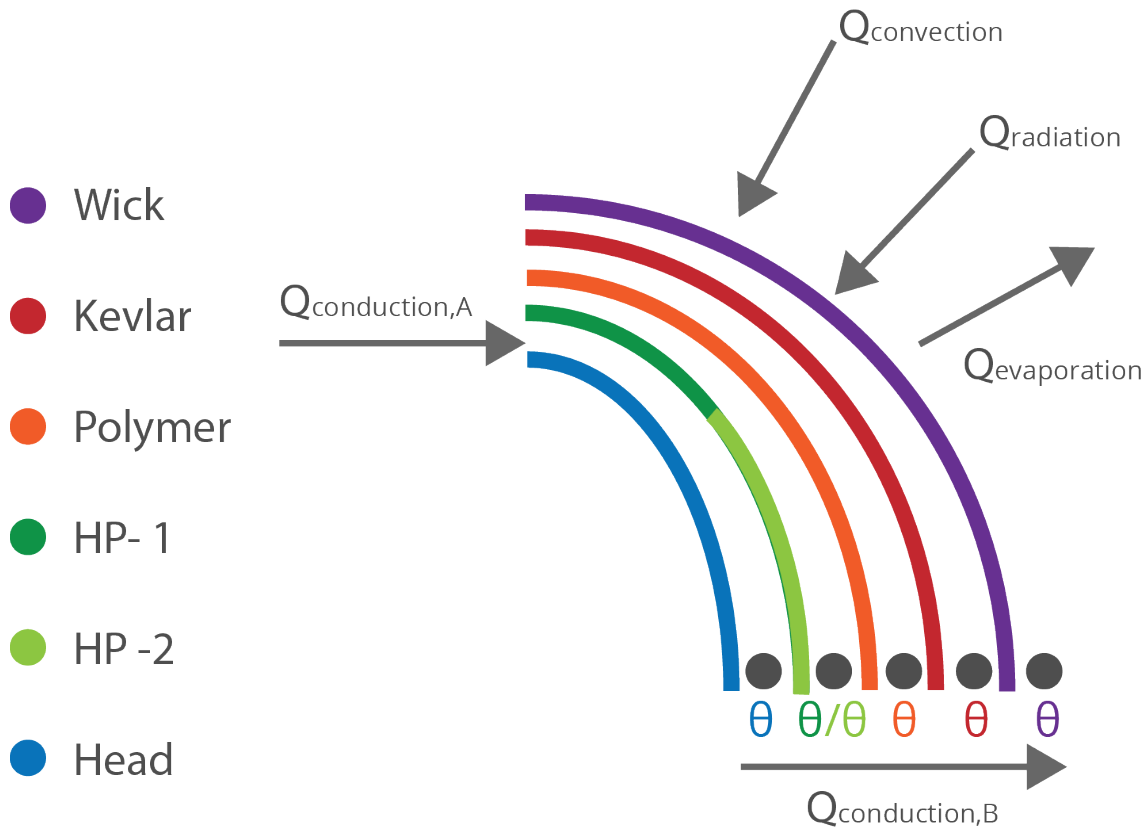


Figure 9.21: Modes of Heat Transfer in Helmet Thermal Model

helmet system. The horizontal axis, X, refers to the heat being moved along the heat pipes to the back of the head. The vertical axis, Y, is normal to the head as heat moves the each material. A detailed view of the heat transfer systems adapted from the helmet thermal model depicts the paths of conduction, Figure 9.21. Note that the color-coded θ values refer to the temperatures at the material associated with color. The resistive schematic, Figure 9.22 for the conduction calculation in parallel and series provides the R_{total} value for the conduction equation in the helmet thermal model, Equation 9.6.

$$q_{cond,A} = \frac{\theta_s - \theta_{kevlar}}{R_{wick}} + \frac{\theta_{kevlar} - \theta_{polymer}}{R_{kevlar}} + \frac{\theta_{polymer} - \theta_{HP1}}{R_{wick}} + \frac{\theta_{HP1} - \theta_{HP2}}{R_{HP1}} + \frac{\theta_{HP2} - \theta_{head}}{R_{HP2}} \tag{9.4}$$

$$q_{cond,B} = \frac{\theta_s - \theta_{kevlar}}{R_{wick}} + \frac{\theta_{kevlar} - \theta_{HP1,2}}{R_{kevlar}} + \frac{\theta_{HP1,2} - \theta_{head}}{R_{HP1//HP2}//R_{polymer}} \tag{9.5}$$

$$R_{total} = R_{wick} + R_{kevlar} + R_{HP1,2} \tag{9.6}$$

The resistance of materials is calculated in the following manner $R = \frac{\Delta T}{q} = \frac{L}{k}$, where q is the heat flow rate, L is the thickness of the material, and k is the thermal conductivity. In the R_{total} equation, Equation 9.6, the resistance of the wick and the helmet shell which is made of Kevlar can be calculated with the thickness of the material and thermal conductivity since these values are known. The resistance of the $R_{HP1,2}$ measured in $\frac{m^2 \times K}{W}$ is where the integration of the surrogate model occurred. More specifically, $R_{polymer}$, Equation 9.10, in R_{par} (parallel heat pipes) is precisely where the surface temperature for the surrogate model was integrated as the ΔT value along with the surface temperature of the head, Equation 9.9. q_{exp} is the experimental value derived from the Minco™ white paper based on heat losses in experiments [174]. Thus, the heat pipe resistance values are further dissected to reveal where the integration of the surrogate model for the surface temperature, θ_{surf} of the AM material under variable manufacturing conditions occurs, Equation(s) 9.7, 9.8, 9.9 and 9.11. The heat pipe characterization was not considered in the Engineering Equation Solver (EES)® model. Thus, the values used for the heat

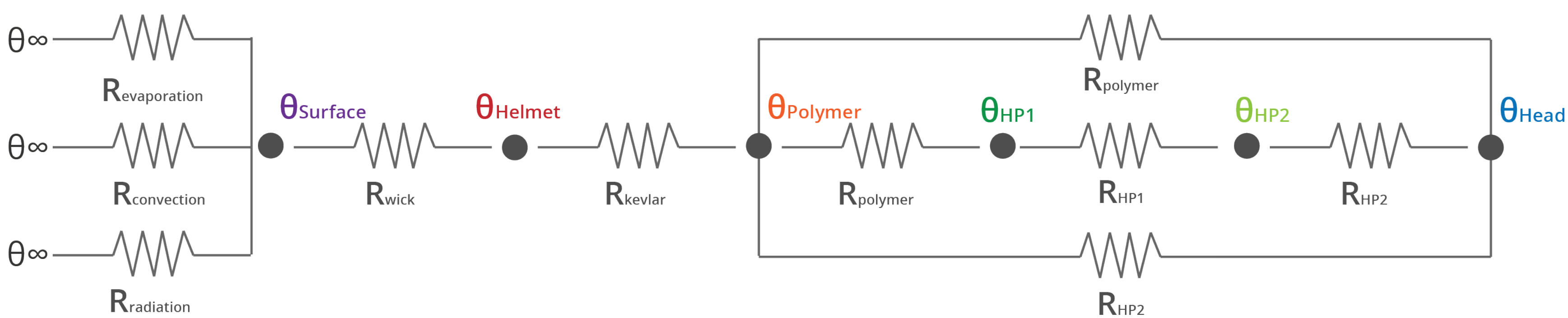


Figure 9.22: Resistive Schematic of Thermal Helmet Model

pipes k_{bronze} was for pure bronze. With the integration of the surface temperature surrogate model revealed in Equation(s) 9.9 and 9.10, the complete model that integrates AM characteristics and helmet surface temperature was presented. The next section will discuss the formation of the optimization model, which integrates the ANSYS® thermal models and EES® models from the previous section.

$$
\begin{aligned}
&R_{HP,ser} = R_{HP1} + R_{HP2} \\
&where \\
&R_{HP1} = R_{HP2} = \tfrac{L_{HP1}}{2\times k_{bronze}}
\end{aligned}
\tag{9.7}
$$

$$R_{HP,par} = \frac{R_{HP1} \cdot R_{HP2}}{R_{HP1} + R_{HP2}} \tag{9.8}$$

$$R_{par} = \frac{R_{HP,par} \cdot R_{polymer}}{R_{HP,par} + R_{polymer}} \tag{9.9}$$

$$R_{polymer} = \frac{\theta_{surf} - \theta_{head}}{q_{exp}} \tag{9.10}$$

$$R_{HP1,2} = \frac{R_{HP,ser} \cdot R_{par}}{R_{HP,ser} + R_{par}} \tag{9.11}$$

9.4.4 Formation of Problem

The formation of the helmet optimization model has similarities to the hand-held device. The result of the AQFD for this application revealed that a metric of surface area would be best for calculating the fit and accommodation of the human head in the Kevlar helmet. In addition, the top thermal performance metric

Table 9.14: Constraint Variables for Population Accommodation

Variable	US Adult Population			
	Men		Women	
	μ (mm)	σ (mm)	μ (mm)	σ (mm)
Head Length	195	8	180	8
Head Breadth	155	6	145	6

was surface temperature. The thermal models developed provide direct input for the objective function that sought to keep the human head cool by maintaining a low surface temperature on the helmet given different environmental factors such as temperature and humidity and the modes of heat transfer. The constraints for the helmet application consists of the human head parameters including head length and head breadth for the male and female populations, Table 9.14.

The design variables, objective function, and constraints included in the formation of the helmet optimization problem are defined, Figure 9.23. The helmet represents the static application and does not need to define region of interaction. Instead the accommodation function measures a fit between the human head and the helmet. This fit value for helmet accommodation is based on a ratio called the standoff distance, which is the area difference between the internal surface of the helmet and human head [175]. An optimal standoff distance is estimated to be x between $4mm \leq x \leq 8mm$. The objective function measures the surface temperature of the helmet to ensure that the human head remains under 35 C°. The design variables are important here because they determine the size of the helmet and

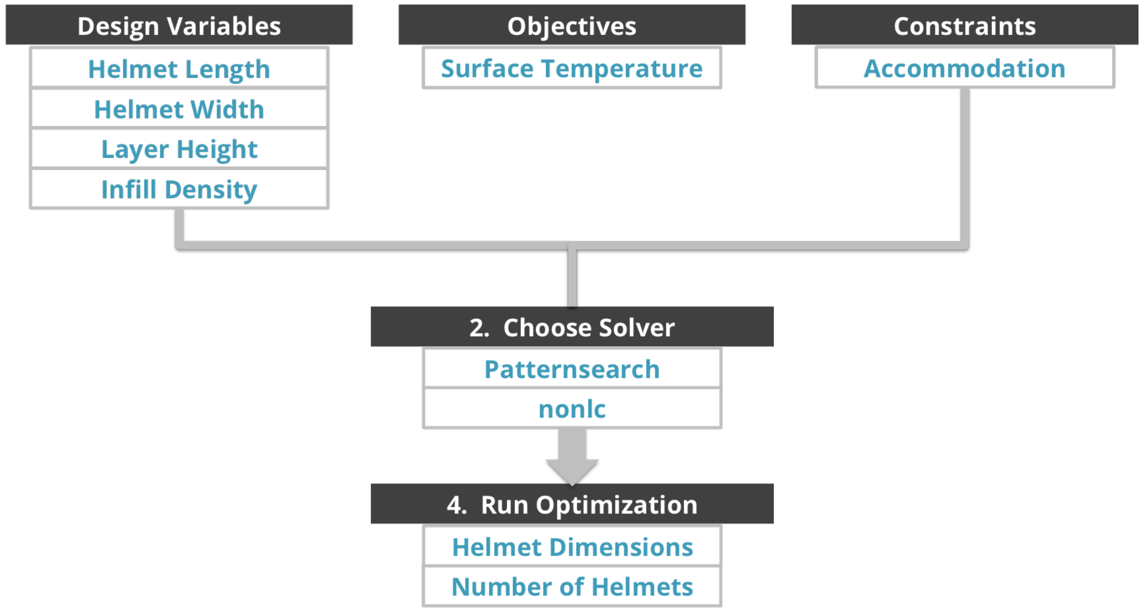


Figure 9.23: Optimal Design Plan

subsequently the number of helmets required to accommodate the population. The design variables included the helmet length and width, which are used to calculated the area, and the layer height and infill density. Currently, the 2^3 DOE linear model is incorporated into the objective function to gain a sense of the effects of layer height on the helmet surface temperature.

