Impact of Multiple Stakeholder Preferences on Design with a Focus on Demand Models and an Application of Electric Vehicles

by

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A THESIS

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ABSTRACT

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Title: Impact of Multiple Stakeholder Preferences on Design with a Focus on Demand Models and an Application of Electric Vehicles.

The essence of systems engineering lies in enabling rational decision-making that is consistent with the preferences of the system's stakeholders. Traditionally, stakeholder preferences have been communicated through requirements imposed on the design space of the system. The traditional approach's primary drawback is due to capturing what the stakeholders do not want, usually in the form of inequality constraints, rather than what the stakeholders prefer. The alternative systems engineering approach of Value-Driven Design conveys the true desires of the stakeholders through the mathematical means of a value function. Value functions transform system attributes or characteristics into a singular value, enabling the rank ordering of design alternatives. This thesis examines the complex engineered system of electric vehicles using Value-Driven Design. This thesis presents novel consumer, commercial, and government oriented value functions. A novel electric vehicle model is developed to analyze the value functions and the system attributes that are important to form value functions. End user preferences are integrated into the manufacturer's value function through consumer value based demand models, incorporating multiple preferences into the design process. Sources of uncertainty that are deemed crucial in electric vehicle design, including non-designer controlled variables, are identified and incorporated into the Value-Driven Design framework through employment of Monte Carlo simulations. Possible stakeholder risk attitudes are discussed and a rational decision making strategy to maximize stakeholder value under uncertainty is presented. The resulting designs, the influence of the value functions, and the influence of the stakeholder risk attitude are discussed.

Abstract Approval: Committee Chair ______________________

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"Hayatta en hakiki mürşit ilimdir"

Mustafa Kemal Atatürk

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CHAPTER I

INTRODUCTION

In many large scale complex systems engineering applications, the role of the systems engineer is undervalued. Completion of the design at the desired time, satisfying all the requirements, and being within budget is usually perceived as success. As a natural consequence of this perception, systems engineers are compelled to concentrate on the process and achievability of the design, often ignoring the elegance of the system [1]. Although the definition of "elegance in system design" is not the subject of this study, it is beneficial to mention properties of an elegant design to understand the underlying motivation behind this thesis. Properties of an elegant design can be summarized as the following: functionality, robustness, efficiency, and the last and probably the most neglected "minimizing unintended actions, side effects, and consequences of the system" [2]. Violation of this last property may result in severe consequences- consequences that may exceed the benefits of the system. One example of this phenomenon is climate change.

In order to understand the underlying causes of the climate change phenomenon, one has to look back in time. Fossil fuel dependent economic expansion strategies, dating back to the Industrial Revolution, brought us to a state of serious crisis. Global dependency on carbon based fossil energy sources resulted in an accumulation of greenhouse gasses (GHGs) in the atmosphere over the last 250 years [3]. This accumulation has disturbed the balance of Earth's thermal cycle causing a steady increase in the average temperature. This phenomenon is shortly denoted by the term “climate change”.

Public attention on climate change increased rapidly after the formation of the International Panel on Climate Change (IPCC) in 1988 [4]. The IPCC provided an international platform for investigating, in a scientific manner, the causes of climate change [5]. The IPCC drove research on the topic, leading to improved climate modeling and temperature projection tools [5], [6]. These results compelled the United Nations (UN) to agree upon the Kyoto Protocol [7], imposing sanctions to the global economy. The Kyoto Protocol was a driving force in initiating climate reform in many countries around the world.

The Kyoto Protocol had varying impacts on member nations of the UN. This was due to the UN being a non-legislative body where the countries were agreeing on a protocol that was not an enforceable law. The United Kingdom, one of the many countries that may face severe consequences [8] if temperature projections are accurate, declared that the sanctions of the Kyoto Protocol were not sufficient and developed a more radical policy to reduce domestic GHG emissions [9]. Contrary to the United Kingdom’s course of action, the United States government never ratified the Protocol through the senate, despite signing the Protocol in 1998. Being the only developed country that has not applied the Protocol, the US responded to the critics by claiming the environmental benefits of applying the Kyoto Protocol would not compensate for the economic losses, and the Protocol would seriously harm the economy [10]. In the following years some research supporting for this decision evolved, emphasizing the lack of accuracy of the current climate prediction models [11]. Despite the ongoing controversies on the subject, need for an alternative policy for the climate change problem is apparent. The alternative policy should consider both the environmental and macro-economic aspects of the climate change phenomenon. Nordhaus compared the economic impact of existing climate change policies varying with GHG emission levels [12]. His studies indicated that an alternative policy, that balances the transition from fossil fuel based infrastructure to a greener alternative, should yield a dominant benefit to cost ratio compared to existing policies [7], [9]. This transition should cover all the areas contributing to the climate change phenomenon including energy, transportation, industry, and agriculture.

As a systems engineer, considering the level of "know-how", the technological readiness level, and the percentage of GHG emission generated, a necessary change in the transportation industry emerges. Transportation accounts for 28% of the GHG emission in the United States [13] where 83% percent of the transportation emissions are produced by trucks and passenger cars [14]. As of 2013 the vast majority of these vehicles run on fossil fuels and electric vehicles (EVs) only represented 0.5% of the total automobile transportation market share in the US [15]. Taking into account that EVs have zero GHG emission, a nationwide change from fossil fuel powered vehicles to EVs would significantly reduce the overall GHG emission that is generated by personal transportation vehicles.

In addition to environmental concerns, another negative aspect of fossil dependency are the problems related to oil demand. In 2013 the U.S imported 2.8 billion barrels [16] of crude oil. Even though this amount was an all-time low since 1985, it accounted for 51% of the crude oil that was processed in U.S refineries. This high percentage begins to paint a portrait of the level of import dependency and the possible energy security problems it may cause. Besides these issues, depleting oil reserves, constantly rising gas prices, and increasing global awareness about GHG emissions are increasing the customer demand for EVs; therefore, compelling the automotive industry towards EV development and production.

EVs are complex engineered systems with many interacting subsystems. The discipline of systems engineering explores these interactions and how to go about the design of such products. One of the complications involved with the design of complex systems is in identifying the stakeholders and determining their preferences. For example, a governmental design institution in a developing country could have a preference of taking over some of the domestic market share that mostly belongs to foreign companies, meanwhile trying to reduce GHG emission by creating an EV design. On the other hand, a commercial company would be more concerned with increasing their profit by dominating the expanding market. Questions to be answered in this environment are challenging. How can these institutions decide on the design alternative that gives them the best option to accomplish their respective goals? How can they evaluate design alternatives and how can they develop methods to overcome project risks and uncertainties?

The discipline of systems engineering enables designers to fulfill stakeholder desires by capturing and understanding the actual needs and converting them to design. A role of the systems engineer in the design process is to act as a bridge from the ideation to the materialization of the product. This role cannot be fulfilled without completely understanding the stakeholder preferences that forms the foundation of the design.

Following that, the design process progresses by a string of strategic and technical decisions in which every single aspect of the design and associated uncertainties play a critical role. It is the challenge of the systems engineer to foresee potential obstacles and proceed accordingly. Ability to quantitatively assess the impact of subsystem-system configurations, market share, integrating unproven new technologies, and risks associated with them becomes an essential skill to be successful. This quantitative assessment capability provides the systems engineer with a rational platform for decision making; allowing the designer to rank the options by comparing expected outcomes.

This thesis explores the design process for complex engineered systems, through an application to electric vehicles. The primary question that this thesis strives to address is “How do various stakeholders impact the design of a system.” Two major research questions with appropriate sub-questions will be investigated.

Q1: How do EV designs differ depending on the stakeholder preferences?

Q1.1: What is the value of an EV for the customer?

Q1.2: What are the possible value functions for an EV system for industry?

Q1.3: What are the possible value functions for an EV system for the government?

Q1.4: How do the designs for EVs differ between industry and government value functions?

These questions will be addressed using a generic electric vehicle model that will be composed of 4 critical subsystems. Stakeholder preferences for both the government and industry will be captured separately to form respective value functions. These value functions will then be used to optimize within the design space and to obtain the most appropriate system configurations for each stakeholder. Reflections of stakeholder preferences on the design will then be analyzed by comparing the resulting EV configurations. The second research question and associated sub-questions are as follows.

Q2: How does uncertainty impact the design decisions of an electric vehicle system?

Q2.1: What are the major areas of uncertainty with the system design?

Q2.2: What are the possible risk preferences for industry and the government?

Q2.3: How do the system designs change depending on the uncertainties and risk preferences of the stakeholder?

Areas of uncertainty within the system design will be identified. Then, decisions under uncertainty will be investigated by identifying corresponding stakeholder risk preferences. Utility Theory will then be used to evaluate design alternatives.

The thesis will be structured in the following way. Technical background of the study and literature survey will be given in Chapter 2. Chapter 3 will contain information about the mathematical model for EVs, definition of stakeholder preferences, and formation of the corresponding value functions. Chapter 3 will also include identification of sources of uncertainties and their anticipated effects on the overall system design depending on the risk preferences of the stakeholders. Results and discussions related to the outcomes of Chapter 3 will be presented in Chapter 4. Chapter 5 will contain a summary of the study and a guideline for further work related to the subject. References will be presented in Chapter 6.

CHAPTER II

BACKGROUND

In this chapter, a brief summary of the theoretical background for this study will be presented along with a literature survey of previous research. The chapter will start a discussion regarding the issues with the traditional systems engineering approach. Following that, an alternative approach to overcome these setbacks will be reviewed. Sources of uncertainty in design and its implications to the overall system will next be reviewed. Decision making under uncertainty will be discussed include an examination into the application of new technology integrations to reduce the risk. These background topics will set the stage for the study of multiple stakeholder value functions.

II.1. Importance of Early Decisions

Decisions made earlier in the design process, such as during conceptual and preliminary design phases, are important as they tend to dictate the overall efficacy of the system. These decisions result in dedication of the available resources to a concept deemed as the better option, therefore making it rather costly to go back [17]. Another implication of these decisions is the adversity they create later on if they are abortive, often disenabling any effort to solve the issue. Fixing these errors becomes more and more expensive farther into the process [18]. This situation can be made comprehensible by considering the circumstances of the designer in these phases. In early design phases, the systems engineer has to make decisions in a situation where uncertainty and imprecision dominate the design space. Therefore these preliminary decisions regarding the system's design are made with highly uncertain information about the system and the system's environment [19].

II.2. Traditional Systems Engineering Approach to Decision Making

The decision making approach used traditionally for systems engineering decisions is flawed. Before defining these pitfalls, it is beneficial to take a step back and look at the bigger picture. The outcome of accepting this approach as a rule of thumb is perfectly summarized by Collopy and Hollingsworth in 2011 with the following statement:

> *"The Department of Defense executes a large enough set of complex development programs to yield some meaningful statistics. The set of 96 major weapon system development programs currently underway have overrun by a total of $296 billion, with an average development cost growth of 42%, and an average delay of 22 months. Extrapolating to completion shows that the total loss to delay, overruns, and reductions in materiel (generally caused by overruns) is $55 billion per year, or $150 million each day.* [20]*"*

Considering a common systems engineering decision making process is applied to these designs, it is apparent there is an inefficiency in the process rather than the designers or the projects. The root of this problem can be traced back to the essence of the traditional systems engineering process; that is designing the system through defining and verifying the requirements. Requirements based design communicates preferences through statements of things stakeholders do not desire. Doing so inevitably restricts the applicable design space, ruling out some portions of the system design space as infeasible, without sufficient insight. Another aspect of this problem is the indifference it creates for the alternatives that are deemed feasible. Designs that are deemed feasible or allowable are not ranked with respect to each other, since the requirements do not offer such service. This puts the system engineers in a position where they are indifferent between the alternatives that are deemed allowable by the requirements. Under these circumstances, systems engineers cannot make rational decisions between the allowable alternatives because they are not scientifically ranked with respect to each other. This problem can be visualized by the figure shown below.

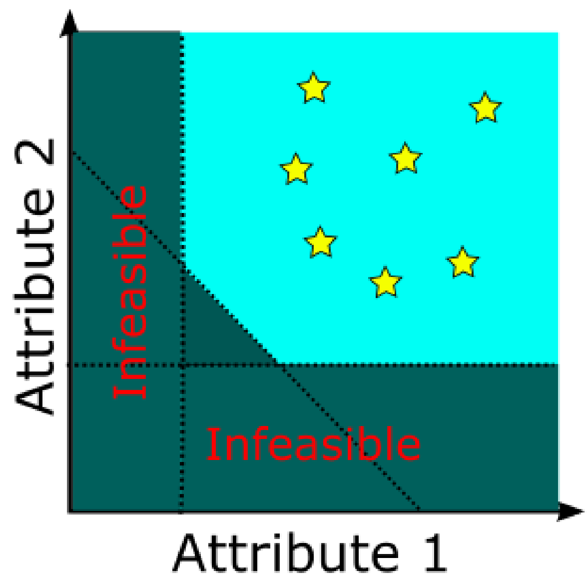

Figure II-1 Effect of Requirements on the Design Space

Requirements are often defined without proper consideration of the overall system needs. This statement holds especially true for the requirements that are being assigned to the system early in the design. These requirements are often created under great uncertainty. Further in the process, these requirements create such an environment that failure to comply with any; results in failure. This creates a binary judgment criterion where a system either passes or fails. Personal observations showed that, system solutions that fail to meet the requirements are often extrapolated in order to keep the alternative alive, creating a derived solution rather than a novel design alternative.

Trade studies are preferred by many system designers in the traditional approach for decision making during initiating design phases [21][22]. Even though the exact pattern of performing a trade study depends on the application, most trade study shares a common pattern. A common pattern for trade studies can be summarized as the following:

a) Define minimum requirements to be met by the system
b) Generate alternatives that satisfy requirements
c) Choose a set of attributes to support the selection of the most preferred alternative. (e.g. cost, schedule, technical)
d) Develop metrics for evaluating alternatives
e) Define weighting factors for each attribute
f) Perform ranking

Within requirements based design, multi-attribute decision making is used to compare design alternatives that have been deemed feasible [23]. This method takes the attributes of the system and associates weights to each, typically summing to one. Maximizing or minimizing the multi-attribute function is presumed to lead to the stakeholder's preferred design. The downside to such a process lies in the determination of the attribute weights. There is no physical meaning to the weights; they only describe how important one attribute is compared to another from the perspective of a specific stakeholder. They do not relate the attributes to a standard unit of measure with a physical meaning. This inherent ambiguity in the function can cause disagreements on the importance or weighting of an attribute.