9.4.5 Optimization Design

The objective calculates the surface temperature of the Kevlar helmet and estimated the layer height and infill density required to obtain a minimum surface temperature Equation 9.12. In addition, the accommodation function, Equation 9.13 minimizes constrains the objective based on the fit of the helmet and a slightly larger gap range than presented in the literature [175]. The conduction equation is being solved based for the surface temperature of the head based on a thermal model developed at LANL. Q is conduction produced from a modified thermal model, R_{total} includes the variables and equations discussed in the thermal and surrogate modeling section, and A is the fin area at 1/3 of the internal surface area of the helmet and the human head.

$$\begin{array}{rcccl} \min\limits_{x} & T(x) = \frac{Q \times R_{total}}{A} - T_{head} & & & \\ \text{s.t.} & A(Y) & \geq & 95 & \\ 0 & \leq & x_1 & \leq & 1 \\ 0 & \leq & x_2 & \leq & 100 \\ 145 & \leq & x_3 & \leq & 219 \\ 180 & \leq & x_4 & \leq & 265 \end{array} \tag{9.12}$$

$$A(Y) = \frac{\sum_{i=1}^{N} Y_i}{N} \times 100 \tag{9.13}$$

where

$A(Y)$: is a binary variable for fit or accommodation

N : is the population sample.

9.4.6 Optimized Helmet Design Results

The optimized helmet results reveals that thermal comfort can be guaranteed with an optimal surface temperature of 17 C° for all helmets generated. This result can be compared to the thermal model generated in the previous chapter which states that an internal head temperature of 35 C° was achievable for humidity values under 35% and external temperatures under 35 C°.The Monte Carlo sample size approximation generates a population of 500 people. This occurs when the standard deviation of the temperature integrated in to the approximation factor $4 \times \sigma^2 \div \epsilon^2$ is less than or equal to the sample size [176]. In addition, 6 helmets are required to accommodate the entire population of human head lengths and breadths, Figure 9.24. Three helmets are required for the male distribution and two helmets for the female distribution. The gap for all helmets is at the maximum fit of $8mm$ for each helmet produced for the population. The population can be accommodated with 97.8% confidence in terms of thermal comfort. Furthermore, the model was able to produce a surface temperature at the required 17 C° and thus can guarantee an accommodating temperature to the participants in the populations.

9.5 Conclusions

The results of the AQFD were applied in the development of the optimization problem, Section 9.4. There are several applications where understanding performance limits and behaviors along with the conceptual development of the product can improve the overall design. Understanding the effects of manufacturing parameters on performance can also reduce the number on incidents and recalls due to unanticipated product failures. Future work should explore the relationship between manufacturing characteristics and performance. The final chapter will discuss the overall conclusions, limitations, and future work related to the demonstrated methodology.

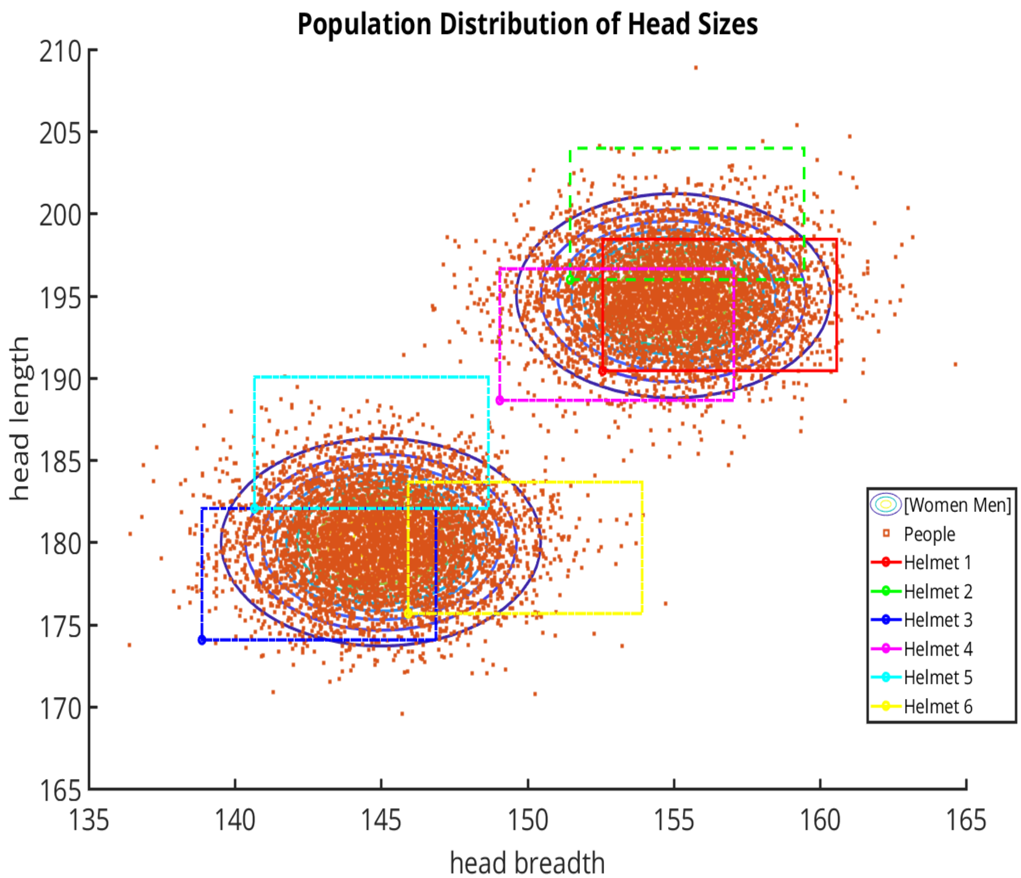


Figure 9.24: Optimization Results for Helmet Model

Chapter 10: Conclusion and Future Work

The final Sections 10.1, 10.2, and 10.3, present the overall discussion of this research as well as the conclusions and future work. The primary and fundamental contribution of this work was the introduction of the concept *Interaction Variability*. Interaction variability allows researchers to define the interaction design space based on human interaction factors. In addition, the 5-step method demonstrated in Chapters 7, 8, and 9 presented a practical and feasible process for method implementation. The novel aspects of this method enable the identification of human interaction factors with controllable performance metrics based on manufacturing process parameters that define static and dynamic interaction design spaces for the purpose of addressing feasible MC for mass production.

The novelty of *Interaction Variability* lies in structured, repeatable method for mapping human-component interactions and the functional behavior of human parameters during interactions. In addition, the product classification scheme provides insight into interaction spaces, product architectures, and component orientation. The "dynamics of interaction" truly depicts the paramount contribution of this work. This contribution required the identification of human parameters from a functional or biomechanical perspective along with the functional requirements of the product components to create interaction spaces for class III or dynamic product applications. This information was missing in the literature especially in the product design process. In the application of the 5-Step method the algorithms created to define accommodation functions are novel and demonstrate an application of interaction spaces for both class II (static) and III (dynamic) products. The demonstrations presented in here represent fit and one of the functional classifications reach. Future work will emphasize the development of accommodation algorithms and subsequently "Interaction Variability" design spaces for the other three functional classifications force, tactility, and maneuverability.

The major contributions of each Chapter in this methodology are presented with their respective limitations and general conclusions drawn from the demonstration of the methodology for the dynamic and static applications. The conclusion section highlights the most significant contributions and the future work section explores research areas that warrant additional attention in order to enable MC in mass production without sacrificing product performance metrics.

10.1 Discussion

The methodology presented in this dissertation has provided several key insights revealed throughout the previous chapters. The overall goal of this work was to present a structured design methodology that identified, modeled, and optimized traditional engineering performance requirements with consideration of human-component interactions to enable MC while maintaining as a quality performance goal. The design methodology mapped biomechanics information to primary (direct contact with a component) and secondary (indirection reaction to primary interaction with a component) interactions with product components. In addition, this model distinguished between static and dynamic applications and interactions. The direct definitions of terms and mappings enabled a clearer relationship and identification of anthropometric terms in traditional databases.

The MC problem was partially addressed based on objective customization principles of fit, displacement, and interaction regions for the population as opposed to subjective customization features such as color of components. By constraining the objective function by the population distribution of relevant anthropometrics, the optimization model was able to produce the number of products required to accommodate the at least 95% of the population in both demonstrations. Through the identification of the number of products required to accommodate the population, MC in this form can be implemented feasibly in a mass production environment with proper manufacturing layout and design. In the helmet demonstration large amounts of overlap was apparent in two helmets that accommodated the male population. Overlap in the number product applications that accommodate an end user, provide a greater variety for the customer. In these cases, consideration of the product function or end user preference should be incorporated to determine the best product for the end user. For example, the helmet with the smallest gap would provide the coolest helmet for the end user, while the fit may be tighter than customer would prefer. Thus, the preference of the customer followed by the product function represent the order of consideration for customer satisfaction. However, the designer must establish a cutoff point so that product performance is not compromised.

Product overlap could have a significant impact on costs for design, manufacturing, and production of an additional product. Products with large overlaps may not be worth the additional costs because the two products may only fulfill the need of the same population segment. However, for small product overlap, the cost of the additional product may fulfill the need of a segment of the population that was not targeted, resulting in additional sales. Population accommodation and human factors design in general are associated with revered product reputations leading to higher return sales, customer satisfaction, and brand loyalty.

For products with a family of discrete components, where each component has a distinct function, multi-objective optimization would be used to capture the tradeoffs. For example, a bike is being manufactured of a population of riders. The family of components considered is the brakes, bike frame, and battery storage. The primary function of the brakes is to work reliably for a long period of time under different weather conditions. The primary function of the bike frame is to be lightweight and durable, and the primary function the battery is to have a maximum storage capacity but not contribute more that 10% to the weight of the bike frame. Thus, the optimization problem from the performance perspective would be to minimize the weight of the bike frame, maximize battery capacity and brake strength and speed. For the human interaction factor perspective additional objectives would be to minimize force required to engage brakes and maximize pedal and seat size for comfort. The constraint functions take in the population distributions of the hands, feet, and waist sizes for accommodation. This problem would have six objectives and at least three constraints.

This method was designed to consider any manufacturing process. Thus, for more mature and commonly used manufacturing processes historical datasets and research has determined the effects of different process parameters on part performance. Historic information makes other manufacturing approaches, e.g. CNC mills, more attractive, insightful, and accurate when incorporated in this method. For other AM process parameters that were not evaluated in this study, such as extrusion temperature and build orientation have significant impact on thermal and mechanical properties but have began to be widely investigated [30,179]. Other AM methods that do not consider part density and infill pattern would be less computationally intensive to model for after build parts although the process may be more complex. Process complexity requires in-situ monitoring to determine the material behavior during part manufacture.

The use of this method is appropriate for any manufacturing process. The more product components and additional, distinct manufacturing processes required for a single product, the more historical or experimental data required. The process for generating additional data makes this method expensive. On the other hand, the availability of historic data makes the application of this method cheap. This method was demonstrated in an AM process to assess the feasibility of the method when the generation of experimental data is mandatory. Since information on the effects of process parameters in AM was limited, a concerted effort in AM is being undertaken to improve processes and parts produced. Future applications of this method will benefit from current research efforts. This work provided insight into the use of AM to facilitate MC through component isolation and optimization of relative dimensions demonstrated with the handheld device application. Other insights into AM revealed that infill density had the largest impact on thermal conductivity and surface temperature but at larger increments layer height may also impact thermal conductivity.