This multi-attribute decision making technique is far from accurate, as grading design alternatives by combining individual attribute assessments may discard some design solutions which are better overall prospects. An empirical study performed by Dahlstrand and Montgomery in 1984 can be used as a case example to clarify the underlying reasoning. Students were asked to evaluate 5 alternatives with 8 attributes each; however, they eliminated alternatives based on failure to meet a single requirement if that requirement had the highest relative weight [24]. This conclusion can also be linked to the sluggishness of the human mind, as the time pressure on the decision maker is increased, decision making logic gravitates towards simpler, more descriptive techniques[25]. These arguments can be linked to the multi-attribute decision making logic that examines each attribute of the system separately.

In order to overcome the concerns of this decision making approach, an alternative approach is necessary. A single ranking function that holistically captures the stakeholder preferences can be used. Such a function would enable the designers to create a single score for each design alternative, therefore easing the process of concept selection regarding any variation of alternative attribute sets. It can also be used to fine tune the system attributes to obtain the best possible design for the given problem.

II.3. Value Focused Thinking

Value-focused thinking is a technique for ranking alternatives. It is instinctively applied when making decisions regarding everyday situations. It is a technique for ranking the possible decision options for any applicable decision situation. To illustrate with an example, imagine a scenario where you are invited to a friend's house and offered something to drink. Your host asks you whether you would like to have a cup of tea or coffee. In order to answer this question, instinctively, you make a ranking between a cup of tea and a cup of coffee. What is happening here is a comparison of the benefits you would receive by having either beverage. Since this is a complimentary beverage that is basically free, you don't have to consider how much it would cost you to have either option. Costs can be perceived as negative benefits that are directly quantified in monetary units. On the other hand, benefits depend on your personal preferences and may depend on your current needs, the beverages you might have consumed earlier that day, any allergies or digestion issues, et cetera. You would quickly evaluate both beverages with respect to your personal preferences, rank the outcomes accordingly, pick the option which is ranked highest (i.e., the one with the greatest value) and respond to your host's question. The scenario described here is a natural thought process for making decisions, often done without any recognition of the necessity of making a decision. This rational and natural thought process is the essence of value-focused thinking.

Value focused thinking enables us to make decisions after equalizing two different units, such as tea and coffee in the previous example. In essence, value is a measure of preferences and values can be ranked by applying property of order. Property of order implies that two values are either desirable to each other or equivalent to each other. This implies that one of the three must be true:

$$V_A > V_B \text{ or } V_B > V_A \text{ or } V_A = V_B \qquad \text{(II-1)}$$

where V is the quantified value and A and B subscripts represent alternatives A and B.

Application of value-focused thinking in engineering decision making is possible through some modifications. Referring back to the logic of beverage selection, the decision is made after reducing the problem into a common frame, the frame of value. In 1992, Keeney showed that in order to apply the same procedure to a complex engineering problem, a transfer function denoted as "the value model" [26] is necessary. The purpose of this transfer function is to capture all the system attributes, stakeholder preferences, costs, and risks and to transform them to a common basis. A transformation between a variety of units such as kilograms, meters, system specific performance parameters, costs, probability of success, etc. is possible through conversion of these units into monetary units such as the net present value (NPV). Other base units are also possible with appropriate transformations but NPV is typically seen as a straightforward and understandable basis.

This ability to transform a set of attributes into a meaningful quantification grants a powerful tool for decision makers in various situations. The first application of using value models to aid strategic decision makers was demonstrated by Keeney through an application on the British Columbia Hydro and Power Authority [27]. Other applications of value models in various fields include: operations research [28], demand-side planning [29], resource planning [30], and implication of new technologies [31][32].

II.4. Value Driven Design

Design of large scale complex engineering systems involves an array of decisions. Approaching the design process as a series of technical decisions enables systems engineers to combine the concept of value with the design of complex engineering systems. This leads to the incorporation of value in design which, or value driven design

(VDD) [20]. The use of VDD in the design process grants systems engineers dominant advantages compared to the traditional approach. VDD provides a scientific, formal, transparent, and repeatable tool for designers to compare design alternatives. This property of value functions solves one of the major problems of the traditional systems engineering approach, the indifference caused between designs that are in the feasible design region. By reflecting stakeholder preferences to the design and providing a way of evaluating the design alternatives, value functions enable systems engineers to rank the designs alternatives that are deemed allowable or feasible. In the Figure II-2 the same design space seen in the previous figure is altered to include the value of design alternatives that populate the space, visualized with color. Green represents less preferred alternatives and blue represents the most preferred alternative. With this incorporation of value the designer is able to distinguish between feasible alternatives where the best available alternative is represented by the star.

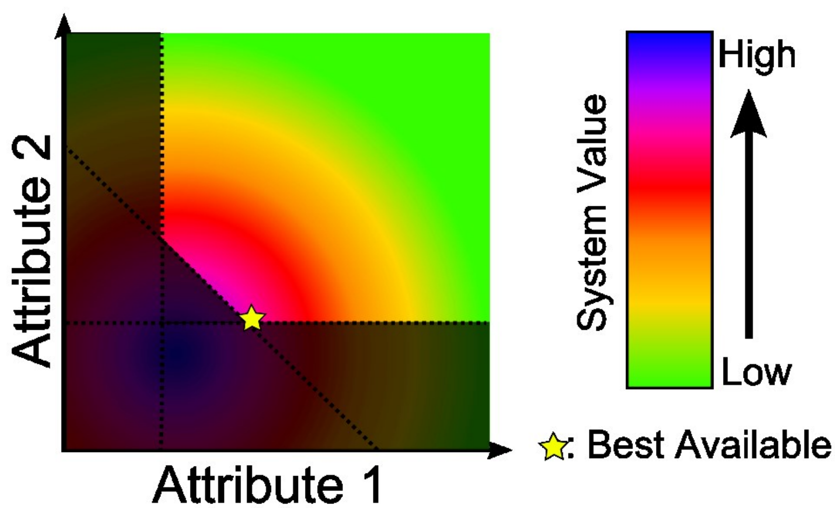

Figure II-2 Effect of Introducing Value Functions to the Design Space

Value models eliminate the weighted grading system used in the traditional systems engineering approach which has obvious technical flaws. Assuming that the attributes composing the system have a property of order, values generated using the value model also should [33]. This property of VDD can be traced back to the transitivity property of rationality [34]. The transitivity property of VDD can be used to rank overall system configurations and can be used to determine which design configuration is better with respect to the value model that is defined in accordance with the stakeholder preferences for that system. This can be shown mathematically as:

$$If\ V_A > V_B\ and\ V_B > V_C;\ then\ V_A > V_C \tag{II-2}$$

Besides improving the alternative selection, VDD enables an improved utilization of multidisciplinary design optimization (MDO) [35] in system design, giving designers the ability to fine tune the system attributes through the design variables. MDO can be used to capture and leverage the system couplings in a single optimization problem, allowing the parallel design of all the subsystems constituting the system. In MDO the value model serves as the objective function. The MDO algorithm is run through the design space to find the design configuration that has the maximum achievable value [36].

MDO is designed to incorporate both objective functions and constraints (requirements). The value function takes over the evaluation role of the requirements without constraining the design space. Due to this characteristic the requirements become redundant and are viewed more so as restrictions than a communication means. Introducing value functions and keeping the design space unrestricted (by reducing the amount of constraints and by keeping the value function non-specific to a design configuration) the design team is free to explore unintuitive designs. Figure II-3 shows the design space of the previous figures without requirements, allowing the true optimal value to be realized. These unintuitive designs may be better overall alternatives with respect to the stakeholder's preferences.

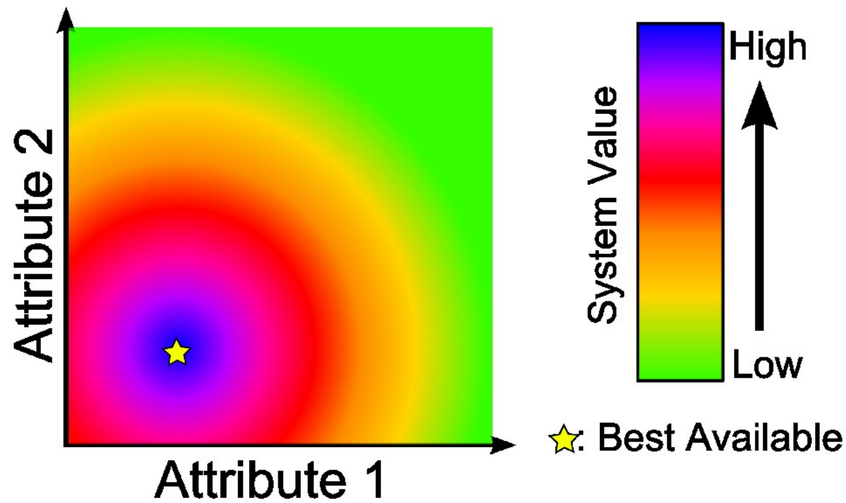

Figure II-3 Effect of Designing without Requirements May Lead to Unintuitive Alternatives

Another drawback of having constraints at the system level is that these requirements flow down to the subsystems [18][19], therefore limiting the achievable performance by each subsystem separately [37]. This leads to an avalanche effect on the overall system deviating the system from the optimal configuration. In 2001, Collopy showed that the VDD process enables the subsystems to be designed independently without introducing requirements and still yield an optimum system solution [38]. In addition to that, subsystem level requirements are allocated from system level requirements which are the result of assumptions made in earlier phases of the design where uncertainty dominated the design space. Therefore, these hard constraints either degrade the value of the system or do not affect the system value at all given that the value function successfully captures all relevant values associated with the system [39].

Another benefit of VDD is the increased assessment capability it provides over the n-dimensional design hyperspace. Through VDD, a surface of the design space can be generated. Through this surface, alternative designs can be evaluated and compared through the optimization framework as they can be substituted in to the value model and the optimum can be discovered. The use of VDD in systems engineering can also be used to identify more robust areas in system solution options. This can be achieved by replacing systems to subsystems requirements allocation with the flow of the decomposed system value function to the subsystems [38]. This value-based assessment enables systems engineers to evaluate the design space comprehensively in accordance with the stakeholder's preferences.

VDD can also offer technical computation aid to critical technology evaluation. This can be achieved by using sensitivity analysis techniques and measuring system's sensitivity to design variables. Some of the design variables at the early stages of design may define technologies, and the attributes associates with such design variables will be representative of the technological limits of that technology. VDD enables an objective evaluation opportunity for the possible impact of a technology development on system value. Constraints, such as technological limits, can also be examined to determine the system's sensitivity to technological limit changes. Impact on the overall system value can be analyzed by perturbing the constraint and updating the system design by re-optimizing the design in accordance to the new technological capability. Comparing the new value of the system to the previous value indicates the expected overall improvement on the system value. This property of VDD can be used as a powerful tool for economic evaluation of Research and Development (R&D) investments. A company or an institution interested in improving their technological limits, can perform a sensitivity analysis to their existing systems and see the expected improvement that can be achieved by the new technology [40]. Since value is measured in monetary units, communication with the management becomes much easier based on the results of the sensitivity analysis. This feature simplifies the situation to a point where systems engineers can express themselves as “we are going to get $x worth of value back for this $y investment”. This property of VDD allows it to be used as a tool to adjust the R&D budget rationally, as the expected improvements on the system value by improving each technological capability can be analyzed with this method.

II.4.1. Applications of VDD

There are numerous applications of VDD in systems design, especially in the aerospace industry. In 1999, Collopy showed that VDD can be applied to contract acquisitions processes to reduce program costs radically [41]. This study demonstrated the capability of VDD as a means for contract incentives and the advantages of its system evaluation capability compared to the traditional evaluation methods. Benefits of value centric evaluation in contract assessments to cost centric evaluation in spacecraft systems was demonstrated by Brathwaite and Saleh [42].

A value model for the Global Positioning System was developed and value of reliability in satellite constellations varying on cost, constellation size, replacement launch time, and the cost of failure was investigated [43]. The value of having alternative spacecraft architectural configurations were investigated through Defense Advanced

Research Projects Agency (DARPA) contracts [44]. The main alternative investigated was the fractioned configuration, which is defined as a distributed set of interconnected spacecraft acting as a single system. The value of having a fractioned architecture rather than a singular spacecraft was evaluated [45]. The studies concluded that despite higher cost of deployment, fractioned spacecraft architecture benefit/cost ratio is much higher compared to traditional single spacecraft systems [46]. This conclusion is a typical example of improved design space exploration as the fractioned design configuration is a non-intuitive system architecture compared to traditional system configurations. In 2013, Keller demonstrated an application of VDD on space launch systems, considering the benefit of the system to be created by lunar mining mission [47].

Communication satellite systems are another great example of the power of VDD oriented research. Revenue models have been developed based on satellite communications load and the benefit it generates through an association with the market price for communications [48]. Another application on a communication satellite illustrated the effectiveness of incorporating VDD with MDO. Systems designed by traditional methods, by MDO, and by MDO incorporating VDD were compared. The comparison showed that MDO incorporating VDD design yielded nearly 6 times the profit of the system designed by traditional systems engineering approach and 50% more profit than the system designed by MDO with non-holistic objective functions [49].

Utilization of VDD in aircraft systems is pretty common due to the systems' inherent complexity and concerns with schedule and cost overruns. An application to propulsion system design demonstrated that VDD can be used as a tool to maximize the overall profitability for all the stakeholders in the program, creating a win-win environment [50]. Chung [51] performed VDD based analysis on air breathing engines for an air transportation system, investigating the system attributes and their impacts in the system value. Optimal maintenance scheduling for aircraft engines have been analyzed through value analysis - investigating the fuel consumption and cost of maintenance effect on total airline operation cost [52]. As a consequence of this study it was found that maintenance durations for the company could be reduced, therefore lowering maintenance costs. Besides these propulsion system related studies, benefits of applying VDD principles on structural design is also validated by a study on aircraft fuselage panels. Cost was introduced as a conceptual design parameter in fuselage panel design and its impact on manufacturer's profitability was evaluated through the system [53].

II.4.2. VDD Research on EV Design

Despite various applications of VDD in the aerospace industry there are significant research gaps in its application to automotive design. The nature of the automotive market makes it particularly challenging for VDD, as many intangible product characteristics, such as aesthetics, play an important role in certain stakeholder preferences especially related to the customer.