While more work is necessary to create part performance consistency in AM, this work provided a approach for integrating parts, varying performance capabilities, into a performance driven optimization model that can accept these parts and maintain an minimum specified performance requirement. This is useful because it alters the narrative of the inconsistency in AM and states that it can be utilized under specified conditions and preform at the minimum specification. The integration of "Human Interaction Factors" and "Manufacturing Characteristics" in the trade-off analysis was also presented. The utilization of traditional design decision methods such at AHP and QFD were instrumental for integrating the constructs in Chapter 4. The second phase of the QFD method is not often utilized in the literature but was particularly appropriate for selecting the performance requirement and the product measure for the helmet in a structured way after an AHP was performed to narrow the options.

The AQFD results for the helmet were integrated into the optimization model. The manufacturing effects on certain metrics required additional experimentation and modeling which was demonstrated in previous sections of this Chapter. The optimization models presented in this work were single objective non-convex optimization problems. The selection of a solver was important for obtaining an optimal solution. Fmincon was determined to be limited to convex problems, thus the Patternsearch algorithm was applied.

This method was demonstrated in two applications: 1) a handheld device and 2) a Kevlar military helmet. The handheld device model was confined to the top surface of the device and accurate reach zones were defined with the positions defined earlier in the chapter. The reach zone calculation enabled the development of a boundary that defined the interaction space for each person sampled. It is important to capture the variation in interaction spaces for humans in order to design user friendly and functional devices, which may directly impact customer satisfaction. The identification of reach zones or interaction spaces expands beyond satisfaction but also into the prevention of musculoskeletal disorders that are onset by repetitive non-optimized human interactions. This is important because workers' compensation costs for organizations can range in the billions for injured employees [177].

In developing the surrogate model for the Helmet demonstration, the assessment of the thermal conductivity for the cylinder experiment was limited. However, the results supported the expected conductivities, which were calculated based on material bulk conductivities for correction and verification of experimental results. Although heat losses were over 90% of the expected power input, valid surface temperatures were still observed on the cylinder test artifacts. These heat losses did impede the calculation of thermal conductivity, which was calculated based on surface temperatures after steady state is achieved. Upon the application of the corrected power input, accurate approximations of the thermal conductivity for the cylinder experiments were achieved. The demonstration of the helmet application provided insight into the trade-off relationship between fit and helmet surface temperature. This work was also able to garnish some insights into AM thermal conductivity, which relates to surface temperature. These insights were particularly important because they defined relationships between particular AM controls for FDM processes and revealed additional research opportunities in AM performance based model development for predictive and surrogate modeling. The results reveal the number of helmets required to accommodate the population, the thermal performance of the helmet heat exchanger for the helmet application, and the interaction region and component displacement for the handheld device application. These results along with the surrogate and thermal models that linked AM process parameters to LANL's helmet surface temperature thermal [165, 166] model were also key contributions of this research. Note that the helmet surface temperature thermal model was not developed in the work but was modified for integration of models presented in this work.

10.1.1 Limitations

The key-limiting factor of this work is the data-dependent nature of the method. This means that quality and reliable data is needed in order for the model to provide useful results. Although some data sources are outdated, in general they provide enough useful information to positively impact designs resulting in a demand for "ergonomic" products. In addition, where data is not widely available this method may be too costly to implement, for small firms. Another notable limitation of this work lies in the validation of the methodology in the human population. The design of the model was based on outdated databases military databases that target a highly fit population. Although, recent literature was also referenced the older databases are still more robust. New methods that utilize 3D scanning and virtual or augmented reality could be useful in capturing anthropometric data feasibly but was outside of the scope of this work. Since this method utilized outdated databases and was not validated in the population, the accuracy of accommodation is questionable.

Different aspects of this method were demonstrated in the handheld device and helmet applications. Specifically, steps 1, 2, 4 and 5 were demonstrated in the handheld device application. Manufacturing characteristics, step 3, was not defined in this demonstration due to cost restrictions on additional testing, which was required to establish performance metrics. Performance metrics considered included force feedback from button presses, stress and strain load of materials for button and casing, etc. These measures could not be captured computationally and thus required additional experimentation. Moreover, the handheld device represented a dynamic application so the focus of the Chapter 8 demonstration was to ensure that the interaction space could be demonstrated and integrated in an optimization model. The trade-off (step four) analysis was only performed for the product metrics as well.

For the helmet application, the complete method was performed. The helmet application consisted of additional innovation in the form of a passive heat exchanger, which was the focus of the performance metric, thermal performance, with the requirement of cooling the human head. Thus, the helmet was the system and a subsystem of that helmet was the heat exchanger. The material in the subsystem included the AM heat pipe holders and heat pipes, while the helmet system consisted of the Kevlar helmet shell, wicking material, and water reservoir, for rewetting the wicking material. Department of defense military standard specified standardization of certain dimensions, e.g. padding thickness, for all helmet sizes [178]. However, there were no specifications of the process parameters for AM. Thus, for the padding with directly interfaces with the human head the layer height and part density was optimized while the thickness was fixed. Additionally, the actual helmet parameters, including the helmet length and width, were optimized for the helmet shell, which must fit both the heat pipe and padding subsystem and the head or braincase. The entire system is considered optimized for each helmet generated because both the subsystem and system parameters that impact helmet surface temperature were optimized.

Another limitation includes the validation of the "human interaction factors." An underestimation of the background knowledge required for incorporating biomechanics in design may have been assumed. It is clear based on the time it took participants to complete the study and difficulty faced by junior and senior mechanical engineering students that a course on biomechanics for consumer product design or a general course of biomechanics would be useful. In addition, implementing a 2-day shortened study with a training component could also be useful. Moreover, simplified, interactive confirmation procedures for instructions may be useful for providing instantaneous feedback of participant understanding during experiments.

Future validation efforts should be implemented amongst engineering students with a background in biomechanics to determine if an observable difference in student populations exists.

The handheld device application is limited by defining the reach zone of the thumb only on the top surface of the device. This does not allow for the prediction of extension and flexion of the thumb from one position to the side bodies of the device. Moreover, the positions defined do not model the rotation in the joints of the thumb to define a broader reach zone. Inverse kinematics could provide are more realistic calculation of the thumb reach zone while also considering rotation of the joint in the thumb and interacting with the side body of the handheld device. More efforts could have been applied to developing a more robust model that provides deeper insights into thumb orientations on different surfaces.

The next limitation was in the modeling of the layer height variation in CAD. This work was able to model the infill densities in CAD, which was then run in a finite element analysis (FEA). The layer height was more problematic to model with infill density. There is currently no software that analyses G-Code applied to solid CAD parts for the purposes of FEA. The means that you must build the variation AM controls such as layer height, infill density, and infill pattern into the actual CAD model in order to model the effects of AM controls on different performance metrics in FEA prior to building parts. Due to the limitations of modeling and importing layer height based geometric shapes into ANSYS®, the ANSYS® model is limited to modeling infill density.

There are additional limitations at the process level for AM that impact part builds. Specifically, AM path effects including build orientation and print raster path or fill pattern have been determined to impact material anisotropy [30,179]. Material anisotropy occurs when a dependent relationship is determined between the physical properties of a material along horizontal or vertical direction. Anisotropy has been determined to have significant impacts on mechanical response [29,30,32,179]. The build orientations of XYZ (axial) versus ZXY (traverse) yield distinct results with parts build in the axial orientation resulting in stronger mechanical properties [179]. Moreover, material blends resulted in smaller differences part strength regardless of build orientation suggesting a path for developing consistent parts.

Multi-objective optimization was not applied in the demonstration of this method but could be easily adapted. Modeling multiple primary function of a product application along with competing performance metrics will instantly create a multi-objective optimization problem. For example, crack propagation of Kevlar material along with helmet surface temperature could have been modeled with the goal of minimizing both objectives. With surface temperature cooling the human head and crack propagation maintaining the strength of materials. In this approach the human interaction factors would still be modeled with the constraint function.

As an alternative the human interaction factors could be modeled as an objective function in the dynamic application (e.g. button) case, where the strength of the material, fit, and interaction could be modeled. Thus, objective functions would be a performance metrics such as modulus of elasticity of the material and force feedback. Where the modulus of elasticity is derived based on the manufacturing characteristics and force feedback is based on human interaction factors specifically function classifications. The goal of the optimization problem would minimize both objectives because for a button you want a flexible material that deforms and recovers with minimal force exertion.

In general, the numbers of variables or parameters in an objective function are reduced for performance metrics derived from human interaction factors based on direct (or primary) interactions (component and human parameter directly tough or interact). Primary interactions carry the highest degree of importance in this method because they assist in defining the interaction space. However, when extreme limits are approached in primary or secondary interactions additional problems may arise justifying the consideration of secondary interactions or the subsequent effects of primary interactions. Thus, when time and costs are restrictions modeling the most critical primary interactions (determined by historical data or product primary function) should be modeled in objective functions. For manufacturing characteristics derived performance objective functions the primary function and risk and reliability data, if available, should drive the variables included in the objective functions.

10.2 Conclusion

This methodology developed an approach that integrates biomechanics, product design, and manufacturing controls for the development of optimized product design that could accommodate a population group. With an interdisciplinary research goal, this work was able to identify relationships between manufacturing, MC, and interaction variability. This goal was accomplished though the identification of the number of products required to accommodate the population and different dimensions of products that facilitated accommodation. In general, an important question for the MC community lies in the scope of the approach. Does MC mean that every individual human being requires a custom design? Or does it instead mean that in a population there are several people that prefer the same things or are roughly the same size? If the later question is true, then firms or designers just need enough information to determine exactly how many designs are needed and the associated costs. This method addresses the how many designs are needed based on physical customization criteria defined by accommodation and the interaction design space. However, costs still need to be addressed and will vary from product to product. For example, in the design of a driver seat in a vehicle, the design firm can go with a one size fits all and/or add adjustability. However, for most drivers seat comfort is a factor in the decision to purchase. If seven seats are required to accommodate the target market of the population and maintain all other performance requirements associated with seat function, e.g. airbag deployment force, the firm must decide if the increase in sales is worth designing custom seats.

The present work also presents a cost efficient approach that provides direct, feasible and implementable solutions to design firms and consumer-driven corporations. This method enables the identification of non-verbal, physical interactions that people have with artifacts through the creation of "interaction variability design spaces." With the large scale research in artificial intelligent interaction variability could enable this method to be highly reliable and accurate in defining the interaction design space. A well-defined interaction design space would result in product options that are highly usable and appealing to targeted population segments or populations that have relevant and available data.

Implementing this new method into existing product design processes requires additional resources including manpower, equipment, and computational power for data processing. Additional manpower would require expertise in engineering design, biomechanics, ergonomics, manufacturing, optimization, and design of experiments. To obtain expertise in these particular focus areas, master level degree holders are necessary. The annual salary range for hiring employees with the aforementioned expertise and degree level is $\$69,355$ to $\$139,000$.

There are three possible scenarios for implementing this approach including a best case, worst case, and subcontract case. The expected time and costs change with each case. Implementing step one of the method, Identifying Product Application, should add no additional time to the design process in the best-case scenario. In the worst-case scenario, the product application has not been formulated so engineers would need to identify the product functions, requirements, and components. This step is still not expected to add additional time because this is a part of the traditional design process and not novel. Another option is to subcontract to a design firm, which could cost up to $\$500,000$ for a functional prototype.