In 1997, Donndelinger performed a study applying reverse engineering principles [54] to existing automobiles to estimate the value of design attributes [55], but his definition of value theoretically differs from the economic value that VDD principles are built upon. Michalek developed a quantitative model for automobile design, considering the system performance, customer preferences, market competitiveness, and environmental constraints focusing on impacts of environmental policies on the design in terms of gas mileage [56]. Optimal design studies of plug in hybrid electrical vehicles (PHEVs) focusing on minimizing cost, consumption, or GHG emissions have also been performed [57]. Michalek et. al. [58] conducted a study comparing types of electrical vehicles in terms of life cycle air emissions and oil displacement benefits. Frischknecht investigated the vehicle design problem through metrics for measuring multi stakeholder objective trade-offs [59]. This study provides improved insight on maximizing corporate value by taking the competitor effect, existing market conditions, and a detailed demand model into account. On the other hand, due to weighted grading method applied when defining metrics, results are coupled to the weights assigned to each attribute as expected.

II.4.3. Demand Models

Design by applying VDD methodology requires a detailed market or customer demand model to yield reasonable results, especially when applied to commercial products such as EVs. This is due to the subjective nature of human perception. Every individual has different preferences therefore perceived value for every specific customer is different. This fact makes it rather complicated to generate a rational population choice model. In order to avoid this obstacle, designers usually make a decision regarding the market segment of the product before the design process begins. In other words, designers start out by defining a constraint on the design space even before the whole process begins simply by deciding on the market segment for the car. This attitude causes drawbacks that have been discussed in the previous sections. This contradicts the primary objective of VDD which is basically designing the best overall system - or the EV in this case - that can be designed. It is obvious that “the best” or “the optimum” system configuration should account for the whole population or the whole market demand and the EV should be designed accordingly. In order to so, a customer demand model is required.

Demand modeling should be an integral part of capturing industry and government preferences, especially when designing systems that are meant for the general population such as EVs. This is due to the direct impact of “the quantity of the systems that can be sold” on the overall commercial value of the product that is being designed. The scale of impact on the commercial value of the system is much different when compared to Department of Defense (DoD) projects. It is pretty common in the defense and space industry to have highly descriptive contracts, strictly defining the quantity of units that will be produced or purchased (especially in a foreseeable future). For commercial products such as EVs, this is not the case. “The quantity of the systems that can be sold” is not bound nor defined by any contract or requirement. In other words there are no boundaries set except the customer demand and the supply and manufacturing capabilities of the company. Demand on the system will somehow be related to its perceived value for the customer and this relationship will greatly influence the overall commercial value of the product. This will be discussed in more detail in the methodology section.

Generating customer demand models is a popular research area due to the critical role it plays for many commercial industries. It is a matter of survival to estimate the preferences of the population that the product is being offered to. In order to compete and be successful in a competitive market, companies in any field of business need to understand the customer preferences. This is not the case if the company exists in a monopoly. In a monopoly, the company can decide on the selling price of the product or products they are offering depending on the company preferences. The customers will end up buying their products regardless due to the lack of competition. This holds true until a competitor arises and tries to take over some of the market share. Considering the current economic system, most of the business markets are highly competitive, especially the automotive industry. The competition is mostly global, dynamic, and fierce as the companies who fail to understand the customer preferences are often forced out of business or get taken over by their competitors [60]. Considering circumstances related to this specific business area, rather than employing a simple supply and demand curve in order to represent the customer demand, an approximation for a realistic demand model based on customer value will be developed for the purposes of this thesis. It should be noted that, this demand model will not be focused solely on academic research, on demand modeling, or customer behavior analysis. It is developed in order to realistically demonstrate the benefits of applying value functions to capture customer preferences - employing these preferences in order to improve consistent decision making for industry and government designer preferences.

In order to discuss the demand modeling approaches that will be applied in this thesis, it is beneficial to make a brief review of milestones of the personal choice and consideration literature. In 1957, Simon proposed the principal of satisficing [61], arguing that people in a decision situation tend to continue their evaluation between alternatives until one of the alternatives are deemed suitable. It was proposed that customers would quit searching for the best alternative if the alternative they have settled for was good enough. This principal was later enriched by studies on introducing the behavior of customers evaluating multiple aspects of a product based on individual preferences [62]. Tversky took a reverse approach to customer alternative evaluation and proposed that decision makers tend to eliminate available alternatives based on the comparison of each attribute with the desired attribute value. Tversky suggested the decision maker discards alternatives if they fail to satisfy an attribute and make the decision in favor of the remaining alternative [63]. Human capability of evaluating multiple alternatives based on task complexity was investigated by Payne in 1976. Payne observed that decision makers were acting consistently with the previous principals argued in this paragraph when making decisions between limited alternatives but they were failing to apply the same principals when number of alternatives and the complexity level of alternatives were increased. This lead to the definition of consideration sets, stating that decision makers limit their viable options first and then make more detailed evaluations to make the final decision. After this brief summary of rational human behavior milestones, we return to discussing demand modeling approaches.

Discrete choice analysis (DCA) is one of the methods that can be applied in order to define customer demand. DCA is a form of a generalized linear model that assumes that customers will act rationally and choose the products that are the best option in terms of their own perceived utility [64]. The utility for the customer is calculated through an array of predicted customer decisions regarding the product attributes. This calculation is done in a multi attribute utility theory fashion; thus, DCA enables designers to estimate the expected market share of the product that is being designed in a pre-defined market environment. Another technique for developing a customer demand model is called "consider then choose" [65]. This technique assumes that the customers are making decisions by eliminating the choices that are not applicable to their specific needs. This method is descriptive rather than predictive and takes advantage of the advances in the marketing literature. Morrow et al. [66] demonstrated that this demand modeling technique can be used as an input for designing optimum products for a specific market.

The demand model that will be a part of the commercial value function formed in this study will be a novel model utilizing the two methods that have been described. This method will take in the existing EV market data and combine that with the customer value model that is developed for this thesis. Customers will be assumed to be making decisions in a "consider then choose" fashion. This artificial customer would first consider their individual household income (which will be based on the US household income data) and then the selling price of the product to decide whether the product is affordable. Next, the model will predict the estimated number of products that will be sold based on comparing the customer value of the product to existing competitor's customer value. In other words, it will be assumed that the customer will decide based on annual income and their value of the vehicle.

II.4.4. Sensitivity Analysis

After completing the discussion related to the pieces of the value model that will capture industrial and governmental preferences, we can discuss some of the complimentary technology management capabilities the VDD approach offers. One of the most beneficial properties of VDD is the sensitivity analysis capability it provides to systems engineers. Sensitivity analysis is performed through disturbing design parameters (energy density of the battery, electricity price, willingness to pay, etc.) (x_o) and measuring the change in system's value (ΔV) due to those parameter changes. It is also important that, when possible, design variables be examined due to the desire of ensuring a consistent system. If attributes are altered directly it may lead to a design that is not physically possible. This is less of a concern if the original starting point is physically possible and only a very small change in attributes is investigated. In order to define mathematically [41]:

$$V(x) - V(x_o) = \Delta V \tag{II-3}$$

An important aspect that should never be skipped is to run the system design model again to evaluate the new value ($V(x)$) due to updated design parameter. Since the effect of having different design parameters is being investigated, the whole process has to be repeated and optimized by using the new design parameter(x). This is necessary in order to embrace the fact: the whole design would have been done in a different way given that design parameters were different. Therefore, running the optimizer is necessary. Once obtained, this change in value ΔV can be compared to the marginal cost of improving the design parameter x_o to x. This capability provides systems engineers a repeatable, objective, and quantitative tool to communicate with the management for technology development budgets and for sub-contractor or supplier selections.

The arguments presented in the previous sections sum up the framework of VDD in a deterministic environment. Once this framework is established additional important aspects related to the systems design can be easily incorporated through some modifications. One of the most important realities regarding the system design process is the uncertainties associated with it. Following subsections will present information regarding sources of uncertainty in design and how to make rational decisions under uncertainty.

II.5. Uncertainty in Design

Decision making under certainty consists of defining possible alternative actions, determining the outcome of each alternative action, evaluating the value of each outcome based on personal preferences, identifying the outcome that has the highest value and taking action towards what would lead to the highest value outcome. This logic seems so simple and straightforward it inevitably raises the question "if that's the case why can't people make proper decisions?" There are plenty of answers to this question, but if a single answer is to be given, it would be very few to none of the decisions people make are made under absolute certainty. There is uncertainty related to any task that a person considers doing. In order to investigate decision making under uncertainty, the word "uncertain" needs to be understood. Furthermore, who is to say what decision is proper, as everyone has very individualistic preferences and beliefs.

The term uncertainty is so immersed in our daily lives most people do not even question the definition of the word "uncertain". Uncertainty has various definitions for different branches of science. Statisticians define uncertain events as events that are not yielding expected measurements in a consistent manner, or in other words, define uncertainty as the "*probability distribution of a variable or its mode of occurrence being unknown*" [67]. In decision making, a more general definition is employed. Uncertainty is defined as being in a stage of knowledge where the consequences, extent, or magnitude of circumstances, conditions, or events is not known with certainty.

Properties listed above exist for every decision in life, especially for decisions in large scale complex engineered systems design. This is due to the system design processes being a series of technical decisions. Decisions regarding design have multiple sources of uncertainty. In order to reduce the ambiguity generated by multiple unknowns, these uncertainties can be identified based on their origin or the source of their occurrence. Identifying and classifying these sources of uncertainty would provide systems engineer a basis to work. Starting from there, uncertainties can be incorporated in the design process based on their source of occurrence. This may aid systems realization and may help to aid the chronic problem of traditional engineering, preventing schedule delays and cost overruns. Throughout this thesis, uncertainties related to the systems design and its effect on the system will be evaluated.

II.5.1. Literature Survey on Uncertainty in Design

Defining and tracing uncertainties to the origin is the first step to incorporate uncertainty to the design. Once clearly defined, uncertainties can be quantitatively modeled in detail and integrated in system design. Before moving on to the discussion of the literature it is beneficial to define the terminology that will be used throughout this thesis.

- *Design Parameters:* represent the assumptions or constants used when designing the system and are not changed throughout the design. They are composed of the technological capabilities of the designer, conversion ratios, and beliefs. (such as the power density of a battery, material density, unit cost of a component, etc.)
- *Design Attributes:* are measures of subsystems or components that do not directly reflect on to the value of the system, and are not explicitly controlled by the system designer. (battery mass, engine weight, etc.)

- *Design Variables:* are measures that represent the general characteristics of the system, and are under direct control of the designer throughout the design process. Therefore changes on design variables directly reflect on the value of the system.

Du and Chen investigated the impacts of uncertainty in MDO frameworks and used a verbal classification to categorize sources of uncertainty [68]. Using a MDO point of view, sources of uncertainty were broken down to three major components. First group was denoted as the input uncertainty and it includes uncertainties associated with the design parameters and design variables. In order to deal with these type of uncertainties, researchers suggest solving the optimization problem by maximizing the mean performance of the system while minimizing the deviations on the system attributes [69]. A second group of uncertainties are associated with the constants that are used as the design parameters. These may depend on insufficient information regarding the subsystems or ambiguity regarding system components [70]. The third group of uncertainties represents the uncertainty of the model structure. Uncertainties in the model structure are caused by the assumptions being used while building in the model. In order to avoid uncertainties related to the model structure, Laskey suggested utilizing multiple models regarding a single problem until there is a model that is proven reliable [71].

McManus and Hastings have proposed a framework for verbally classifying sources of uncertainty [72]. This study mainly focuses on characterizing and identifying sources of uncertainty through a verbal taxonomy. Researchers argued that through successful identification of uncertainty sources, resulting effects on the system design may be estimated and designers may take preventive action accordingly. Classifying uncertainties for early design phases was also investigated through context by de Weck et al. [73] Effects of unaccounted uncertainty on complex systems that are in use have been discussed as case examples. Moving on from these examples, unaccounted uncertainty related problematic areas in the preliminary design phase are clustered based on source relative to the system boundary. Parallel to common sense, researchers argued that uncertainties based within the system can be handled by the designers to a greater extend. Uncertainties that are based from outside the designer's boundaries are harder to account for due to framing issues. Studies discussed in the previous paragraphs provide a significant insight on the classification of uncertainties.

In order to incorporate this insight to the systems design process, a quantitative approach is required. The necessity for quantitative models is similar to the need for value driven design - to provide systems engineers a mathematically rigorous, formal, repeatable, and scientific tool. The subject of modeling uncertainties in system design has therefore become an attractive subject in literature. Barton et al. argued that in order to make consistent decisions in systems design, the series of decisions that follow the initiating decision have to be taken into account [74]. In order to evaluate this series of decisions and their impact on the design, a simulation of a holistic business model was built. Design strategies and effects of design decisions were investigated through this model. Chen et al. argued that uncertainties related to the series of system design decisions that will be made during the realization process cannot be modelled in high fidelity [75]; therefore suggested that, designers should make robust decisions that are unresponsive to the minor design changes that would occur later on. Chen also discussed that by adjusting the system properties, earlier design decisions can be made to cover up possible larger scale design changes [76]. It was shown that uncertainties could be introduced to the system design through uniform probability distributions. This approach was later criticized for using uniform distributions to represent uncertainty since uncertainty is rarely uniformly distributed. Wood et al. suggested the non-uniform nature of the uncertainties can be reflected in design by using subsystem and component level test data [77]. This enables introducing uncertainties related to the component within the extent of the available test range, given that the data is available. Unfortunately it does not offer any reliable solution regarding to the external uncertainties.

Based on the complementary highlights of the research discussed above, Malak applied parameterized efficient sets to improve decision making in system design [78]. Malak demonstrated that system level attributes can be related to the component level attributes [79], and inferior decision alternatives can be eliminated based on Pareto dominance [80]. This method relies on value models to evaluate system level impact of the subsystem decision. This falls on the same page with the proposed technique offered in this thesis. In opposition to studies mentioned above, Aughenbaugh and Paredis evaluated the value of defining uncertainties with imprecise distributions rather than fixed probability distributions [81]. The study provided significant improvements on robustness by utilizing uncertainty representations that are largely imprecise but some crucial implications on systems design such as the computation time was neglected.

Besides these one decision maker point of view studies, Kalsi et al. studied robust design techniques under a scenario of multiple decision makers by incorporating a game theoretic approach [82]. Minimizing the deviation from the design attributes (that are caused by uncertainties) were defined as the objective function of the MDO model. The unaccounted effect of one subsystem designer's decisions on the other was investigated in order to investigate uncertainties related to concurrent decision making.

A brief review of the literature on incorporating uncertainty to design process and sources of the uncertainties related to system design was presented above. In the scope of this thesis the effect of uncertainties that are caused by external sources on the overall system value will be investigated through probability distribution configurations. In order to perform these tasks, the utility theory, a mathematical technique that enables making rational calculations using an array of possibilities, needs to be discussed. The utility theory, its axioms, and its applications will be discussed in the following subsection.

II.5.2. The Utility Theory

The primary objective of the systems engineer is to make decisions throughout the systems design process. Prior to discussing the right strategy for decision making under uncertainty, it is beneficial perform a quick walkthrough of the decision making terminology. First, a decision is an almost irreversible commitment of resources. An idea does not represent a decision unless a commitment is made through thoughtful action. Moreover, a decision is also a choice between existing alternatives. The term "alternative" represents an alternative action. An outcome is the associated probabilities that might result from an alternative action. Under certainty, the outcome of an action would only result in a certain way, with an associated probability of occurrence of one. Whereas under uncertainty, the action results in a single outcome out of an array of possible outcomes. The size and distribution of this array of possibilities depends on the uncertainties associated with the event. In order to make decisions consistent with how the stakeholder would make those decisions, the preferences and the risk attitude of the stakeholder has to be captured by the systems engineer. Expected outcome of the distribution of all possible outcomes has to be considered in accordance with the stakeholder's risk preference. Optimization in this scope is the discipline that studies decisions with an infinite or finite amount of alternatives and searches for the best possible outcome amongst these alternatives. Optimization integrated in VDD helps systems engineers to evaluate possible outcome of alternative events rationally, based on the stakeholder preferences.

Value and risk preferences can be defined together through utility. The idea that lead to the definition of utility was first brought up by Nicolas Bernoulli's observations regarding an addictive gambling game. Bernoulli witnessed a game where the expected outcome of the game was infinitely large but the outcome for the players were extremely low. This was due to the fact that players needed to pay infinitely large amounts of money in order to stay in the game to win, but very few could afford that. Nicolas Bernoulli wrote his observations in a letter to his cousin Daniel, these observations would later be named the St. Petersburg Paradox. The solution offered to this problem by Daniel Bernoulli represents the essence of rational decision making. The paradox was resolved by Daniel Bernoulli in 1738 by introducing the utility function and the expected utility hypothesis [83] as a solution to this paradox. Bernoulli simply flushed out the fact that in a lottery condition (a condition where the outcome is zero or some maximum prize), a fixed and certain amount of money that would replace the lottery ticket would not be the same for two different people, because their risk attitudes were not identical. A hundred dollars for a poor man was not equal to a hundred dollars for a rich man. In other words, worth of outcomes should not be the ranking measure to the decision maker but instead the utility it yields. Even though the main idea was created in the 18th century, the rules of the theory that would rationalize decision making were not developed until the 20th century.

Rational behavior is defined by Simon as: finding the occasion for rational action, devising alternative courses of action, and choosing which action to pursue [84]. Subjective expected utility theory (SEU) also known as Von Neumann – Morgenstern Utility Theorem [85] can be used as a basis for making rational decisions using the utility theory. SEU was the theory that rationalized the principles that was stated by Bernoulli two hundred years ago. SEU states that in order to make a rational decision, the first thing a decision maker has to do is to realize that they are in a decision situation and to comprehend the conditions regarding this decision environment. This is denoted as framing a decision. After successfully framing a problem, rational decision making principals can be applied if the events associated with the situation are passing "*the clarity test*". Howard defined the clarity test as: if occurrence of an event can be determined without ambiguity by visiting any place in space and time and if any information regarding the subject can be collected by any means necessary, then the event passes the clarity test [86]. After performing the clarity test rational decision making can be performed by following five axioms of the SEU listed below:

- *Probability Axiom:* states that a decision maker must be able to assign a probability to any chance event that passes the clarity test. This statement does not dictate that the assigned probabilities should be accurate.

- *Order Axiom:* states that the possibilities (possible outcomes) in a decision frame can be ranked from most preferred to the least preferred, with allowance for ties. In order to preserve rationality, this ranking cannot be recursive.
- *Equivalence Axiom:* states that, if $A > B > C$ then there exists a probability q such that;

$$B \cong q * A + (1 - q) * C \tag{II-4}$$

- *Substitution Axiom*: states that if a decision maker is indifferent between a certain outcome and an uncertain outcome then the decision maker should act consistently and make decision as if these two situations are indifferent from each other.
- *Choice Axiom*: states that if a decision maker prefers one possibility (outcome) to another ($A > B$), and if one of the alternatives leads to A with a higher probability than the others (assuming that there are only two outcomes A and B), then the decision maker should choose that alternative with the higher possibility of outcome A.

Risk preferences of the decision maker must be used in order to proceed further into details of decision making under uncertainty. As the name implies, SEU is subjective and this subjectivity cannot be treated separately from stakeholder's risk preferences. Risk can be expressed as a curve that converts worth to utility. Shape and characteristics of this curve depends on the preferences of the decision maker. Major risk preferences can be broken down by Figure II-4 that is adopted from Hazelrigg [87];

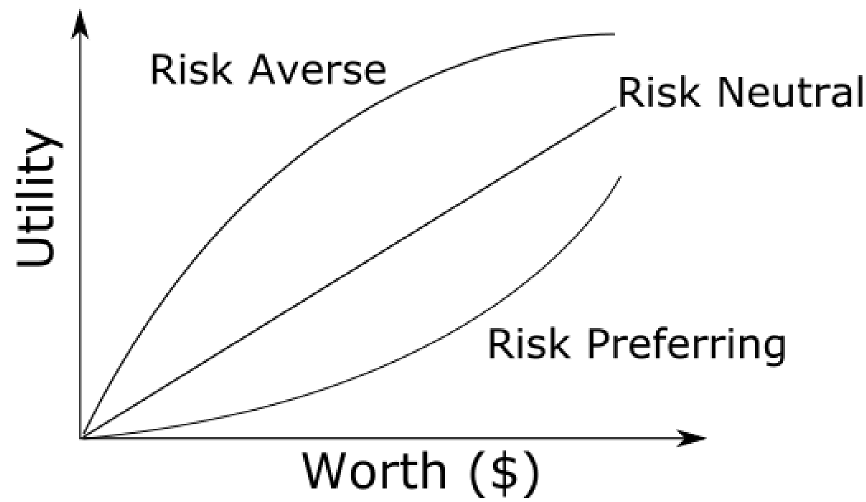

Figure II-4 Risk Attitudes

It is beneficial to mention major risk attitudes briefly before moving on to the next subject. Mathematical definitions and specific risk attitudes that will be employed in this thesis will be discussed in detail in the methodology section:

- *Risk Neutral:* This attitude represents having a constant slope utility equivalent of chance events. Risk neutral decision makers are also called expected value decision makers by Hazelrigg [87] and are willing to trade in chance events for their expected outcome. With a simple example; a risk neutral person would be indifferent between $10 and a lottery with two outcomes of $0 and $50 with a 0.20 chance of winning.
- *Risk Averse:* Risk aversion can be summarized geometrically in Figure II-4 by two properties, a positive slope and a negative second derivative that gives it a concave down shape representing decreasing slope with increasing amounts of worth. In plain English this attitude represents a decision maker who does not like risk. Their respective utility decreases with increasing worth. This represents

decision maker's attitude of preferring smaller worth of certain outcome to larger expected outcome of a chance event. Using the same example from the risk neutral case; a risk averse decision maker would trade in his lottery ticket for less than or more than the expected outcome such as $8.

- *Risk Preferring:* Also known as risk loving, decision makers are willing to pay more than the expected outcome of chance events. Following the lottery example equivalent of the same ticket for a risk preferring decision maker is more than the expected outcome, such as $12.

The use of expected utility theory when making decisions under uncertainty is to collapse the probability distribution of uncertain events to a single expected utility using utility functions that represent decision makers preferences. This enables the decision makers to compare various distributions with their expected utility and make rational decisions in accordance with their stakeholder preferences. Last missing pieces of this puzzle is the risk tolerance and risk premium. Risk tolerance represents the amount that a decision maker can afford to risk when making decisions. When talking about commercial industries this can be represented by a certain portion of the annual revenue of the company. Risk premium on the other hand depends on the distribution of the possible outcomes of an event and the risk tolerance of the decision maker. Utility equivalent of an outcome can be calculated by subtracting the risk premium from the expected worth.

II.5.3. Monte Carlo Simulations

Incorporating uncertainties related to internal or external sources of the design, changes the problem configuration from a deterministic problem with a single outcome to a problem with multiple possible outcomes. The most common approach to incorporate these uncertainties into design is to define the associated uncertainty with a probability distribution and integrate it through direct simulation [88]. This is achieved through generating a set of random numbers and through a transformation with the distribution associated with the variable, each random number is assigned a variable's value. Quantity of the random number set depends on the level of fidelity the designer wants to achieve [89]. The larger the set the more computational power required. The set has to be large enough to represent the whole uncertainty distribution that is trying to be captured in accordance to the law of large numbers [90]. If the set is too small to capture the uncertainty properties of the target distribution, the calculations may not yield consistent results. Details regarding the integration of the Monte Carlo simulation and its content will be discussed in the methodology section.

II.6. Thesis Motivations

The scientific background mentioned in this chapter has not focused on creating a holistic customer preference for electric vehicle and has not compared commercial and government preferences. Furthermore, there is a lack of research in developing stakeholder value models for commercial products that incorporates the customer value. This thesis aims to fill that research gap. The modeling of government preferences for commercial products is especially relevant since the 2008 government bailouts of the automotive industry [91], where government took a significant role in driving automotive companies to future successes. In the following section, multiple preferences concerning an electric vehicle will be discussed and associated value functions will be created. These preferences will include consumer, commercial, and governmental stakeholders.

Preferences and the designs that they drive towards will be compared through the use of a battery powered electric vehicle model. Using the information presented in the previous section, impact of internal and external uncertainties related to the system's environment will be identified. Their respective impact on the system design, depending on various stakeholder risk preferences, will be investigated. The following chapter presents the methodology that will be applied in the investigation of these research questions.

CHAPTER III

METHODOLOGY

In this chapter, value functions are formulated to capture simple preferences from the perspective of the consumer, commercial, and government stakeholders concerning electric vehicles. Assumptions and system attributes needed to form the value functions are discussed. A simple electric vehicle model is created to explore the impact of using the various value functions. A particle swarm optimization algorithm is implemented around the electric vehicle model in order to optimize the design in accordance with the stakeholder preferences. Specific sources of uncertainty in the system's environment are identified and their impact on the overall system configuration is investigated through implementation of Monte Carlo simulations. Decision making strategies under uncertainty for industrial and governmental stakeholders are studied through a discussion on possible preferences and their implications.

III.1. Customer Value Model for Ground Transportation

In order to define the value of EVs for the user (i.e., the customer), one has to understand the value of personal transportation. Personal transportation vehicles come in various shapes and sizes in order to satisfy the infinite combinations of personal preferences the customers have. Manufacturing capabilities are enormous with state of the art manufacturing facilities capable of producing more than 10 million cars in a year [92]. EVs are just a subset of the vehicles that can be utilized to satisfy the need of personal transportation. Therefore the value of EVs can be derived from a more generic representation of the value of personal transportation based on other means of transportation.

Defining the value of personal ground transportation is a challenging task due to the many irreducible benefits modern era vehicles offer. A personal ground transportation vehicle has become more than a mean of transportation for many people, representing social status and personal preferences such as policy statements and style. Despite these new roles, personal ground vehicles still have the primary function of transportation. In this thesis, the value of personal transportation is used to derive the consumer's value of an electric vehicle.

The value of personal transportation can be described as the worth of being able to transport oneself from one location to another. In this thesis, the value of transportation is monetized, capturing the desire of an individual to receive the most money. Monetization is just one possible representation that can be used to capture the individual's value of transportation and is used in this paper due to its meaningful nature. This value is related to the benefits and the life time costs of the vehicle. Equation III-1 captures this top-level value function(Vt), where Ct represents the costs associated with owning a vehicle and Bt represents the benefits associated with attributes that may not initially be in units of money.

$$Vt = Bt - Ct \qquad \text{(III-1)}$$

III.1.1. Cost for the Customer

The lifetime cost of a vehicle for the consumer/owner has several key components, including: purchase cost; taxes and penalties; cost of driving; maintenance costs; insurance cost; and salvage of the vehicle (which is a negative cost). In order to make a fair comparison at the time of purchase all costs occurring during the lifespan (l) are related to their present worth, accounting for the individual's time value of money. The generic cost equation for a consumer is seen in Equation III-2, rearranged in Equation III-3

$$Ct = Sp + \sum_{j=0}^{l} \frac{Gt}{(1+r_p)^j} + \sum_{j=0}^{l} Gp_j + \sum_{j=0}^{l} \frac{CPM*d_j}{(1+r_p)^l} + \frac{SV_j}{(1+r_p)^l} + \sum_{j=0}^{l} \frac{MC_j}{(1+r_p)^l} + \sum_{j=0}^{l} \frac{CI_j}{(1+r_p)^l} \quad \text{(III -2)}$$

$$Ct = Sp + \frac{SV_j}{(1+r_p)^l} + \sum_{j=0}^{l} \frac{Gt*Sp+Gp_j+CPM*d_j+MC_j+CI_j}{(1+r_p)^j} \quad \text{(III -3)}$$

The first term, purchase price (Sp), is the price that has to be paid to purchase the vehicle. For the customer, it is a price that has to be paid without any control on it besides whether or not to pay it. It is an outcome of the manufacturing company's preferences, based on the manufacturer's value function. Underlying factors determining the purchase price will be discussed in the commercial value subsection.

The second term, salvage value (SV_j), represents the positive cash flow that would occur due to the salvage of the vehicle. It is expressed without a summation sign because it is a onetime inflow occurring at the year of salvage, which is assumed to be occurring at the end of owning period (at year l). Owning period in this study is fixed to be 10 years in order to represent the national average for owning new cars [93]. Due to the infancy of the EV market, the salvage value (SV_j) data is not yet available. Therefore an approximation has been made based on gas powered vehicle (GPV) salvage data. It is assumed that the vehicle value depreciates 10% each year over the purchase cost.