For step two, Human Interaction Factors, the implementation for an engineer with human factors and engineering design expertise in the best-case scenario would require additional time, assuming a $\$100,000$ salary. Additional time is necessary for performing the mapping relationships and functional classifications for related to predicted interactions or historical data. In the worse case scenario, an engineer with this expertise is required and that would cost the company approximately 1.4 times the base salary, and up to 2.7 times the base salary, plus any relocation or bonus costs due to employer taxes and benefits [180]. At a base salary of $\$100,000$, the company could spend more than $\$140,000$ on hiring a new employee with this expertise. The third option is to subcontract to a human factor consultant, which could cost up to $\$70,000$ because the organization should have an ideal of the product and functionality.

For step three, Manufacturing Characteristics, the best-case scenario would require a controlled manufacturing process with discipline specific design engineers currently employed. Under a controlled manufacturing process implementation of this step would be cheap because relationships between manufacturing processes and performance would be known. If not, simulations could be performed which will create additional expenses to the firm in the form of labor and software costs. In the worse case scenario, multiple design engineers would need to be hired and the manufacturing process is not controlled. An uncontrolled manufacturing process could cost a company millions in defected parts and rework, thus hiring the appropriate subject matter experts would be cheaper. For a manufacturing subcontractor, which many large corporations currently use, the cost is significantly cheaper and flexible.

For steps four and five, Trade-off Analysis and Optimization, respectively, the process would add additional time in all cases. In the best-case scenario, expertise is already in-house and costs to the company are in the form of modeling and implementation in the product line integrating information from previous steps. The most complex aspect of this approach is modeling the optimization problem and modeling accommodation functions for interaction variability. The trade-off analysis will assist in reducing the complexity of the problem. In addition to computation power the best case could cost up to $\$250,000$ for 10 engineers to work on modeling for an extended time period. In the worse case scenario, the firm would need to hire a team of optimization experts and design engineers which could cost the company up to 1.4 million dollars for a team of 10 engineers. For subcontracting, a data analytics team could cost up to $210.00 per person per hour. For long term projects over 6 months this option could be more expensive than the worst-case scenario.

The total costs for implementing this method in the worse case scenario could be millions and would not be worth the expense to implement for firms that are not fully developed. In the best-case scenario, the costs would total to less than 1 million dollars and would be beneficial to implement in the event of lowering annual litigation costs. Subcontracting in attractive for steps 2 and 3 of the method but in other stages it can be extremely costly. Overall, additional workload will be added to the firm to implement this method. This workload will be significant in the full product development process is not currently conducted by the firm.

This method would be extremely beneficial for businesses and firms that provide consumer-facing product. For companies selling consumer goods, the application of this method could result in reduced manufacturing, litigation, and damaged reputation costs associated with product failures. Lower percentages of tort claims associated with product use and consumer injury and manufacturing costs could result in millions of dollars in savings for firms annually.

In a world where options are overwhelming and plentiful, consumers have the ability to be more selective and alert than ever. Don Norman [45] discussed concepts of intuitive design nearly 30 years ago, we are finally able to understand what intuitive designs means for many people though understanding "interaction variability" design spaces. While the application of artificial intelligence can make this method extremely informative in the immediate future, this work provides the fundamental knowledge basis for identifying and defining "interaction variability" design spaces for static and dynamic product applications. Moreover, this work provided insight into the impact of AM characteristics after build on the performance expectations and requirements of a design. Design methods were incorporated in this method to structure the integration of a reduced set of metrics into the optimization model. This was an essential step of this process because it influences the pre-design, experimental and/or modeling necessary to build a useful optimization model based the true physics of performance. Overall, the method presented a structured approach for integration critical biomechanics and anthropometrics into traditional engineering design techniques in order to optimize engineering performance metrics, influence product dimensions and interaction spaces to facilitate accommodation in a variable human population.

10.3 Future Work

Each chapter of the document briefly discussed areas of future work. The section will briefly summarize the areas of future work from each chapter with additional insights and challenges in different research areas. The most urgent overall need of this method is to population the "product interaction design space." The can be done with artificial intelligence, specifically machine learning techniques to capture large amounts on interaction data. The immediate next steps would be a classification scheme, which is defined in this dissertation for classifying interactions.

In the five-step method presented in this work, two of the steps, human interaction factors and manufacturing characteristics, are information intensive and define the most rigorous aspects of automation for this method. In the first step, product application, a database of products with primary functions can be developed. Products may have more than one primary function. The interaction design space associated with each primary function should be defined independently although overlap is expected. For the second step, human interaction factors, a network human-component interaction mappings and functional classifications should be developed. For automating the third step, manufacturing characteristics, a schema that relates process parameters to product performance metrics, where failures occur should be established. These relationships are already well documented for some manufacturing processes but it is important to document all processes that are currently employed or researched in manufacturing industries. In the trade-off analysis step, step 4, one part of the AHP is automated, however the AHP method could be further automated by visualizing the each pairwise comparison in a click through process that would create each matrix and generate a YAML script that would be integrated into the AHP software tool used in this approach. Each AHP can then be integrated into the AQFD method by extracting the product and performance metrics from the AHP results and performing a similar visual click through comparison process for each pair in the matrix to obtain the final product and performance metrics. The final output for the AQFD method can be tailored to generate scripts for the optimization model and insight into a multi or single objective optimization problem, depending on the number of performance metrics required for the product function (primary or secondary). Step five, the optimization process, is already automated.

Furthermore the automation process for human interaction factors requires additional discussion. In order to create an interaction network, machine learning and artificial intelligence methods should be developed or applied to learn the full interaction design space based on discrete postures that change with each interaction. The postures associated with different interactions can be extracted for images, video, and/or interaction experiments. Then the kinematics data for each posture can be extracted to define the interaction design space. Kinematics data will consider the full range of motion (ROM) associated with each posture in the design space. Thus, each posture could identify extension, flexion, rotation, and deviation values associated with each parameter of the human body. This will allow for the estimation of risk associated with interaction postures based on the ROM limits.

Chapter 3 discussed the selection of the product application. For this process future work should specify in the product conception phase components, assemblies, and subassemblies that directly interface with the end user. This could be developed in the form of structured database or drawing or model notation. In Chapter 4, which discussed the human interaction factors, additional training on biomechanics should be incorporated in all design focused fields including engineering design. This is important for the consideration of humans that interface with products. Future work in design with biomechanics should focus on developing a standardized approach to assist designers with embedding biomechanics consideration for human component interaction in the design of consumer products.

Chapter 4 also discussed manufacturing characteristics, which provided insight into the integration of MC with consideration of AM. The method can be applied to any manufacturing process but was demonstrated on AM in this method. Addressing the aforementioned limitations associated with AM will be critical. Creating more instances were minimum performance requirements can be met with AM should be investigated in addition to standardizing part-to-part builds. A G-Code to FEA system where analysis of the part to be additively manufactured is analyzed prior to build would be useful for estimating performance. In addition, it would allow researchers to model the effects of layer height and other AM characteristics such as infill density simultaneously, making it possible to conduct model based DOE. Another useful tool would be the development of a method for the mass production of the optimized parts with feasible manufacturing solutions that incorporate modularity and product platform design. For example, all common modular features could be produced in a few platforms, while the custom features are produced in distinct processes. The goal is to reduce the number of distinct processes and add modularity where plausible. The advantage is knowledge of products needed for population accommodation.

For the Trade-off Analysis, presented in Chapter 5, the integration of "Human Interaction Factors" and "Manufacturing Characteristics" should be further investigated in the application of AQFD for product and performance metrics in dynamic applications. In addition, a streamlined application for completing the AQFD method electronically in incremental steps would also be useful. The optimization process, Chapter 6, could be improved with the application of inverse kinematics for determining the interaction space for dynamic applications based on the orientation of components and human capacities. This would be useful for capturing the full rotation for the joints in the hand in the handheld device demonstration. There is also an opportunity to apply machine learning in the identification of reach zones with inverse kinematics or designer defined reach zones. Consideration of cost as a MOO problem should also be investigated as it can either positively or negatively affect the current results.

In the helmet demonstration, for the DOE application in FDM printers, additional experiments that assess the impact of layer height in larger increments of surface temperature and/or thermal conductivity should be investigated as it appears to have the strongest negative effects based on the 2^3 DOE performed. Moreover, a demonstration of MOO problem that considers performance, cost, and interaction space accommodation for a dynamic application is also an interesting problem that would provide real meaningful insights.

Appendix A: Human Component Interaction Mapping Results

The following tables outline the human component interaction mapping results for two applications including a water bottle, Table A.1, and sunglasses, Table A.2. An interaction was performed with each of the applications based on the primary function of the application. The primary function of the water bottle was to provide access to store liquid while the primary function sunglasses was to protect the eyes from solar radiation. The results were obtained through a method validation study that consisted of 16 participants. One participant failed to complete the sunglasses application so the number of subjects evaluating the water bottle and sunglasses applications were 16 and 15 participants, respectively. The tables represent the anatomical mapping consistency amongst participants for selecting anthropometric measures based on the relevant musculoskeletal interfaces also referred to as anatomical regions and the functional classifications of these interfaces discussed in Chapter 5.4.

Table A.1: Human Interaction Factors Pairwise Comparisons for Water Bottle Application

Human Interaction Factors	> 1	< 1	$= 1$	**Majority Consensus (%)**
Fingers				
Fingers - Palm	6	3	7	43.8
Fingers - Wrist	10	2	4	62.5
Fingers - Mouth	8	3	5	50.0
Fingers - Reach	7	7	2	43.8
Fingers - Force	9	3	4	56.3
Fingers - Tactility	6	7	3	43.8
Fingers - Maneuverability	8	6	2	50.0
Palm				
Palm - Wrist	8	6	2	50.0
Palm - Mouth	6	6	4	37.5
Palm - Reach	6	7	3	43.8
Palm - Force	5	6	5	37.5
Palm - Tactility	6	7	3	43.8
Palm - Maneuverability	5	8	3	50.0
Wrist				
Wrist - Mouth	8	5	3	50.0
Wrist - Reach	6	6	4	37.5
Wrist - Force	8	4	4	50.0
Wrist - Tactility	4	10	2	62.5
Wrist - Maneuverability	5	7	4	43.8
Mouth				
Mouth - Reach	6	8	2	50.0
Mouth - Force	8	7	1	50.0
Mouth - Tactility	7	5	4	43.8
Mouth - Maneuverability	5	9	2	56.3
Reach				
Reach - Force	7	7	2	43.8
Reach - Tactility	5	10	1	62.5
Reach - Maneuverability	6	6	4	37.5
Force				
Force - Tactility	3	8	5	50.0
Force - Maneuverability	5	9	2	56.3
Tactility				
Tactility - Maneuverability	6	8	2	50.0

Table A.2: Human Interaction Factors Pairwise Comparisons for Sunglasses Application

Human Interaction Factors	> 1	< 1	$= 1$	**Majority Consensus (%)**
Fingers				
Fingers - Wrist	7	2	6	46.7
Fingers - Face	7	5	3	46.7
Fingers - Ears	5	5	5	33.3
Fingers - Reach	3	4	8	53.3
Fingers - Force	4	7	4	46.7
Fingers - Tactility	6	8	1	53.3
Fingers - Maneuverability	5	5	5	33.3
Wrist				
Wrist - Face	10	5	0	66.7
Wrist - Ears	5	9	1	60.0
Wrist - Reach	4	4	7	46.7
Wrist - Force	4	6	5	40.0
Wrist - Tactility	4	9	2	60.0
Wrist - Maneuverability	3	5	7	46.7
Face				
Face - Ears	4	3	8	53.3
Face - Reach	4	7	4	46.7
Face - Force	6	7	2	46.7
Face - Tactility	3	7	5	46.7
Face - Maneuverability	5	6	4	40.0
Ears				
Ears - Reach	5	7	3	46.7
Ears - Force	7	5	3	46.7
Ears - Tactility	4	8	3	53.3
Ears - Maneuverability	6	7	2	46.7
Reach				
Reach - Force	3	4	8	53.3
Reach - Tactility	6	9	0	60.0
Reach - Maneuverability	3	7	5	46.7
Force				
Force - Tactility	4	9	2	60.0
Force - Maneuverability	5	7	3	46.7
Tactility				
Tactility - Maneuverability	5	6	4	40.0

Appendix B: Pairwise Comparison Tables for Analytical Hierarchy Process

The pairwise comparison tables along with the decision matrix for each AHP performed is provided in the following sections. The tables are meant to provide clarification for the AHP results and explicitly detail the importance ratings and comparisons that were produced in YAML scripts for automation in the demonstration chapters. The rating criteria for each comparison is defined where:

1. 1 means: A is equal to B
2. 5 means: A is highly preferable to B
3. 1/5 means: B is highly preferable to A

B.1 Chapter 8: Handheld Device Pairwise Comparisons

The pairwise comparison performed in Chapter 9 depict the full method for the dynamic application of the Handheld Device. The product metrics considered for the dynamic application included a *Button Metric* and *Casing Metric*. There were no AM performance metrics linked to the interaction variability performance metric thus a performance metric AHP was not conducted.

Table B.1: Pairwise Comparison Matrix for Anthropometric Criteria of Button Metric

Anthropometric Criteria	Thumb Length	Hand Length	Hand Breadth	Palm Length	Reach
Thumb Length	1	2	3	2	1
Hand Length	1/2	1	1	2	1/2
Hand Breadth	1/3	1	1	1	1/3
Palm Length	1/2	1/2	1	1	1/4
Reach	1	2	3	4	1

B.1.1 Analytical Hierarchy Process for Button Metric

The following tables represent the process for using anthropometric criteria to rate the button metric options, which represent one portion of the product metrics for the handheld device demonstration.

B.1.2 Analytical Hierarchy Process for Casing Metric

The following tables represent the process for using anthropometrics criteria to rate the casing metric options, which represent the other portion of product metrics for the handheld device demonstration.

Table B.2: Thumb Length: Button Options

Thumb Length	Circle	Ellipse	Triangle	Rectangle
Circle	1	3	3	1
Ellipse	1/3	1	2	1/2
Triangle	1/3	1/2	1	1/3
Rectangle	1	2	3	1

Table B.3: Hand Length: Button Options

Hand Length	Circle	Ellipse	Triangle	Rectangle
Circle	1	2	2	1
Ellipse	1/2	1	2	1/2
Triangle	1/2	1/2	1	1/3
Rectangle	1	2	3	1

Table B.4: Hand Breadth: Button Options

Hand Breadth	Circle	Ellipse	Triangle	Rectangle
Circle	1	2	2	1
Ellipse	1/2	1	2	1
Triangle	1/2	1/2	1	1/2
Rectangle	1	1	2	1

Table B.5: Palm Length: Button Options

Palm Length	Circle	Ellipse	Triangle	Rectangle
Circle	1	2	3	1
Ellipse	1/2	1	1/2	1
Triangle	1/3	2	1	1/2
Rectangle	1	1	2	1

Table B.6: Reach: Button Options

Reach	Circle	Ellipse	Triangle	Rectangle
Circle	1	1	3	1
Ellipse	1	1	2	1/2
Triangle	1/3	1/2	1	1/4
Rectangle	1	2	4	1

Table B.7: Pairwise Comparison Matrix for Anthropometric Criteria of Casing Metric

Anthropometric Criteria	Thumb Length	Hand Length	Hand Breadth	Palm Length	Reach
Thumb Length	1	1/2	1/2	1	1
Hand Length	2	1	1	3	1
Hand Breadth	2	1	1	2	1
Palm Length	1	1/3	1/2	1	1/2
Reach	1	1	1	2	1

Table B.8: Thumb Length: Casing Options

Thumb Length	Ellipse	Rounded Square	Rectangle
Ellipse	1	3	2
Rounded Square	1/3	1	1/2
Rectangle	1/2	2	1

Table B.9: Hand Length: Casing Options

Hand Length	Ellipse	Rounded Square	Rectangle
Ellipse	1	2	1
Rounded Square	1/2	1	1/2
Rectangle	1	2	1

Table B.10: Hand Breadth: Casing Options

Hand Breadth	Ellipse	Rounded Square	Rectangle
Ellipse	1	3	2
Rounded Square	1/3	1	1/3
Rectangle	1/2	3	1

Table B.11: Palm Length: Casing Options

Palm Length	Ellipse	Rounded Square	Rectangle
Ellipse	1	4	2
Rounded Square	1/4	1	1/3
Rectangle	1/2	3	1

Table B.12: Reach: Casing Options

Reach	Ellipse	Rounded Square	Rectangle
Ellipse	1	4	2
Rounded Square	1/4	1	1/3
Rectangle	1/2	3	1

Table B.13: Pairwise Comparison Matrix for Anthropometric Criteria of Helmet Metric

Anthropometric Criteria	Head Length	Head Breadth	Head Circumference
Head Length	1	1	2
Head Breadth	1	1	2
Head Circumference	1/2	1/2	1

B.2 Chapter 9: Helmet Pairwise Comparisons

The pairwise comparison performed in Chapter 9 depict the full method for the static application of the Helmet. The product metric is the *Helmet Metric* and the performance metric is *Thermal Performance Metric*.

B.2.1 Analytical Hierarchy Process for Helmet Metric

The following tables represent the process for using anthropometrics criteria to rate the helmet metric options, which represent the product metrics for the military helmet demonstration.

B.2.1.1 Analytic Hierarchy Process for Thermal Performance Metric

The following tables represent the process for using AM process metric criteria to rate the thermal performance metric options, which represent the performance metrics for the military helmet demonstration.

Table B.14: Head Length: Helmet Options

Head Length	Helmet Surface Area	Helmet Circumference	Hemisphere Surface Area	Body Surface Area	Ellipsoidal Cap Surface Area	Spherical Cap Surface Area
Helmet Surface Area	1	3	3	2	1	2
Helmet Circumference	1/3	1	1	1/4	1/3	1/2
Hemisphere Surface Area	1/3	1	1	1/3	1/3	1/2
Body Surface Area	1/2	4	3	1	1	2
Ellipsoidal Cap Surface Area	1	3	3	1	1	2
Spherical Cap Surface Area	1/2	2	2	1/2	1/2	1

Table B.15: Head Breadth: Helmet Options

Head Breadth	Helmet Surface Area	Helmet Circumference	Hemisphere Surface Area	Body Surface Area	Ellipsoidal Cap Surface Area	Spherical Cap Surface Area
Helmet Surface Area	1	3	3	2	1	2
Helmet Circumference	1/3	1	1	1/4	1/3	1/2
Hemisphere Surface Area	1/3	1	1	1/3	1/3	1/2
Body Surface Area	1/2	4	3	1	1	2
Ellipsoidal Cap Surface Area	1	3	3	1	1	2
Spherical Cap Surface Area	1/2	2	2	1/2	1/2	1

Table B.16: Head Circumference: Helmet Options

Head Circumference	Helmet Surface Area	Helmet Circumference	Hemisphere Surface Area	Body Surface Area	Ellipsoidal Cap Surface Area	Spherical Cap Surface Area
Helmet Surface Area	1	2	3	2	1	2
Helmet Circumference	1/2	1	2	1/2	1/3	1/2
Hemisphere Surface Area	1/3	1/2	1	1/3	1/4	1/2
Body Surface Area	1/2	2	3	1	1	1
Ellipsoidal Cap Surface Area	1	4	3	1	1	2
Spherical Cap Surface Area	1/2	2	2	1	1/2	1

Table B.17: Pairwise Comparison Matrix for AM Process Criteria of Thermal Performance Metric

AM Process Criteria	Layer Height	Infill Density	Material	Print Speed	Extrusion Temperature	Print Bed Temperature
Layer Height	1	1/3	1	3	4	5
Infill Density	3	1	1	4	5	5
Material	1	1	1	5	4	5
Print Speed	1/3	1/4	1/5	1	1/2	1/2
Extrusion Temperature	1/4	1/5	1/4	2	1	2
Print Bed Temperature	1/5	1/5	1/5	2	1/2	1

Table B.18: Layer Height: Thermal Performance Metric Options

Layer Height	Surface Temperature	Internal Temperature	Thermal Conductivity	Heat Flux	Thermal Resistance	Heat Transfer Efficiency	Power Dissipation	Power-Weight Ratio	Power-Cost Ratio
Surface Temperature	1	3	2	3	2	2	3	4	4
Internal Temperature	1/3	1	1/3	1	1/2	1/3	1/2	1	1/2
Thermal Conductivity	1/2	3	1	2	1	1	2	3	2
Heat Flux	1/3	1	1/2	1	1/3	1/2	1	1/2	1
Thermal Resistance	1/2	2	1	3	1	1	2	3	3
Heat Transfer Efficiency	1/2	3	1	2	1	1	2	2	1
Power Dissipation	1/3	2	1/2	1	1/2	1/2	1	3	2
Power-Weight Ratio	1/4	1	1/3	2	1/3	1/2	1/3	1	1/2
Power-Cost Ratio	1/4	2	1/2	1	1/3	1	1/2	2	1

Table B.19: Infill Density: Thermal Performance Metric Options

Infill Density	Surface Temperature	Internal Temperature	Thermal Conductivity	Heat Flux	Thermal Resistance	Heat Transfer Efficiency	Power Dissipation	Power-Weight Ratio	Power-Cost Ratio
Surface Temperature	1	3	1	2	1	2	3	5	5
Internal Temperature	1/3	1	1/3	1/2	1/3	1/2	1/2	1	1/2
Thermal Conductivity	1	3	1	3	1	2	3	4	3
Heat Flux	1/2	2	1/3	1	1/3	1/2	1	1/2	1
Thermal Resistance	1	3	1	3	1	1	2	2	3
Heat Transfer Efficiency	1/2	2	1/2	2	1	1	1	2	3
Power Dissipation	1/3	2	1/3	1	1/2	1	1	3	2
Power-Weight Ratio	1/5	1	1/4	2	1/2	1/2	1/3	1	1/2
Power-Cost Ratio	1/5	2	1/3	1	1/3	1/3	1/2	2	1

Table B.20: Material: Thermal Performance Metric Options

Material	Surface Temperature	Internal Temperature	Thermal Conductivity	Heat Flux	Thermal Resistance	Heat Transfer Efficiency	Power Dissipation	Power-Weight Ratio	Power-Cost Ratio
Surface Temperature	1	4	1/2	3	1/2	2	3	4	5
Internal Temperature	1/4	1	1/4	1/2	1/3	1/3	1	1	1
Thermal Conductivity	2	4	1	4	1	3	4	5	5
Heat Flux	1/3	2	1/4	1	1/3	1/2	1	1/2	1
Thermal Resistance	2	3	1	3	1	3	2	4	5
Heat Transfer Efficiency	1/2	3	1/3	2	1/3	1	2	1	2
Power Dissipation	1/3	1	1/4	1	1/2	1/2	1	3	2
Power-Weight Ratio	1/4	1	1/5	2	1/4	1	1/3	1	1/2
Power-Cost Ratio	1/5	1	1/5	1	1/5	1/2	1/2	2	1

Table B.21: Print Speed: Thermal Performance Metric Options

Print Speed	Surface Temperature	Internal Temperature	Thermal Conductivity	Heat Flux	Thermal Resistance	Heat Transfer Efficiency	Power Dissipation	Power-Weight Ratio	Power-Cost Ratio
Surface Temperature	1	4	2	3	1	1/2	3	5	5
Internal Temperature	1/4	1	1/4	1/2	1/3	1/2	1/2	1	1/2
Thermal Conductivity	1/2	4	1	2	1	2	2	3	2
Heat Flux	1/3	2	1/2	1	1/3	1	1	1/2	1
Thermal Resistance	1	3	1	3	1	2	1	3	3
Heat Transfer Efficiency	2	2	1/2	1	1/2	1	2	1	2
Power Dissipation	1/3	2	1/2	1	1	1/2	1	2	2
Power-Weight Ratio	1/5	1	1/3	2	1/3	1	1/2	1	1
Power-Cost Ratio	1/5	2	1/2	1	1/3	1/2	1/2	1	1