The third term collects costs occurring every single year that the vehicle is owned and operated. The vehicle is assumed to be operational every single year it is owned. The term (Gt) stands for the government tax the customer has to pay for the state governments. Currently the US government has an incentive of $7,500 for EVs. This value is used for calculating the value represented in this thesis and must be modified if it applied to other countries. The term (Gp_j) represents the penalty applied by some state governments for vehicles with low fuel efficiency or high carbon emission. This is a critical term that captures the regulation known as the Corporate Average Fuel Efficiency (CAFE) in 1975 [94]. Effects of government regulations such as CAFE are another popular subject of academic research [95]. For the sake of this thesis, only the governmental penalties that would be applied to the EVs will be taken into account. These penalties are equal to zero since we are only concerned with battery powered electric vehicles which have zero tailpipe emission.

An essential component of system life time costs occurring to the owner for GPVs is the miles per gallon. Considering the generic form of the value formula, this should be converted into cost per mile. The specific source of energy the vehicle consumes should be remained undefined. This component is captured in the generic value equation through the cost of energy per mile driven, abbreviated as (CPM) in the equation given above. One has to be aware of the fact that different from GPV's mpg, CPM is not only related to the efficiency of the engine, it is also related to the efficiency of the charging infrastructure. EVs are usually charged at home stations where the cost of operating the vehicle is reflected in the electricity bill. CPM, for the scope of this study, will be used as the total cost from the energy source. CPM will be calculated by using 0.12$/kWh which is the national average [96]. CPM will then be multiplied by the average distance a US citizen travels during a year which is 15,000 miles [97]. Again, these values must be modified appropriately when examining different countries

Another major source of costs incurred to the owner is the maintenance costs of the vehicle (MC_j). Often overlooked, maintenance costs reflect the quality of the vehicle and has a great impact on the perceived quality of the manufacturer for some customers. Approximating maintenance costs of vehicles, especially for new brands, can be challenging. Due to the infancy of the EV market, life term maintenance cost data is not available. However GPV maintenance cost data is well established and is given as 0.0497$/mile [97]. An approximation can be made by considering the fact that the EVs are composed of fewer components than GPVs and are therefore expected to have lower maintenance costs. For this study it will be assumed that the maintenance costs of EVs are half of GPVs [98].

The final cost in the equation (CI_j) represents the insurance expenses and is typically a function of the vehicle and the consumer's driving history. A constant value of $960 per year is used [99]. These costs, many of which are partially a function of the vehicle's attributes, are then used in Equation III-3 to determine the present cost of the vehicle using an individually specific discount rate (r_p) over multiple years. For the sake of this study a 7% customer discount rate is used.

III.1.2. Benefit to the Consumer

As opposed to the cost function, the benefit function examines the attributes important to an individual that are typically not in monetary units. The benefits were investigated by first examining the savings compared to other modes of transportation.

This is necessary to get a representation of the value of transportation in the most generic sense. In this way, such hard to quantify benefits as the number of passengers can be related to monetary value. Unlike the previous section, it is technically not possible to define a generic benefit formula for personal ground transportation since it is highly subjective. Value functions are inherently individualistic. While the basis of the value functions can be captured in a general form to model many different types of individuals, the specific value functions described in this thesis are for a single, fictional individual. Cost models are relatively straight forward in calculation, however the benefit models can be driven by many subjective desires (such as the desire for speed or the desire for safety). The model in this thesis can be used as a stepping stone for future models that would capture greater complexities, such as aesthetics and interior comfort.

The system attributes used in this benefit model, that the individual deems important, are the vehicle's range, number of passengers, power, and charging rate. In order to relate these attributes to monetary units different modes of transportation were examined to form a basis. It is important to note that this basis is just a set of data points and does not represent perfectly an individual's preferences. One approach to estimating benefit elements is to use taxi fares, which provides a similar means of transportation. In order to obtain a mathematical relationship for taxi fare with respect to the distance travelled and number of passengers transported, the average taxi fares in 5 largest cities in U.S. are used [100], as seen in Table III-1.

Table III-1 Taxi Fares

	City Name	Opening Fare	Per Km	Extra Fees
Taxi Fares	NYC	$2.50	$1.55	None
	LA	$2.85	$1.68	None
	Chicago	$3.25	$1.12	$1 per person
	Houston	$2.75	$1.37	None
	Philadelphia	$2.70	$1.43	$1 per person
	Average	**$2.81**	**$1.43**	**$0.4 per person**

By using the average taxi fare, the benefit of transportation (Bt) with respect to the number of passengers (n) and the range (d_j) can be defined in Equation III-4.

$$Bt = \{[(2.81 + 0.4 * (n - 1)) + (1.43 * d_j)] * H(n)\} \text{ in US Dollars} \quad \text{(III -4)}$$

$$H(n) = \{= 0 \text{ for } n < 1, = 1 \text{ for } 1 \leq n \leq 3, = 2 \text{ for } 4 \leq n \leq 6, \ldots.\} \quad \text{(III -5)}$$

Where $H(n)$ represents the number of taxis that has to be hired. It is defined by taking into account that front seats are not available due to legal restrictions and for more than 3 passengers multiple taxis are needed. It is important to realize that d_j is roughly 15,000 miles or 24,000 km [97], which makes the cost of travel using taxis extremely expensive when considered as a permanent mean of transportation. Considering the short-term, high-cost solution taxis offer, a more meaningful long-term benefit approach is desired.

Another possible approach for developing the benefit of transportation is to use government rates for mileage. For this thesis, this was done by using the costs to rent a vehicle (Br) for personal transportation is used as a basis. The general form of the benefit value (Bt) is seen in Equation III-6, an assumed equation for a fictional individual.

$$Bt = Br * Bn + Bp * Hp - Pd \quad \text{(III-6)}$$

Equation III-6, given above, assumes that the benefit of transportation (Bt) is associated with rental vehicle costs as the need for transportation can be satisfied by renting a car for a time span. The costs related to renting a vehicle are given in Equation III-7, where Rc is the rental cost, Rci is the insurance cost of the rental vehicle, and Rcg is the fuel cost. Equation III-7 represents one of many forms of representing the value of transportation.

$$Br = Rc + Rci + Rcg \quad \text{(III -7)}$$

The transportation need applies to a vehicle capable of moving a large number of passengers. The benefit must reflect the positive correlation between an increase in the number of passengers the vehicle is capable of carrying and an increase in transportation benefit. To reflect this nuance, a multiplier of Bn, capturing the discount of transportation due to the number of passengers, is added and is mathematically defined in Equation III-8. In order to represent the contribution of passenger capacity to the overall value, the coefficient Bn is defined with a negative exponential decay that starts at 0 for 0 passengers, drives towards 1 for infinite passengers, and stagnates after 5 people (a common number of passengers in GPV). This equation reflects the average American family consisting of 2.58 members [101].

$$Bn = -e^{-number\ of\ passengers} + 1 \quad \text{(III -8)}$$

Represented with the second summation term in Equation III-6 is the benefit of a powerful car, a highly individualistic preference. The coefficient of the benefit of having a powerful engine (Bp) can be approximated by comparing vehicles of the same make and model that only differ in engine size. This is highly dependent on the car type and make which is used in this study as a low fidelity basis for the monetary value of the horsepower. Based on market data, Bp is significantly higher for performance cars [102] than family sedans [103], as expected. This coefficient is multiplied by the EV's horsepower (Hp) to determine the benefit through engine power.

The last term in Equation III-6 is the downtime penalty function (Pd) representing the value of time lost during recharging. This representation is required since a major drawback of buying an EV is the relatively high recharging time compared to GPVs. A logical mathematical expression is established to estimate the number of times in a year the owner has to stop travelling and recharge due to limitations of the battery capacity. This expression is multiplied by the time value of money to reflect the annual worth of the time lost due recharging. The downtime penalty is defined with respect to the range of the electric vehicle (Rev), range of an average gas powered vehicle ($Rave$), charging time (t_{charge}, which is a function of the battery size and charging rate of the EV), average distance travelled per year ($dave$) [97], and the mean value of time for an American (DPH) [104]. The mean value of time for an American is approximated using the Bureau of Labor Statistics average hourly earnings for employees on nonfarm payrolls [104]. By assuming recharging stations are available, the downtime penalty is defined in Equation III-9.

$$Pd = \left(\frac{Rave}{Rev} - 1\right) * \left(t_{charge} * DPH\right) * \left(\frac{dave}{Rev}\right) \quad \text{(III-9)}$$

As can be seen in the above equations, a key component to value functions is understanding the balance that occurs with system attributes. Without capturing all of the interactions between attributes in the value function a design is likely to drive to an irrational alternative, such as a vehicle with no cost that does not exist. This will be explored further in the results section.

III.2. Commercial Value Model for Electrical Vehicles

In this subsection a value model for commercial industries will be developed. Similar to the previous subsection, commercial value is also subjective and therefore strictly depends on the stakeholder. Unlike the previous subsection though, commercial industries in general have a preference of maximizing profit [41]. Other preferences may vary depending on the commercial industry's status, market share, future business expansion strategies, etc. Some of the preferences may include establishing market share for companies that are relatively new in the business or improving the company's image for a company with unreliable product history.

In this thesis, the preference of maximizing profit will be analyzed, one of many possible desires. Profit (π) can be defined as the margin between the revenue (R) and total system cost (IC_{total}), represented in Equation III-10. Revenue is equivalent to the total quantity (Q) of vehicles sold times the selling price (Sp), seen in Equation III-11.

$$\pi = R - IC_{total} \tag{III -10}$$

$$\pi = (Q * Sp) - IC_{total} \tag{III -11}$$

III.2.1. Cost for the Commercial Industries

In order to develop a realistic value function for commercial industries an increased understanding of the costs are necessary. Total system cost has many contributors, spanning from the cost of system ideation to customer delivery. It is the role of the systems engineer to take life cycle costs of the project into account. Total system costs should include the costs that would occur starting with the acquisition of the project (which may include capital investments), design, manufacturing, and in some cases maintenance of the system during the operations phase. System costs do not occur at an instant but are distributed over time. Therefore time value of money and the discount rate related to the commercial industry has to be taken into account when making decisions.

In this thesis total system cost is broken down to the costs to the commercial industry of: investment and infrastructure (Cv), design (Cd), manufacturing (Cm), and transportation from manufacturing plant to dealership (Ctr). These costs are discounted (using commercial discount rate r_c) to a net present cost, with an initial period at k=0 (time of initial investment) and terminal m years. Cost of investment and infrastructure depends on such business characteristics as the current status of the commercial industry in terms of technical knowledge, existing facilities, and experience in the business field. Investments costs for an established company expanding business would be significantly different for a new startup company trying to initiate business. Design costs of the product are a function of the number of R&D personnel employed for the project and their relevant experience in the field (or namely the "know-how"). The manufacturing costs has similar personnel and experience factors. Transportation costs depends on the supply chain of the company and the location of the manufacturing facilities. As in the consumer model, the cost portion of the commercial model is formed with empirical data. The total system cost is expressed mathematically as seen in Equation III-12.

$$IC_{total} = \sum_{k=0}^{m} \frac{(Cv_k + Cd_k + Cm_k + Ctr_k)}{(1+r_c)^k} \qquad \text{(III -12)}$$

III.2.2. Benefit for the Commercial Industries

The benefit for commercial industries, as discussed in the commercial value subsection, may vary depending on the preferences of the specific industry. In this thesis commercial industry is assumed to be interested in maximizing profit, and secondary income sources made through maintenance, customer support, spare parts, future contracts, company image, etc. will be ignored. Therefore the total benefit is directly related to the revenue the company makes by selling that specific EV. Mathematical relationship governing the revenue is given at Equation III-11.

Revenue has two major components: the quantity of vehicles to be sold (Q) and the selling price of the vehicle (Sp). The selling price is dependent on the total cost of the vehicle, taxes and/or penalties, and the profit margin of the manufacturer. The manufacturer has the ability to change the selling price of the vehicle by adjusting the profit margin. Profit margin can be defined as the ratio of the selling price and the total product cost. Profit margin can either be decreased to increase the demand or increased to improve the profit per vehicle. Profit margin may also be variable, related to production volume. The profit margin itself can be a design variable to optimize the net present profit of the company. The selling price of the EV is calculated by multiplying the company's profit margin and cost per vehicle (C_{pv}), seen in Equation III-13. C_{pv}, is calculated using the battery, engine, and structural costs of the vehicle. For the scope of this study, design cost (Cd_k), manufacturing cost (Cm_k), and transportation cost (Ctr_k) occurring in various time spans are assumed to be captured in C_{pv}. Investment costs Cik are evaluated separately as an approximation using a current vehicle as a case study [105].

$$Sp = PM * C_{pv} \tag{III -13}$$

The quantity of the vehicle sold (Q) is tightly coupled to the selling price (Sp) of the product, the attributes of the system, and the consumer preferences. The consumer will be comparing the system attributes of many alternatives, including alternatives that are from other companies. Each consumer will have a different preference, affected by their driving profiles, habits, purpose of the vehicle, etc. Probability distributions capturing the various preferences of the consumers can be used to determine the demand a vehicle with specific attributes will have in the marketplace. In the case that a more precise representation of the customer demand model is required, such as in the case of a multimillion dollar investment, information that was stated in the background section has to be recalled. Deriving a realistic model for the customer demand is a highly complicated process that is a research topic unto itself. Considering the competitive automotive industry this should be an integral part of a systems engineer's inventory, and therefore it is worth the effort. Detailed information regarding the demand model employed in this thesis will be presented in the following sections.

III.3. Government Value Models

The value functions of governments are particularly varied due to the large number of stakeholders that are striving to define the single, mathematical preference. Government preferences concerning EVs may focus on nationalizing the domestic market, creating more attainable systems for the citizens, improving their rank with other countries, or improving their positive impact on the environment. In this thesis two of these preferences are investigated. These fictional government value functions described offer two of many possible preferences that can be used to logically determine the best from a set of widely varied alternatives.