Table B.22: Extrusion Temperature: Thermal Performance Metric Options

Extrusion Temperature	Surface Temperature	Internal Temperature	Thermal Conductivity	Heat Flux	Thermal Resistance	Heat Transfer Efficiency	Power Dissipation	Power-Weight Ratio	Power-Cost Ratio
Surface Temperature	1	4	1/2	3	1/2	1	3	5	5
Internal Temperature	1/4	1	1/4	1/2	1/3	1/3	1/2	1	1/2
Thermal Conductivity	2	4	1	3	1	3	2	3	2
Heat Flux	1/3	2	1/3	1	1/4	1/2	1	1/2	1
Thermal Resistance	2	3	1	4	1	2	2	3	3
Heat Transfer Efficiency	1	3	1/3	2	1/2	1	2	1	2
Power Dissipation	1/3	2	1/2	1	1/2	1/2	1	3	2
Power-Weight Ratio	1/5	1	1/3	2	1/3	1	1/3	1	1
Power-Cost Ratio	1/5	2	1/2	1	1/3	1/2	1/2	1	1

Table B.23: Print Bed Temperature: Thermal Performance Metric Options

Print Bed Temperature	Surface Temperature	Internal Temperature	Thermal Conductivity	Heat Flux	Thermal Resistance	Heat Transfer Efficiency	Power Dissipation	Power-Weight Ratio	Power-Cost Ratio
Surface Temperature	1	4	1	3	1	2	3	5	5
Internal Temperature	1/4	1	1/4	1/2	1/3	1/2	1	1	1/2
Thermal Conductivity	1	4	1	3	1	3	3	4	3
Heat Flux	1/3	2	1/3	1	1/3	1/2	1	1	1
Thermal Resistance	1	3	1	3	1	2	3	4	3
Heat Transfer Efficiency	1/2	2	1/3	2	1/2	1	2	1	1
Power Dissipation	1/3	1	1/3	1	1/3	1/2	1	2	2
Power-Weight Ratio	1/5	1	1/4	1	1/4	1	1/2	1	1
Power-Cost Ratio	1/5	2	1/3	1	1/3	1	1/2	1	1

Bibliography

[1] Yoji Akao. *Quality function deployment : integrating customer requirements into product design*. Productivity Press, Cambridge, Mass. :, 1990.

[2] Eshan S Jaiswal. A case study on quality function deployment (qfd). *IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE)*, 3(6):27–35, 2012.

[3] Inc. MathWorks. *Optimization Techniques in MATLAB*. 2014.

[4] B. Joseph Pine. *Mass customization : the new frontier in business competition*. Harvard Business School Press, Boston, Mass., 1993.

[5] P. Reeves, C. Tuck, and R. Hague. *Additive Manufacturing for Mass Customization*, pages 275–289. Springer Series in Advanced Manufacturing 1860-5168. London : Springer London, 2011.

[6] American Society for Testing and Materials. Standard terminology for additive manufacturing technologies, 2012.

[7] Terry Wohlers and Tim Gornet. History of additive manufacturing. 2014.

[8] Julie Z Zhang, Joseph C Chen, and E Daniel Kirby. Surface roughness optimization in an end-milling operation using the taguchi design method. *Journal of materials processing technology*, 184(1):233–239, 2007.

[9] Ramakrishna Arni and S. K. Gupta. Manufacturability analysis of flatness tolerances in solid freeform fabrication. *Journal of Mechanical Design*, 123(1):148, 2001.

[10] R. Paul and S. Anand. Optimization of layered manufacturing process for reducing form errors with minimal support structures. *Journal of Manufacturing Systems*, 2014.

[11] R. Paul and S. Anand. A combined energy and error optimization method for metal powder based additive manufacturing processes. *Rapid Prototyping Journal*, 21(3):301–312, 2015.

[12] G. Strano, L. Hao, R. Everson, and K. Evans. Multi-objective optimization of selective laser sintering processes for surface quality and energy saving. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 225(9):1673–1682, 2011.

[13] Robert Bogue. Design for manufacture and assembly: background, capabilities and applications. *Assembly Automation*, 32(2):112–118, 2012.

[14] Stanley M. Davis. *Future perfect.* Addison-Wesley, Reading, Mass. :, 1987.

[15] R. S. M. Lau. Mass customization: The next industrial revolution: One of industry's newest paradigms for excellence in manufacturing is the concept of mass customization. *Industrial Management, Chicago then Atlanta*, 37(5):18–19, 1995.

[16] Thorsten Blecker and Nizar Abdelkafi. *Mass Customization: State-of-the-Art and Challenges*, volume 87 of *International Series in Operations Research & Management Science*, chapter 1, pages 1–25. Springer US, 2006.

[17] James H. Gilmore and B. Joseph Pine. Markets of one creating customer-unique value through mass customization. 2000.

[18] Thorsten Blecker, Wolfgang Kersten, and Christian M Meyer. Development of an approach for analyzing supply chain complexity. In *Mass Customization: Concepts–Tools–Realization. Proceedings of the International Mass Customization Meeting*, pages 47–59, 2005.

[19] Jack Buffington and Donald McCubbrey. A conceptual framework of generative customization as an approach to product innovation and fulfillment. *European Journal of Innovation Management*, 14(3):388–403, 2011.

[20] Jack Buffington. Comparison of mass customization and generative customization in mass markets. *Industrial Management & Data Systems*, 111(1):41–62, 2011.

[21] R. I. Campbell, D. J. de Beer, D. A. Mauchline, L. Becker, R. van der Grijp, Y. Ariadi, and M. A. Evans. Additive manufacturing as an enabler for enhanced consumer involvement. *South African Journal of Industrial Engineering*, 25(2):67–74, 2014.

[22] N. Hopkinson, R. J. M. Hague, and P. M. Dickens. *Rapid manufacturing : an industrial revolution for the digital age.* John Wiley, Chichester, England :, 2006.

[23] I. Gibson, D. W. Rosen, and B. Stucker. Additive manufacturing technologies rapid prototyping to direct digital manufacturing. 2010.

[24] R. Hague, I. Campbell, and P. Dickens. Implications on design of rapid manufacturing. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 217(1):25–30, 2003.

[25] Stephen Mellor, Liang Hao, and David Zhang. Additive manufacturing: A framework for implementation. *International Journal of Production Economics*, 149(9):194–201, 2014.

[26] Gideon N. Levy, Ralf Schindel, and J. P. Kruth. Rapid manufacturing and rapid tooling with layer manufacturing (lm) technologies, state of the art and future perspectives. *CIRP Annals - Manufacturing Technology*, 52(2):589–609, 2003.

[27] P. J. de Jager, J. J. Broek, and J. S. M. Vergeest. A comparison between zero and first order approximation algorithms for layered manufacturing. *Rapid Prototyping Journal*, 3(4):144, 1997.

[28] R. Paul, S. Anand, and F. Gerner. Effect of thermal deformation on part errors in metal powder based additive manufacturing processes. *Journal of Manufacturing Science and Engineering, Transactions of the ASME*, 136(3), 2014.

[29] B Clausen, DW Brown, JS Carpenter, KD Clarke, AJ Clarke, SC Vogel, JD Bernardin, D Spernjak, and JM Thompson. Deformation behavior of additively manufactures gp1 stainless steel. *Materials Science and Engineering: A*, 2017.

[30] ANDREW M BAKER, JOHN MCCOY, BHASKAR S MAJUMDAR, BRITTANY RUMLEY-OUELLETTE, JACOB WAHRY, ALEXANDRIA N MARCHI, JOHN D BERNARDIN, and DUSAN SPERNJAK. Measurement and modelling of thermal and mechanical anisotropy of parts additively manufactured using fused deposition modelling (fdm). *Structural Health Monitoring 2017*, 2017.

[31] J. D. Bernardin, J. M. Thompson, A. Wachtor, and J. Zhang. Design and performance of an enviornmental temperature controlled build chamber for a fused deposition method #d printer. 2015.

[32] D. W. Brown, J. D. Bernardin, J. S. Carpenter, B. Clausen, D. Spernjak, and J. M. Thompson. Neutron diffraction measurements of residual stress in additively manufactured stainless steel. *Materials Science and Engineering: A*, 678(Supplement C):291–298, 2016.

[33] W. Oropallo and L. A. Piegl. Ten challenges in 3d printing. *Engineering with Computers*, (1-14), 2015.

[34] Hashem Ghariblu and Saeid Rahmati. New process and machine for layered manufacturing of metal parts. *Journal of Manufacturing Science and Engineering*, 136(4):041004–041004, 2014. 10.1115/1.4026446.

[35] J. Hwang, S. K. Moon, Y. Ho, and C. Noh. Universal product family design for human variability and aesthetics. *Advances in Affective and Pleasurable*, pages 47–56, 2012.

[36] Seung Ki Moon and Daniel A. McAdams. A market-based design strategy for a universal product family. *Journal of Mechanical Design*, 134(11):111007, 2012.

[37] Seung Ki Moon and Daniel A McAdams. Universal product platform and family design for uncertain market. In *DS 58-4: Proceedings of ICED 09, the 17th International Conference on Engineering Design, Vol. 4, Product and Systems Design, Palo Alto, CA, USA, 24.-27.08. 2009.*

[38] Hyunwoong Ko, Seung Ki Moon, and Jihong Hwang. Design for additive manufacturing in customized products. *International Journal of Precision Engineering and Manufacturing*, 16(11):2369–2375, 2015.

[39] David Ben-Arieh. *The Platform Formation Problem*, chapter 6, pages 105–124. Springer Series in Advanced Manufacturing. Springer London, 2011.

[40] Diego de Castro Fettermann and Mrcia Elisa Soares Echeveste. New product development for mass customization: a systematic review. *Production & Manufacturing Research*, 2(1):266–290, 2014.

[41] Sagar Chowdhury and Zahed Siddique. *Shape Commonalization to Develop Common Platforms for Mass Customization*, chapter 7, pages 125–150. Springer Series in Advanced Manufacturing. Springer London, 2011.

[42] Ki Moon Seung, Timothy W. Simpson, Jun Shu, and Soundar R. T. Kumara. *A Platform Identification Method for Service Family Design Using a Process Model and a Clustering Method*, chapter 8, pages 151–170. Springer Series in Advanced Manufacturing. Springer London, 2011.

[43] Jakob Nielsen. *Usability engineering*. Academic Press, Boston :, 1993.

[44] ISO-210. Ergonomics of human-system interaction–part 210: Human-centred design for interactive systems. *Directly by ISO*, 2010.

[45] Donald A. Norman. *The design of everyday things*. Doubleday, New York, 1st doubleday/currency edition, 2013. 89048989 Donald A. Norman. ill. ; 21 cm. Reprint. Originally published: The psychology of everyday things. New York : Basic Books, c1988. Includes index. Includes bibliographical references (p. 241-247).

[46] Chadia Abras, Diane Maloney-Krichmar, and Jenny Preece. User-centered design. *Bainbridge, W. Encyclopedia of Human-Computer Interaction. Thousand Oaks: Sage Publications*, 37(4):445–456, 2004.

[47] Christopher J Garneau, Gopal Nadadur, and Matthew B Parkinson. *Considering Human Variability When Implementing Product Platforms*, pages 559–585. Springer, 2014.

[48] D. Oborne. Human variability. *Applied Ergonomics*, 15(4):314, 1984.

[49] Albert Damon, Howard W. Stoudt, and Ross Armstrong McFarland. *The human body in equipment design*. Harvard University Press, Cambridge, 1966.

[50] R. S. Bridger. *Introduction to ergonomics*. Taylor & Francis, London ;, 2nd ed. edition, 2003.

[51] Stephen Pheasant. *Bodyspace : anthropometry, ergonomics, and the design of work*. Taylor & Francis, London ; Bristol, PA, 2nd edition, 1996. 97103991 Stephen Pheasant. ill. ; 26 cm. Includes bibliographical references (p. 225-238) and index.

[52] Christopher J Garneau and Matthew B Parkinson. A comparison of methodologies for designing for human variability. *Journal of Engineering Design*, 22(7):505–521, 2011.

[53] Bettye Rose Connell, Mike Jones, Ron Mace, Jim Mueller, Abir Mullick, Elaine Ostroff, Jon Sanford, Ed Steinfeld, Molly Story, and Gregg Vanderheiden. The principles of universal design. *Retrieved January*, 11:2005, 1997.

[54] J. T. Reason. *Human error*. Cambridge University Press, Cambridge [England] ;, 1990.

[55] M.F. Story. The fda perspective on human factors in medical device software development. 2012.

[56] W. Correia, M. Soares, M. Barros, and F. Campos. The role of usability in the evaluation of accidents: Human error or design flaw? *Work Work*, 41(SUPPL.1):1202–1207, 2012.

[57] Walter Correia, Fbio Campos, Marcelo Soares, and Marina Barros. Evaluation of safety and usability in projectual methodologies with focus on design of physical artifacts. *Advances in Usability Evaluation*, page 66, 2012.

[58] Martin J. Osborne and Ariel Rubinstein. A course in game theory, 1994.

[59] S. Sangelkar, N. Cowen, and D. McAdams. User activity - product function association based design rules for universal products. *Design studies.*, 33(1):85–110, 2012.

[60] S. Sangelkar and D. A. McAdams. Adapting ada architectural design knowledge for universal product design using association rule mining: A function based approach. *Journal of mechanical design.*, 134(7):071003, 2012.

[61] Seung Ki Moon and Daniel A McAdams. A platform-based strategic design approach for universal products. *International Journal of Mass Customisation*, 3(3):227–246, 2010.

[62] Gopal Nadadur and Matthew B Parkinson. Using designing for human variability to optimize aircraft eat layout. Technical report, SAE Technical Paper, 2009.

[63] Christopher J Garneau and Matthew B Parkinson. Optimization of product dimensions for discrete sizing applied to a tool handle. *International Journal of Industrial Ergonomics*, 42(1):56–64, 2012.

[64] Bram L. Gorissen, ?hsan Yan?ko?lu, and Dick den Hertog. A practical guide to robust optimization. *Omega*, 53(Supplement C):124–137, 2015.

[65] Aharon Ben-Tal, Laurent El Ghaoui, and Arkadi Nemirovski. *Robust optimization*. Princeton University Press, 2009.

[66] Dimitris Bertsimas and Vineet Goyal. On the approximability of adjustable robust convex optimization under uncertainty. *Mathematical Methods of Operations Research*, 77(3):323–343, 2013.

[67] Aharon Ben-Tal, Dick Den Hertog, and Jean-Philippe Vial. Deriving robust counterparts of nonlinear uncertain inequalities. *Mathematical programming*, 149(1-2):265–299, 2015.

[68] Hans-Georg Beyer and Bernhard Sendhoff. Robust optimization ? a comprehensive survey. *Computer Methods in Applied Mechanics and Engineering*, 196(33):3190–3218, 2007.

[69] Dimitris Bertsimas, Omid Nohadani, and Kwong Meng Teo. Nonconvex robust optimization for problems with constraints. *INFORMS journal on computing*, 22(1):44–58, 2010.

[70] A. Charnes and W. W. Cooper. Deterministic equivalents for optimizing and satisficing under chance constraints. *Operations Research*, 11(1):18–39, 1963.

[71] Haiyang Yu, Chengbin Chu, Eric Chtelet, and Farouk Yalaoui. Reliability optimization of a redundant system with failure dependencies. *Reliability Engineering & System Safety*, 92(12):1627–1634, 2007.

[72] Indika Meedeniya, Aldeida Aleti, and Lars Grunske. Architecture-driven reliability optimization with uncertain model parameters. *Journal of Systems and Software*, 85(10):2340–2355, 2012.

[73] Jos Holgu??n-Veras, Wilfredo F. Yushimito, Felipe Aros-Vera, and John Reilly. User rationality and optimal park-and-ride location under potential demand maximization. *Transportation Research Part B: Methodological*, 46(8):949–970, 2012. (Jack).

[74] William Ho, Xiaowei Xu, and Prasanta K Dey. Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research*, 202(1):16–24, 2010.

[75] Hong-Seok Byun and Kwan H Lee. Determination of the optimal build direction for different rapid prototyping processes using multi-criterion decision making. *Robotics and Computer-Integrated Manufacturing*, 22(1):69–80, 2006.

[76] W Cheng, JYH Fuh, AYC Nee, YS Wong, HT Loh, and T Miyazawa. Multi-objective optimization of part-building orientation in stereolithography. *Rapid Prototyping Journal*, 1(4):12–23, 1995.

[77] Nikhil Padhye and Kalyanmoy Deb. *Multi-objective Optimisation and Multi-criteria Decision Making for FDM Using Evolutionary Approaches*, pages 219–247. Springer, 2011.

[78] Anand Gurumurthy and Rambabu Kodali. A multi-criteria decision-making model for the justification of lean manufacturing systems. *International Journal of Management Science and Engineering Management*, 3(2):100–118, 2008.

[79] X. C. Tan, F. Liu, H. J. Cao, and H. Zhang. A decision-making framework model of cutting fluid selection for green manufacturing and a case study. *JOURNAL OF MATERIALS PROCESSING TECHNOLOGY*, 129(1-3):467–470, 2002.

[80] Timothy W Simpson. Product platform design and customization: Status and promise. *Ai Edam*, 18(1):3–20, 2004.

[81] Mitchell M Tseng and Jianxin Jiao. Design for mass customization by developing product family architecture. In *Design Engineering Technical Conferences-Design Theory and Methodology*. Citeseer, 1998.

[82] Javier P Gonzalez-Zugasti, Kevin N Otto, and John D Baker. Assessing value in platformed product family design. *Research in Engineering Design*, 13(1):30–41, 2001.

[83] Timothy W Simpson, Jonathan R Maier, and Farrokh Mistree. Product platform design: method and application. *Research in engineering Design*, 13(1):2–22, 2001.

[84] Javier P Gonzalez-Zugasti and Kevin N Otto. Modular platform-based product family design. In *ASME Advances in Design Automation Conference*. Citeseer, 2000.

[85] Seung Ki Moon, Kyoung Jong Park, and Timothy W. Simpson. Platform design variable identification for a product family using multi-objective particle swarm optimization. *Research in Engineering Design*, 25(2):95–108, 2014.

[86] Achille Messac, Michael P. Martinez, and Timothy W. Simpson. Introduction of a product family penalty function using physical programming. *Journal of Mechanical Design*, 124(2):164–172, 2002.

[87] Ruchit A Shah, Patrick M Reed, and Timothy W Simpson. *Many-objective evolutionary optimisation and visual analytics for product family design*, pages 137–159. Springer, 2011.

[88] B. S. Abbas and W. Kuo. Stochastic effectiveness models for human-machine systems. *IEEE Transactions on Systems, Man, and Cybernetics*, 20(4), 1990.

[89] LR Goel, GC Sharma, and Praveen Gupta. Stochastic analysis of a man-machine system with critical human error. *Microelectronics Reliability*, 25(4):669–674, 1985.

[90] Kang W Lee, James J Higgins, and Frank Tillman. Stochastic modelling of human-performance reliability. *Reliability, IEEE Transactions on*, 37(5):501–504, 1988.

[91] Herbert Dawid, Reinhold Decker, Thomas Hermann, Hermann Jahnke, Wilhelm Klat, Rolf Knig, and Christian Stummer. Management science in the era of smart consumer products: challenges and research perspectives. *Central European Journal of Operations Research*, 25(1):203–230, 2017.

[92] Lan Luo, PK Kannan, Babak Besharati, and Shapour Azarm. Design of robust new products under variability: marketing meets design. *Journal of Product Innovation Management*, 22(2):177–192, 2005.

[93] Elizabeth Hull, Ken Jackson, and Jeremy Dick. Requirements engineering, 2005.

[94] D. Gentry Steele and Claud A. Bramblett. *The anatomy and biology of the human skeleton*. Texas A & M University Press, College Station :, 1st ed. edition, 1988.

[95] J. Mark Porter, Keith Case, Russell Marshall, Diane Gyi, and Ruth Sims ne Oliver. beyond jack and jill: designing for individuals using hadrian. *International Journal of Industrial Ergonomics*, 33(3):249–264, 2004.

[96] Carolyn C Seepersad, Kjartan Pedersen, RR Bailey, Janet K Allen, and Farrokh Mistree. The validation square: how does one verify and validate a design method, 2005.

[97] Paul J. Karanicolas, Forough Farrokhyar, and Mohit Bhandari. Blinding: Who, what, when, why, how? *Canadian Journal of Surgery*, 53(5):345–348, 2010. 20858381[pmid] 0530345[PII] Can J Surg.

[98] Keith L Moore, Arthur F Dalley, and Anne MR Agur. *Clinically oriented anatomy*. Lippincott Williams & Wilkins, 2013.

[99] Merriam-Webster. Merriam-webster's medical dictionary electronic edition, 2016.

[100] Apple. Case design guidelines for apple devices. Technical report, Apple, Inc., 2015.

[101] Contour. The contour next portfolio, 2016.

[102] NASA. Man-systems integration standards:, 2008.

[103] Matthew B. Weinger, Daryle Gardner-Bonneau, and Michael E. Wiklund. Handbook of human factors in medical device design, 2011.

[104] Richard C. Fries. *Handbook of medical device design*. M. Dekker, New York, 2001. 00059022 edited by Richard C. Fries. ill. ; 24 cm. Includes bibliographical references and index.

[105] Bilal M Ayyub. Methods for expert opinion elicitation of probabilities and consequences for corps facilities. *US Army Corps of Engineers, IWR Report No. 00-R-10*, 2000.

[106] Robert M. O'Keefe and Daniel E. O'Leary. Expert system verification and validation: a survey and tutorial. *Artificial Intelligence Review*, 7(1):3–42, 1993.

[107] United States. Office of the Deputy Under Secretary of Defense for Acquisition Reform. *Guidebook for Performance-based Services Acquisition (PBSA) in the Department of Defense*. Defense Acquisition University Press, 2001.

[108] Phil Page. Beyond statistical significance: Clinical interpretation of rehabilitation research literature. *International Journal of Sports Physical Therapy*, 9(5):726–736, 2014. 25328834[pmid] Int J Sports Phys Ther.

[109] William E. Frazier. Metal additive manufacturing: A review. *Journal of Materials Engineering and Performance*, 23(6):1917–1928, 2014.

[110] Russell Harris. The 7 categories of additive manufacturing, 2016.

[111] George Ellwood Dieter and Linda C. Schmidt. *Engineering design*. McGraw-Hill Higher Education, Boston, 2009.

[112] George Ellwood Dieter and Linda C. Schmidt. *Engineering design*. McGraw-Hill, New York, 2013.

[113] Thomas L Saaty. How to make a decision: the analytic hierarchy process. *European journal of operational research*, 48(1):9–26, 1990.

[114] Christoph Glur. *ahp: Analytic Hierarchy Process*, 2017. R package version 0.2.11.