III.3.1. Maximizing Gross Domestic Product

Gross domestic product (GDP) is the most common measure of a nation's economic output or growth. GDP is also a metric for the value generated by all the goods and services produced within the nation during a year. An improvement in GDP can lead to improved influence of a government over other nations. The scenario examined in this paper considers a government starting a design institution to produce a vehicle for the nation. The value function for this scenario is derived from the general GDP formula, seen in Equation III-14.

$$GDP = C + I + G + (Ex - Im) \tag{III -14}$$

In Equation III-14, C represents the total spending of consumers (citizens), I represents the total investment of businesses within the country, G is the total spending/investments of the government, Ex is the total worth of the exported goods, and Im is the total worth of the imported goods. When comparing alternatives, only differences need be examined, understanding the properties of the utility function as it relates to magnitudes. Hence, only the variables related to the automotive market are considered for GDP calculations in this thesis.

For this fictional government, it is assumed that the nation's automotive marketplace is dominated by foreign companies and the fictional nation's government is assumed to have a desire to increase its GDP by starting an EV company. Considering the initial conditions described above, this fictional nation's domestic market is dominated by imported goods and both business and government investments in the automotive industry are zero. Consequently, the worth of exported goods is zero and the worth of imported goods is equal to the total spending of the consumer on automobiles. Therefore, the baseline automotive related GDP is zero. The difference in GDP from the government starting an EV company can be determined using Equation III-15. Worth of exported goods is assumed zero for a worst case scenario. Worth of imported goods is determined in Equation III-16, using the consumer preferences to determine the government manufactured vehicle quantity sold (as was done for the commercial value function). With these assumptions the change in GDP is calculated using Equation III-17 for this specific scenario.

$$C = Total\ Market\ Size * Average\ Car\ Price, I = 0, G = CI_k + Q * C_{pv} \qquad \text{(III -15)}$$

$$Im = (Total\ Market\ Size * Average\ Car\ Price) - (Q * Sp) \qquad \text{(III -16)}$$

$$\Delta GDP = \left(Q * (C_{pv} + Sp)\right) + CI_k \qquad \text{(III -17)}$$

III.3.2. Government Value Function with Environmental Concerns

The desire to reduce the nation's impact on the environment may be another preference of a government. A value function to capture such a preference would maximize the ratio of EVs to GPVs, assuming that the number of vehicles in the country are constant. This value function may also include such design variables as incentives to dispose of GPVs and taxes associated with pollutant generation. A unique property of a value function is the ability to be expanded and generalized to transform attributes of a wide variety of alternatives to a singular metric. The assumption in this thesis is that the environmental impact of concern is the air pollutants caused by operating the vehicle. However, it is important to recognize that the environmental impacts reach far beyond operating pollutants and should include such issues as battery disposal and electrical energy generation. These total life impacts, including manufacturing and end of life, must be considered in a more detailed value function, but are deemed out of the scope of this thesis. A more comprehensive value function would go beyond just the desires related to electric vehicles and explore changes to the country at large. Such a value function would allow for the comparison of such alternatives as hyperloop trains [106], additional bicycle pathways, and additional funding for public transit to improve the environmental impact of the nation. The value function that is defined in the following paragraphs is hypothetical and investigates the fictional scenario of a government starting an EV firm in order to minimize the environmental damage caused by GPVs.

The environmental damage caused by personal transportation vehicles is discussed below. GPVs, as the name implies, run on gas which is a fossil fuel that contains carbon. Thermodynamic reaction that generates the engine power for GPVs produce tailpipe emission which is consisted of greenhouse gases (GHGs). Tailpipe GHG emission of GPVs can be approximated by tracking CO2 emission per mile travelled, as CO2 is the main GHG being emitted. Briefly, regular gasoline produces 8,887 gram

CO_2/gallon [107] after the reaction in the GPV engine. To put it in numbers, we can consider that an average vehicle that gets 21.6 miles per gallon (mpg) [108] would emit 411 grams CO_2 per mile travelled. In order to understand the enormous scale of annual tailpipe emission nationwide, this number has to be multiplied by miles travelled per year (15000) by a single vehicle and number of vehicles (254.4 M). (resulting in 1.568 billion tons of CO_2).

Encouraging public transportation, promoting carpools, or applying higher taxes for low efficiency vehicles may result in slightly reduced nationwide tailpipe emission; not a robust solution to the problem. Even an efficient 50 mpg vehicle emits 177 grams of CO_2 per mile, assuming that the national average was improved to 50 mpg it would only reduce the annual emission by 57%. These numbers point out that improving average engine efficiency would reduce environmental damage but it wouldn't provide a permanent solution due to the scale of the problem. Considering EVs have zero tailpipe emission, governments that are concerned with reducing national GHG emission due to transportation must grasp the permanent solution EVs offer. Based on the arguments presented above, governments concerned with environmental damage of personal transportation vehicles should aim for trading as many EVs with GPVs as possible. Thus government value function with environmental concerns (EGV) can be defined with Equation III-18.

$$EGV = Maximize\ (Q_{Sold}) \qquad \text{(III -18)}$$

In order to achieve this objective, the vehicle being designed has to be aimed for the majority of the population. Income distribution of the population and affordability of the vehicle must be considered. The purchase power of the population has to be considered. Even though there are many facets for understanding the customer desire to prefer an alternative, for the scope of this study the demand model created for the commercial industries will be utilized. Therefore this fictional government will act as a commercial industry with a preference of maximizing the quantity of vehicles that will be sold. Detailed information regarding the demand models will be discussed in the proceeding sections.

III.4. Electric Vehicle Mathematical Model

To investigate the impact of applying these stakeholder preferences on the design, a simple mathematical model of an electric vehicle was created. The model consists of four major subsystems: battery, performance, volume, and mass/cost. A brief representation of the interaction between these sub systems and the data interface is given in Figure III-1. Note that in the figure not all of the interactions are represented, but are mathematically present in the model.

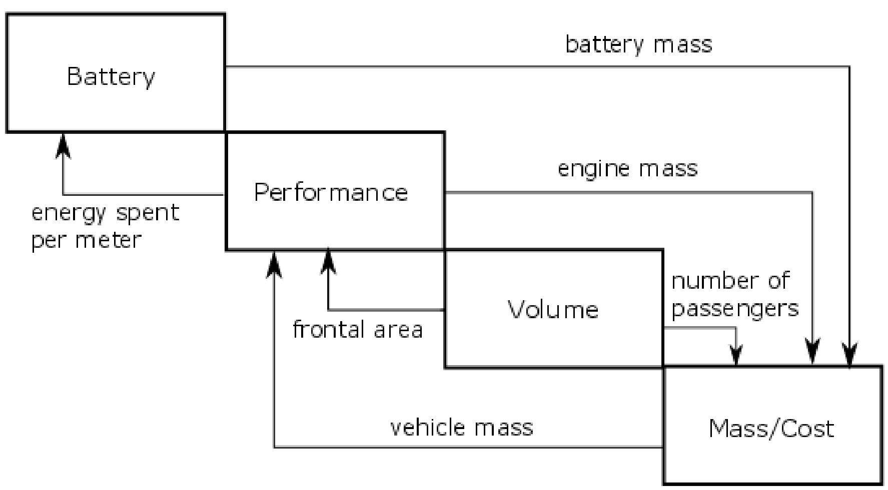

Figure III-1 the Mathematical Vehicle Model - Subsystem Interactions

Each subsystem consists of design attributes that define and represent the subsystem characteristics. Subsystem design attributes contribute to the properties of the system on the subsystem level, but are not design variables. A table summarizing the definition of design attributes that are employed in this mathematical model and their respectful interactions is provided in Table III-2.

Table III-2 Design Attributes and Their Interactions

Abbreviation of the Attribute	Full Name	Allocated Subsystem	Input to
batmass	Battery mass	Battery	General
batcost	Battery cost	Battery	General
batvol	Battery volume	Battery	General
range	Range of the vehicle	Battery	Value Model
acctime	0-60 mph acceleration time	Performance	-
grdblty	Gradeability	Performance	-
jperdst	Energy spent per distance	Performance	Battery
enpow	Engine power in watts	Performance	General
enhp	Engine power in hp	Performance	-
afrnt	Frontal area of the vehicle	Volume	Performance
npas	Passenger capacity	Volume	General
vvol	Vehicle volume	Volume	General
eqvmass	Equivalent mass of the vehicle	Mass/Cost	Performance
syscost	Total cost of the system	Mass/Cost	Value Model
vmass	Total vehicle mass	Mass/Cost	-

The design attributes presented in Table III-2 are captured within subsystem analyses which are themselves captured in a system analysis. The system analysis connects subsystems to each other and allows subsystems to interact. Parallel design of subsystems could be performed under system analysis; however, this paper performed a standard sequential design analysis. This is achieved through a convergence loop where design attributes are updated for each subsystem in a sequential method for a specific set of design variables. This iteration is terminated once design attributes that flow between the subsystems are all within a certain amount to the attribute's previous iteration's value. The mathematical model determines the system attributes that results from an EV defined by 5 simple design variables: the height of the car, the width of the car, the length of the car, the torque output from the power plant, and the battery capacity. The model also uses design parameters [98] to relate the 5 design variables to the system attributes. These parameters are used to approximate performance [109][110], design process [111], manufacturing costs [112], and lifecycle costs [113].

An optimization algorithm is applied to the mathematical system analysis to determine optimal designs. The primary purpose of the optimizer is to evaluate various vehicle configurations with respect to the stakeholder preferences, quantified through the value functions introduced in previous sections. These value functions are used as the objective functions for the optimizer. For preliminary validation purposes the design space was tested with the embedded evolutionary algorithm (based on a genetic algorithm) used in the Excel Solver [114]. The optimization was run multiple times and it was observed that the solution was heavily dependent on the initial design variables. Multiple sets of initial design variables were used in order to reduce the likelihood of a locally optimal, but not globally optimal, solution. Initial point dependency of the embedded Excel Solver algorithm was a recurring problem resulting in a need to change the optimization algorithm approach. The model was then recreated in Matlab to take advantage of the program's advanced computational capability. When the Genetic Algorithm embedded in the Optimization Toolbox was tested it was observed that the algorithm failed to handle steep changes in the design space and repetitively resulted in local optima. A need for a more controllable algorithm was deemed necessary.

In order to improve the fidelity of the optimization module a particle swarm optimization algorithm (PSO) was implemented [115]. PSO was observed to handle the non-smooth design hyperspace of the EV problem more consistently. The optimizer module interacts with the design parameters, generates design variables, calls the mathematical vehicle module iteratively, and uses the value model as the objective function to evaluate resulting system designs. The value function calls the demand model once and obtains the demand estimation. A diagram representing the function interactions is given in Figure III-2.

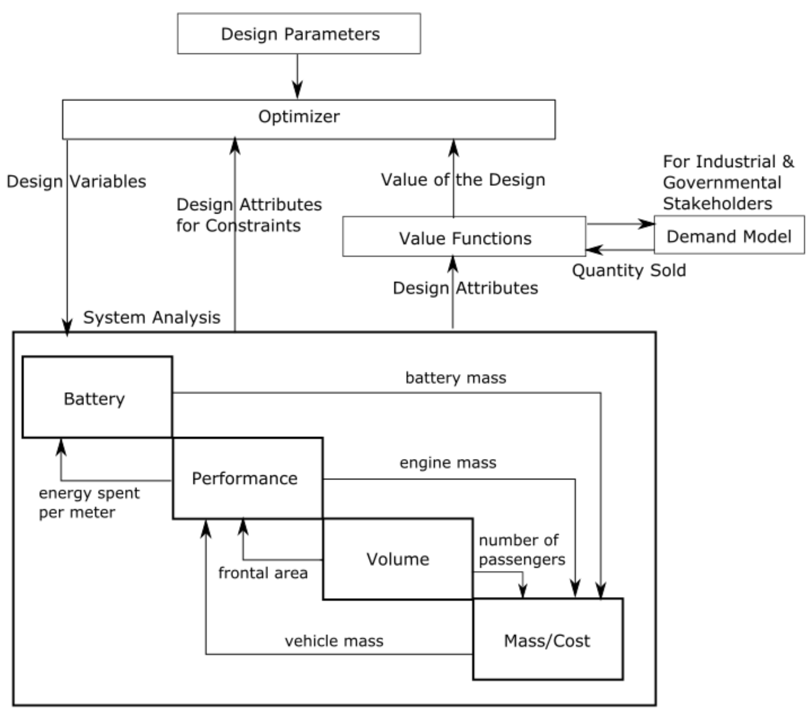

Figure III-2 Value Driven Design Framework

Due to the simple nature of the EV model, the assumptions used in the model, and the relative simplicity of the value functions, some constraints were necessary to ensure a drivable, physically reasonable, vehicle. While constraints are not desired, tradeoffs must also be made between value model complexity and value-lost (and design space lost) from not incorporating performance metrics in the value function associated with the constraints in the model. Furthermore, the constraints may be necessary due to physical limitations, such as component interfaces, or government regulations that are determined a priori. While the performance metrics associated with the constraints can be captured in the value function, it is a tradeoff that must be performed by the systems engineer to determine if there is value-added by incorporating them directly.

In this thesis two performance requirements are incorporated as constraints rather than being captured in the value function. This decision relates to the tradeoff performed in the formation of value functions concerning what is needed and what is not. In an ideal function these performance metrics would be incorporated. The constraints include minimum requirements for the 0-60 acceleration time (9.3s) and the climbable angle at 55mph [116] (6% grade). Climbable angle is also known as the gradeability of the vehicle and represents the maximum inclined surface that the vehicle can climb at a velocity of 55mph. These inequality constraints were introduced to the problem to control design attributes that were not captured by the value functions. These inequality constraint design attributes (i.e. acctime, grdblty) are mathematically determined through the EV model analysis, as are the design attributes that are inputs into the value function. This is seen in Figure III-2 where some attributes determined from the model analysis are inputted into the value function and some are inputted directly into the optimizer in order to determine if the attribute is feasible or infeasible with respect to the constraints. The constraints and the value function are related through the design variables, but not through the design attributes. The value function and inequality constraints use a different subset of the set of design attributes. A specific set of design variables determines a specific set of design attributes, inputs into both the value function and inequality constraints. Constraints perform an inequality control on the design attributes the requirements are defined on (i.e. acctime, grdblty) and apply a penalty to the stakeholder value if corresponding attributes fail to satisfy the preset requirement (i.e. 9.3s, 6°). As a result of the penalty applied, the optimization algorithm discards design configurations that fail to satisfy the requirement and searches for systems with higher stakeholder value. Besides these inequality constraints, side constraints on design variables are defined in order to fit US Department of Transportation regulations [117]. A maximum length of 7m (to fit into current parking structures), and a maximum width of 2.59m (to fit into current travel lanes) is incorporated into the optimization statement. The optimization is run separately with each stakeholder's (customer, government, and industry) value function (described in the previous sections) being maximized.