[115] Patrik Eklund, Agnieszka Rusinowska, and Harrie De Swart. Consensus reaching in committees. *European Journal of Operational Research*, 178(1):185–193, 2007.

[116] Kevin N Otto and Erik K Antonsson. Trade-off strategies in engineering design. *Research in Engineering Design*, 3(2):87–103, 1991.

[117] Lou Cohen. *Quality function deployment : How to make QFD work for you*. Engineering process improvment series. Addison-Wesley Publishing, Massachusetts :, 1995.

[118] M. Benner, A. R. Linnemann, W. M. F. Jongen, and P. Folstar. Quality function deployment (qfd)?can it be used to develop food products? *Food Quality and Preference*, 14(4):327–339, 2003.

[119] Hilma Raimona Zadry, Lusi Susanti, and Dina Rahmayanti. Ergonomics intervention on an alternative design of a spinal board. *International Journal of Occupational Safety and Ergonomics*, 23(3):393–403, 2017.

[120] Hilma Raimona Zadry, Dina Rahmayanti, Lusi Susanti, and Dicky Fatrias. Identification of design requirements for ergonomic long spinal board using quality function deployment (qfd). *Procedia Manufacturing*, 3:4673–4680, 2015.

[121] Jose A. Carnevalli and Paulo Cauchick Miguel. Review, analysis and classification of the literature on qfd?types of research, difficulties and benefits. *International Journal of Production Economics*, 114(2):737–754, 2008.

[122] Rozann Whitaker. Validation examples of the analytic hierarchy process and analytic network process. *Mathematical and Computer Modelling*, 46(7):840–859, 2007.

[123] Janos Fulop. Introduction to decision making methods. In *BDEI-3 Workshop*. Citeseer, 2005.

[124] Clive L Dym, William H Wood, and Michael J Scott. Rank ordering engineering designs: pairwise comparison charts and borda counts. *Research in Engineering Design*, 13(4):236–242, 2002.

[125] Chung-Hsing Yeh and Robert J Willis. A validation procedure for multi criteria analysis application to the selection of scholarship students. *Asia Pacific Management Review*, 6(1):39–52, 2001.

[126] Wade D Cook, Boaz Golany, Moshe Kress, Michal Penn, and Tal Raviv. Optimal allocation of proposals to reviewers to facilitate effective ranking. *Management Science*, 51(4):655–661, 2005.

[127] Emel Kzlkaya Aydogan. Performance measurement model for turkish aviation firms using the rough-ahp and topsis methods under fuzzy environment. *Expert Systems with Applications*, 38(4):3992–3998, 2011.

[128] Jianhua Dai, Wentao Wang, Haowei Tian, and Liang Liu. Attribute selection based on a new conditional entropy for incomplete decision systems. *Knowledge-Based Systems*, 39:207 – 213, 2013.

[129] W. Hu, M. Li, S. Azarm, and A. Almansoori. Multi-objective robust optimization under interval uncertainty using online approximation and constraint cuts. *Journal of Mechanical Design*, 133(6):061002–061002, 2011. 10.1115/1.4003918.

[130] Robert Marijt. *Multi-objective Robust Optimization Algorithms for Improving Energy Consumption and Thermal Comfort of Buildings*. PhD thesis, 2009.

[131] Sauleh Siddiqui, Shapour Azarm, and Steven Gabriel. A modified benders decomposition method for efficient robust optimization under interval uncertainty. *Structural and Multidisciplinary Optimization*, 44(2):259–275, 2011.

[132] Jianhua Zhou, Shuo Cheng, and Mian Li. Sequential quadratic programming for robust optimization with interval uncertainty. *Journal of Mechanical Design*, 134(10):100913, 2012.

[133] Ken Parsons. *Human thermal environments: the effects of hot, moderate, and cold environments on human health, comfort, and performance*. Crc Press, 2014.

[134] G. Chiandussi, M. Codegone, S. Ferrero, and F. E. Varesio. Comparison of multi-objective optimization methodologies for engineering applications. *Computers & Mathematics with Applications*, 63(5):912 – 942, 2012.

[135] Jos Henrique de Freitas Gomes, Aluizio Ramos Salgado Jnior, Anderson Paulo de Paiva, Joo Roberto Ferreira, Sebastio Carlos da Costa, and Pedro Paulo Balestrassi. Global criterion method based on principal components to the optimization of manufacturing processes with multiple responses. *Strojniki vestnik-Journal of Mechanical Engineering*, 58(5):345–353, 2012.

[136] Kaisa Miettinen. *No-Preference Methods*, pages 67–76. Springer US, Boston, MA, 1998.

[137] Herminia I. Calvete and Carmen Gal. Linear bilevel programs with multiple objectives at the upper level. *Journal of Computational and Applied Mathematics*, 234(4):950–959, 2010.

[138] Yibing Lv, Tiesong Hu, Guangmin Wang, and Zhongping Wan. A penalty function method based on kuhntucker condition for solving linear bilevel programming. *Applied Mathematics and Computation*, 188(1):808–813, 2007.

[139] M Saraj and N Safaei. Solving bi-level programming problems on using global criterion method with an interval approach. *Applied Mathematical Sciences*, 6(23):1135–1141, 2012.

[140] Yibing Lv, Zhong Chen, and Zhongping Wan. A penalty function method based on bilevel programming for solving inverse optimal value problems. *Applied Mathematics Letters*, 23(2):170–175, 2010.

[141] Kurt Bryan and Yosi Shibberu. Penalty functions and constrained optimization. 2005.

[142] R. Fletcher. An ideal penalty function for constrained optimization. *IMA Journal of Applied Mathematics*, 15(3):319–342, 1975. 10.1093/imamat/15.3.319.

[143] Joseph L Fleiss, Bruce Levin, and Myunghee Cho Paik. *Statistical methods for rates and proportions*. John Wiley & Sons, 2013.

[144] Tanya Hoskin. Parametric and nonparametric: Demystifying the terms.

[145] Myles Hollander, Douglas A Wolfe, and Eric Chicken. *Nonparametric statistical methods*. John Wiley & Sons, 2013.

[146] Alan Agresti. *Categorical data analysis*. Wiley series in probability and mathematical statistics. Applied probability and statistics; Wiley series in probability and mathematical statistics. Applied probability and statistics. Wiley, New York :, 1990.

[147] Cisco. Cisco visual networking index: Global mobile data traffic forecast update, 20152020, 2016.

[148] Helmets. In helmets: How they work and what standards do?, 2015.

[149] P. Trgout. Helmets or not? use science correctly. *Journal of medical ethics*, 41(8):718–719, 2015.

[150] Helmets. Helmet laws for bicycle riders, 2016.

[151] Hyun K. Kim, Mungyeong Choe, Yeongcheol Choi, and Jaehyun Park. Does the hand anthropometric dimension influence touch interaction? *Journal of Computer Information Systems*, pages 1–12, 2017.

[152] Edward W. Otten, Keith S. Karn, and Kelley S. Parsons. Defining thumb reach envelopes for handheld devices. *Human Factors*, 55(1):48–60, 2013.

[153] Matthieu B. Trudeau, Tawan Udtamadilok, Amy K. Karlson, and Jack T. Dennerlein. Thumb motor performance varies by movement orientation, direction, and device size during single-handed mobile phone use. *Human Factors*, 54(1):52–59, 2012.

[154] Jacob O. Wobbrock, Brad A. Myers, and Htet Htet Aung. The performance of hand postures in front- and back-of-device interaction for mobile computing. *International Journal of Human-Computer Studies*, 66(12):857–875, 2008.

[155] Jaebong Lee and Seungmoon Choi. Real-time perception-level translation from audio signals to vibrotactile effects, 2013.

[156] Jinghong Xiong and Satoshi Muraki. Effects of age, thumb length and screen size on thumb movement coverage on smartphone touchscreens. *International Journal of Industrial Ergonomics*, 53(Supplement C):140 – 148, 2016.

[157] Verónica Gracia-Ibáñez, Margarita Vergara, Joaquín L Sancho-Bru, Marta C Mora, and Catalina Piqueras. Functional range of motion of the hand joints in activities of the international classification of functioning, disability and health. *Journal of Hand Therapy*, 2017.

[158] Esteve Peña Pitarch. *Virtual human hand: Grasping strategy and simulation*. Universitat Politècnica de Catalunya, 2008.

[159] Shrawan Kumar. Biomechanics in ergonomics, second edition, 2007.

[160] Matthieu B. Trudeau, Justin G. Young, Devin L. Jindrich, and Jack T. Dennerlein. Thumb motor performance varies with thumb and wrist posture during single-handed mobile phone use. *Journal of Biomechanics*, 45(14):2349 – 2354, 2012.

[161] Pierre Meunier, David Tack, Angela Ricci, Linda Bossi, and Angel Harry. Helmet accommodation analysis using 3d laser scanning. *Applied Ergonomics*, 31(4):361–369, 2000.

[162] Joseph W Young. Head and face anthropometry of adult us civilians. Technical report, FEDERAL AVIATION ADMINISTRATION WASHINGTON DC OFFICE OF AVIATION MEDICINE, 1993.

[163] T. A. Mattei, Carlos R. Bond Bj Fau Goulart, Chris A. Goulart Cr Fau Sloffer, Martin J. Sloffer Ca Fau Morris, Julian J. Morris Mj Fau Lin, and J. J. Lin. Performance analysis of the protective effects of bicycle helmets during impact and crush tests in pediatric skull models. (1933-0715 (Electronic)), 2012.

[164] RD Mosteller. Simplified calculation of body-surface area. *The New England journal of medicine*, 317(17):1098, 1987.

[165] K. Cage, B. Lucero, D. Spernjak, and J. Bernardin. Helmet heat exchanger thermal final report. Technical report, Department of Energy, 2017.

[166] K. Cage, B. Lucero, D. Spernjak, and J. Bernardin. Heat pipe characterization for axial helmet heat exchanger ? preliminary report. Technical report, Department of Energy, 2017.

[167] David B Saint John, Sanjay B Joshi, Timothy W Simpson, Meng Qu, John David Rowatt, and Yucun Lou. A preliminary examination of variability due to build location and powder feedstock in additive manufacture of inconel 718 using laser-based powder bed fusion.

[168] Jasbir Arora. *Introduction to optimum design*. Academic Press, 2004.

[169] Professional Plastics. *Thermal Properties of Plastic Materials*, 2016 (accessed August 1, 2016).

[170] MakeItFrom. *Polylactic Acid, (PLA,Polylactide)*, 2009 (accessed September 30, 2017).

[171] MakeItFrom. *Polyurethane Rubber, (AU, EU)*, 2009 (accessed September 30, 2017).

[172] Engineering Tool Box. *Air Properties*.

[173] Owens Corning. *Pipe and Mechanical Insulation*, 2017 (accessed January 1, 2017).

[174] Inc. Minco Products. Estimating power requirements of etched-foil heaters, 2017.

[175] T. Perret-Ellena, A. Subic, T. Y. Pang, and H. Mustafa. The helmet fit index-a method for the computational analysis of fit between human head shapes and bicycle helmets. In *icSPORTS 2014*, pages 145–153. Institute for Systems and Technologies of Information, Control and Communication (INSTICC).

[176] Kevin P Murphy. *Machine learning: a probabilistic perspective*. MIT press, 2012.

[177] National Center for Employee Ownership. Employee ownership companies pay less for workers' compensation costs, 2017.

[178] National Research Council. Review of department of defense test protocols for combat helmets, 2014. (U.S.).

[179] Angel R. Torrado Perez, David A. Roberson, and Ryan B. Wicker. Fracture surface analysis of 3d-printed tensile specimens of novel abs-based materials. *Journal of Failure Analysis and Prevention*, 14(3):343–353, 2014.

[180] J. G. Hadzima. *How Much Does An Employee Cost?*, 2005 (accessed January 11, 2017).