Represented in the standard form of optimization:

Min f(x) = -Stakeholder Value (Design Variables) (III -19)

S.T. $g_1(x) = \ acctime - 9.3 \ \leq 0$

$g_2(x) = 6° - grdblty \ \leq 0$

$0.90m \leq x_1 \leq 4.1148m$

$0.95m \leq x_2 \leq 2.5908m$

$1.50m \leq x_3 \leq 7.00m$

$100N.m \leq x_4 \leq 5000.00N.m$

$10000.00J \leq x_5 \leq 100000000.00J$

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} height\ (dvh) \\ width\ (dvw) \\ length\ (dvl) \\ torque\ output\ (dvtrqo) \\ battery\ capacity\ (dvbatcap) \end{bmatrix}$$

III.5. The Demand Model

The demand model is a function of the mathematical model and an important step in calculating the commercial and governmental values. The demand model is used to generate an approximation of the total number of vehicles to be sold. The quantity of vehicles sold is heavily affected by the consumer's preferences. The consumer will be comparing the system attributes of many alternatives, including alternatives that are from other companies. Each consumer will have a different preference, affected by their driving profiles, habit, purpose of the vehicle, etc. In order to capture consumer preference and design a system that would maximize stakeholder interest a demand model is necessary.

The customer demand model informs the designers with an approximation for the quantity of vehicles to be sold. Rough approximations based on market data for existing EVs can be formed for academic demonstration purposes. In this thesis a more realistic demand model is desired as the outcome of the value model may lead to designs that are not reasonable. For demonstration and scientific investigation purposes two separate demand model approximations are described in this thesis. One model is a linear demand model based on customer value and existing market data. A second model is developed in order to demonstrate the significance of demand modeling in VDD. The second is a "consider then choose" approach based realistic representation of the customer demand. This model incorporates the existing market data, demographics, affordability of the system, and the value of the ground transportation to the customer to yield the expected quantity of vehicles to be sold.

III.5.1. A Value Linear Demand Model

The quantity of vehicles sold can be approximated by employing a value linear demand model that uses the EV market data. A value linear demand model in this context describes a population preference model that extrapolates market data to form a linear relationship between customer value and estimated quantity of vehicles sold. This is possible by making some assumptions:

- A static market with constant size
- Customers make decisions only regarding to the customer value of the product.

This demand model can be used to evaluate commercial and governmental values of alternative system configurations based on the assumption of customers making decisions on the value of the product only. Simple concerns such as affordability of the product are ignored. A mathematical representation of this demand model is established by using the relationship between the customer value of the new product, customer value of an existing competitor, and the market data of the competitor product. The linear relationship estimating the number of vehicles to be sold (Q) is given in Equation III-20.

$$Q = \frac{Customer\ Value\ of\ the\ New\ Design}{ompetitor\ Customer\ Value} * (CompetitorQuantitySold) \qquad \text{(III -20)}$$

Equation III-20 is an integral part of the commercial and governmental value models, providing an estimation for the quantity of vehicles to be sold. During evaluation of the preliminary results, it was observed that the assumption that "customers will make decision based on the customer value" was partially wrong. It was accurate in terms of the decision making logic in systems design pushing for better vehicles because of the perceived customer value. On the other hand it was incomplete due to the inability to capture the relationship of increasing value yielding designs that were extremely expensive to purchase that were no longer affordable for the general public. In order to fix this issue a modification for the customer demand model was necessary. Therefore a "consider-then choose" based demand model is developed.

III.5.2. Consider-Then Choose Based Value Linear Demand Model

This demand model is developed based on a literature survey on demand modeling rather than a simple value linear approximation. Similar to the value linear demand model, the consider-then choose model is based on the same assumption of customers making decisions according to the customer's value of the product. An element not considered in the value linear model, in this model customers are assumed to be considering the purchase cost of the product before evaluating the value of the product. The portion of the population that cannot afford the product are deemed ineligible and discarded by the model regardless of the customer's perceived value of the product. The model follows by evaluating the remaining portion of the population that may afford the product, and assumes that the possible customers make the decision of purchasing the product based on competitor's market data and their individual value of the product. In a step by step manner, this demand model progresses by the framework given below. It is important to note that steps a-d are one time operations and steps e-g are repeated as a loop during the design process:

a) Get Tesla Model S selling price and market data ($QSold_{competitor}$)

b) Calculate Tesla Model S customer value ($V_{competitor}$)

c) Calculate the eligible population that can afford the competitor product ($EligiblePopulation_{competitor}$) based on income distribution and willingness to pay

d) Find the coefficient of population that would purchase the vehicle based on its customer value ($Coef$) which is:

$$Coef = \frac{QSold_{competitor}}{EligiblePopulation_{competitor} * V_{competitor}} \tag{III -21}$$

e) Get new design customer value from model (V_{new})

f) Get new design cost from model

g) Calculate new design's eligible population ($EligiblePopulation_{new}$) based on income distribution and willingness to pay

$$Q_{new} = EligiblePopulation_{new} * V_{new} * Coef \tag{III -22}$$

The algorithm uses data points for corresponding income ratios to calculate the eligible population by using the willingness to pay. The portion of the population that cannot afford the product is discarded and the eligible population is calculated by summing up the remaining population. The eligible population in this sense can be defined as the number of people that believe they can afford the product and might consider purchasing. US Census Bureau data for household income distribution is available for annual household incomes up to $200K [118]. An extrapolation for higher annual income rates is made to estimate the number of households that make more than $200K annually. An inclusive approximation for the relationship between the number of households and annual household income is established. A fourth order polynomial curve is fitted to the existing data points with an adjusted R^2 of 0.988. The graph of the actual data and the fitted approximation is given in Figure III-3.

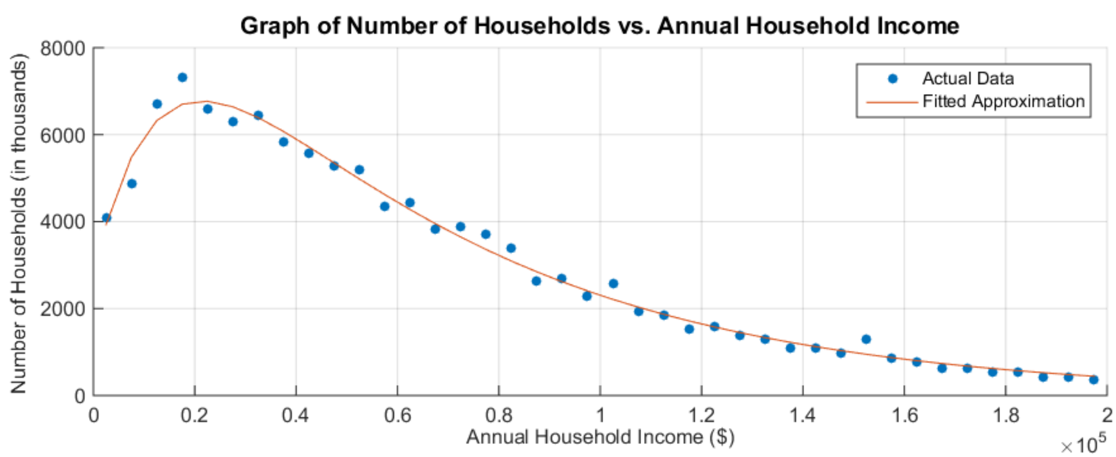

Figure III-3 Actual US Household Income Data and the Fitted Approximation Function

This polynomial curve fit established between the number of households and the annual household income is used to generate additional data points for higher annual income rates. Figure III-4 is the graph of the generated data points for annual incomes up to $1M. This extrapolation is used in this paper due to a lack of available high income data for the U.S. population.

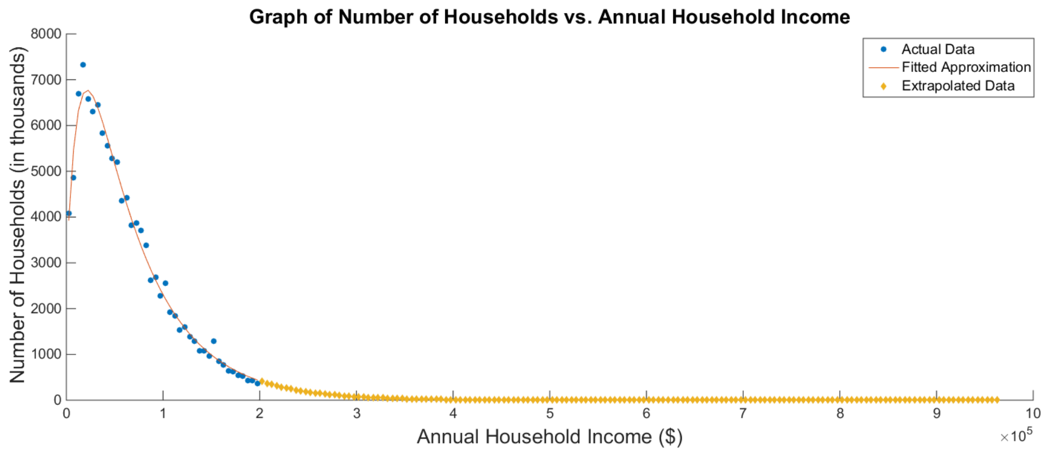

Figure III-4 Extrapolated Data Points for Annual Income up to $1M

In Figure III-4 the number of higher income households are observed to be decreasing steeply. Figure III-5 is the same data set as Figure III-4 but zoomed in on the extrapolated data (extrapolated from Figure III-3 data) that range from $200K to $1M. Data point coordinates are provided in the appendix section.

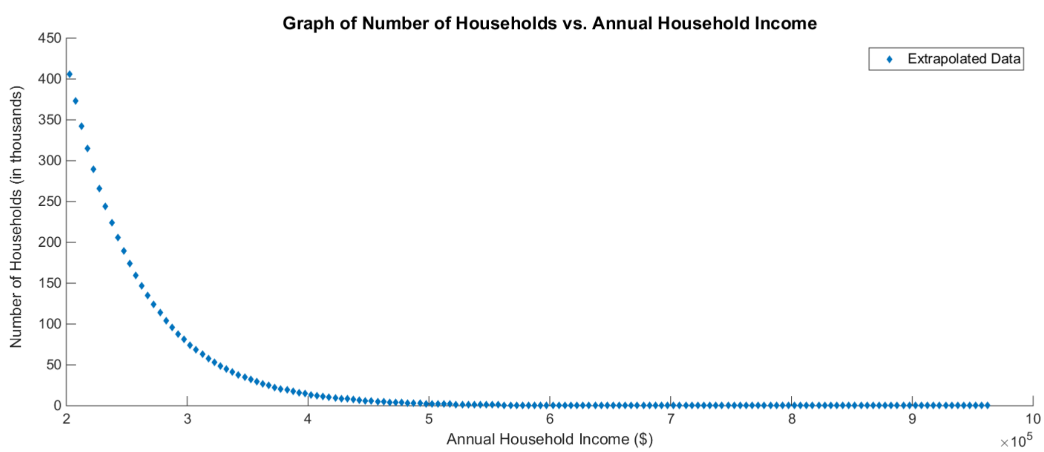

Figure III-5 Extrapolated Income Data

III.6. Incorporating Uncertainty

In this section sources of uncertainty in EV design will be identified along with a brief discussion. Alternative approaches to mathematically represent these uncertainties will be presented. The deterministic VDD framework presented in the previous section will be modified through integration of a Monte Carlo simulation module. The modified framework will use mathematical representations of uncertainty as inputs in order to determine the appropriate outcome distributions. These outcome distributions will be evaluated in accordance with possible stakeholder risk preferences that will be quantified using utility functions. Rational decision making strategies depending on stakeholder risk preferences will be derived.

III.6.1. Identifying Sources of Uncertainty in EV Design

There are infinite sources of uncertainty in design. Considering the uncertainty associated with every element of the system (both internal and external) is not practical. Incorporating the effects of uncertainty on the design requires serious computational power and over emphasizing it might cost more than its benefits. An estimation to identify the critical sources of uncertainty is necessary to avoid excess computation load.

For the purposes of this thesis some examples of the uncertainties that are deemed crucial will be incorporated in the VDD framework. The following subsections will provide information regarding the specific sources of uncertainty examined in this paper and the incorporation method. These sources include a member of the design parameters, electricity cost, and a design attribute, willingness to pay of the population. Willingness to pay plays a critical role in industrial and governmental stakeholder's value due to its strong impact on the customer demand. Uncertainties related to design variables will not be studied in this paper.

III.6.2. Methods to Incorporate Uncertainties to the Deterministic VDD Framework

Uncertainties related to a single parameter such as the uncertainty of the electricity cost and design variable tolerances can be incorporated through use of probability density functions (PDF) and Monte Carlo simulations. The deterministic representation of the single parameter is replaced by a PDF that represents the probabilistic characteristics of the uncertainty. The Monte Carlo simulation uses the distribution to generate an appropriate random value, performs a systems analysis with the generated value, and repeats this process many times, resulting in a set of output data points. These data points can be viewed as a probability distribution themselves, and can be collapsed to a single expected utility in accordance with the stakeholder's risk preference. The optimization algorithm is modified to search for the maximum expected utility of the system incorporating the sources of uncertainty rather than a deterministic values. A diagram representing the interaction of the Monte Carlo simulation with the deterministic VDD framework is seen in Figure III-6.

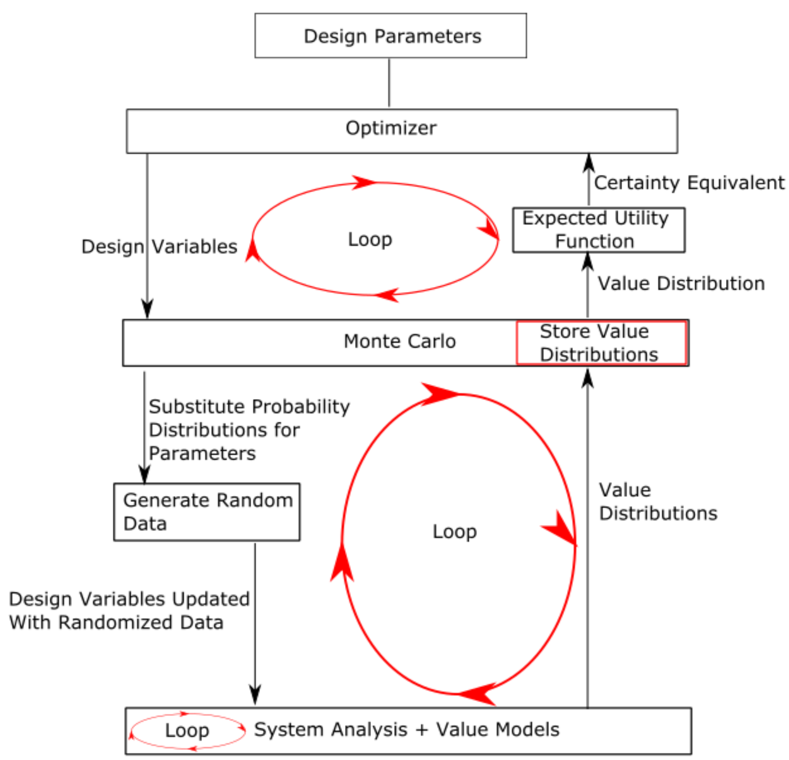

Figure III-6 Monte Carlo Simulation Interaction with the VDD Framework

After the Monte Carlo simulation is integrated with the deterministic model, the first step is to replace the deterministic variable definitions with the uncertain definitions. Triangular distributions that can be used as approximations for normal distributions, are used to represent the PDFs in this thesis. Triangular distributions are continuous functions that are represented by three points (minimum, maximum, and mode). This representation enables Matlab to process triangular distributions faster than normal distributions. A graph representing a normal distribution with a triangular distribution approximation is shown in Figure III-7.

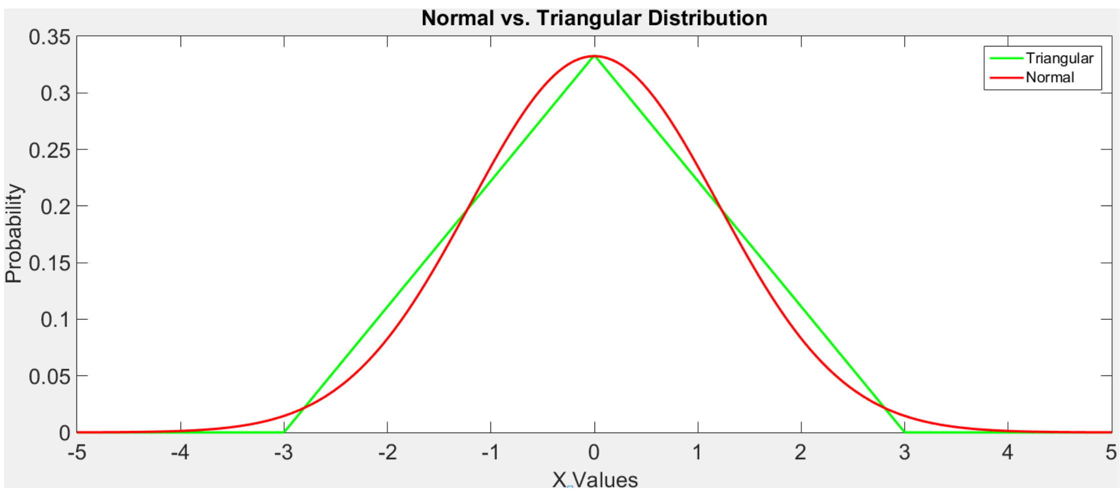

Figure III-7 Normal vs. Triangular Distribution

III.6.3. Incorporating Uncertainties Related to Electricity Cost

Electricity cost is a design parameter. In the deterministic model it is represented with 0.012 $/kWh, the national average [117]. Advances in technology and government legislation towards renewable energy sources make it challenging to predict the behavior of the cost in future. Considering the average owning period of a new vehicle, any drastic change in electricity costs that may be possible in that span of time would reflect directly on the value of the EV. Since this is a parameter that designers have basically zero control on, it is beneficial to incorporate uncertainties associated to the electricity cost in the design process. A representation of this uncertainty can be generated by using the average retail price of electricity to residential customers in the United States by state[119] to form a triangular distribution. This distribution uses a low price state of Washington as the left endpoint of the distribution, a high price state of Massachusetts as the right endpoint of the distribution, and the average price of electricity for the United States as the distribution's mode. This distribution will be used by the Monte Carlo simulation to generate data representing the uncertainty. The data points described above are used to plot the triangular distribution seen in Figure III-8.

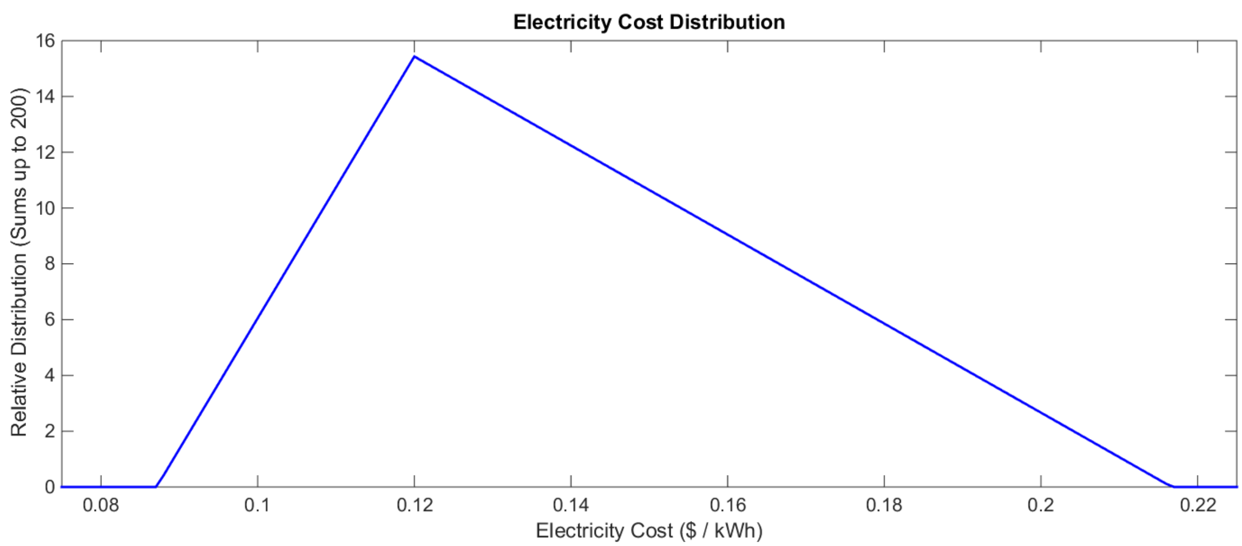

Figure III-8 Electricity Cost Uncertainty Triangular Representation

One assumption on this model is that the electricity price is fixed for the ten years, and this distribution represents the uncertainty concerning that fixed amount. Another important assumption is that this is the uncertainty associated with the electricity costs that will occur to the customer being evaluated by the designer. It is the distribution capturing the beliefs of the designer. In the model, after a random electricity price is determined, the customers know that price with certainty for that randomly determined world. Hence, the customer's risk preference does not come into play with how the model is currently structured. In other words, the uncertainty is incorporated in to the deterministic design model and outcomes are evaluated in accordance with the designers risk preferences not the customer's risk preferences. The designer uses the distribution to consider possible outcomes of an event and makes decisions consistent with their own risk preferences, taking its effect on the customers into account. What is neglected here is the risk preferences of the customers, as every individual might have a different risk preference that might affect their decision making. Uncertainty concerning the customer's beliefs can be evaluated through incorporation of an additional Monte Carlo simulation that would be integrated in the demand model. That Monte Carlo simulation would use a distribution (may be different) and consider individual risk preferences in order to yield a more realistic approximation of the possible customer behavior under the same source of uncertainty. This secondary Monte Carlo simulation will not be incorporated in this thesis and individual customer risk preferences based on the electricity costs will be ignored. The customers' beliefs on electricity price is left for future work.

III.6.4. Incorporating Population Willingness to Pay Uncertainty

In section III.5.2, the effect of the population income distribution and willingness to pay of the population on the product demand was described. This relationship will be captured in a deterministic manner for the first part of the results and discussion section, assuming that the whole population will have a constant will to pay. In reality this statement would not hold true due to a couple of reasons. The first is the subjectivity of preferences. Two people with the same annual income may have different willingness to pay for a personal transportation vehicle with or without any specific reason. The second reason is the circumstances of the customers. Circumstances of the customer may be in such a state that this artificial person might not be able to buy a car regardless of the vehicle's affordability. Customers might be in a state that they prefer to pay for their mortgage rather than purchasing a new car. They may be living in a highly populated area where buying a car may not be a reasonable investment in terms of solving personal transportation issues or they may already have a car. The interest level of a person regarding a personal transportation vehicle that determines a person's willingness to pay depends heavily on their living conditions, a difficult, but not impossible, attribute to quantify. In order to account for the highly individualistic attribute of willingness to pay a random population set with uncertain personal willingness to pay is generated.

III.6.5. Generating a Random Population

Once the characteristics of the US population income data is captured mathematically, as described in the demand models section, a random population can be generated by picking a large enough subset from the whole distribution. The reason behind generating only a subset is to minimize the computation time. If the whole population was used the time required to generate random willingness to pay for each household and integrating it to the Monte Carlo simulation would be highly computationally expensive. Therefore a smaller artificial subset that resembles the general characteristics of the population will be generated in order to save computation time for this thesis. The law of large numbers [90] state that a sample subset would resemble the general set if the sample size is large enough and the consistency between distribution characteristics can be checked in accordance with this law. Therefore according to the law of large numbers if the new subset is big enough to represent the characteristics of the general population it can be mathematically employed to make a scaled analysis representing the actual population. Validity of the law of large numbers assumption can be checked through visual inspection by plotting the income rates of the artificial subset and checking the resemblance with the general population. Thus visual inspection method will be used in order to determine the sample size. Plots of the random populations with various size versus the actual household income graph is seen in Figure III-9.

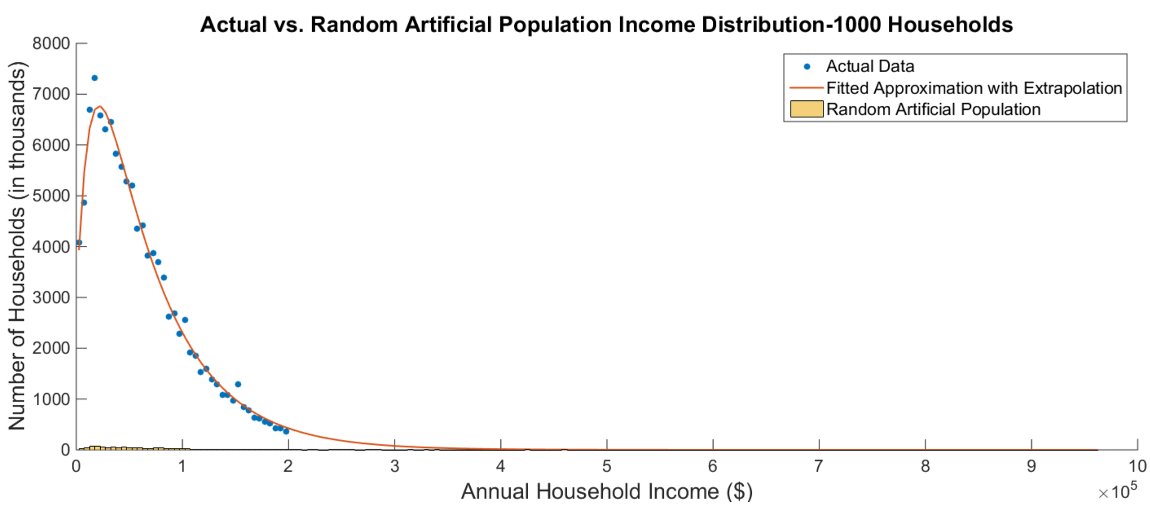

Figure III-9 Random Artificial Population of 1000 Households

It is clearly observed that 1,000 households does not represent the characteristics of general population. The need for a larger population size is obvious. Increasing the size to 10,000 households provides the distribution seen in Figure III-10.

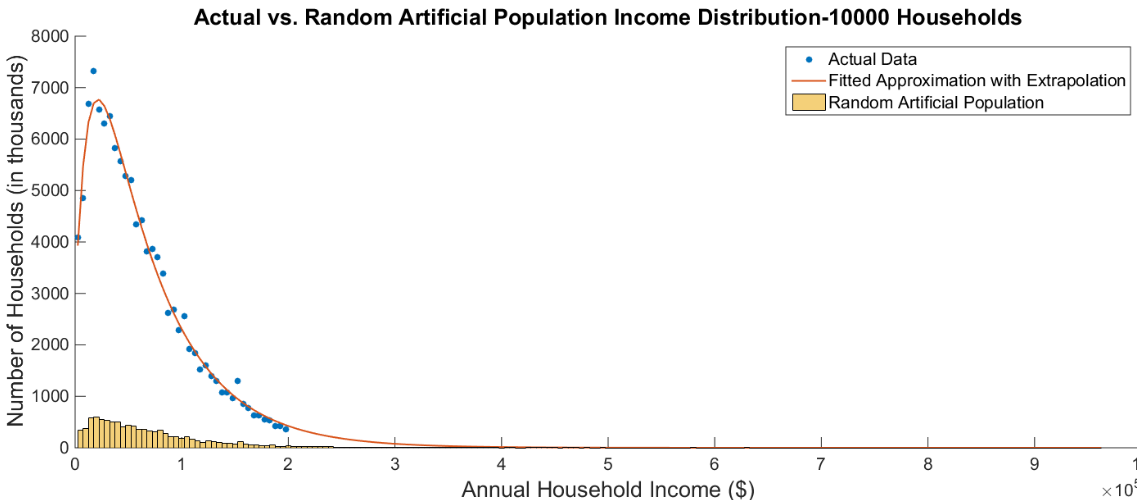

Figure III-10 Random Artificial Population of 10000 Households

Distribution characteristics are observed to be slightly more resembling the general population but the sample size is still very small to capture properties of the actual distribution. Another iteration for a larger population is required. Figure III-11 represents the graph of 50,000 randomly determined households.

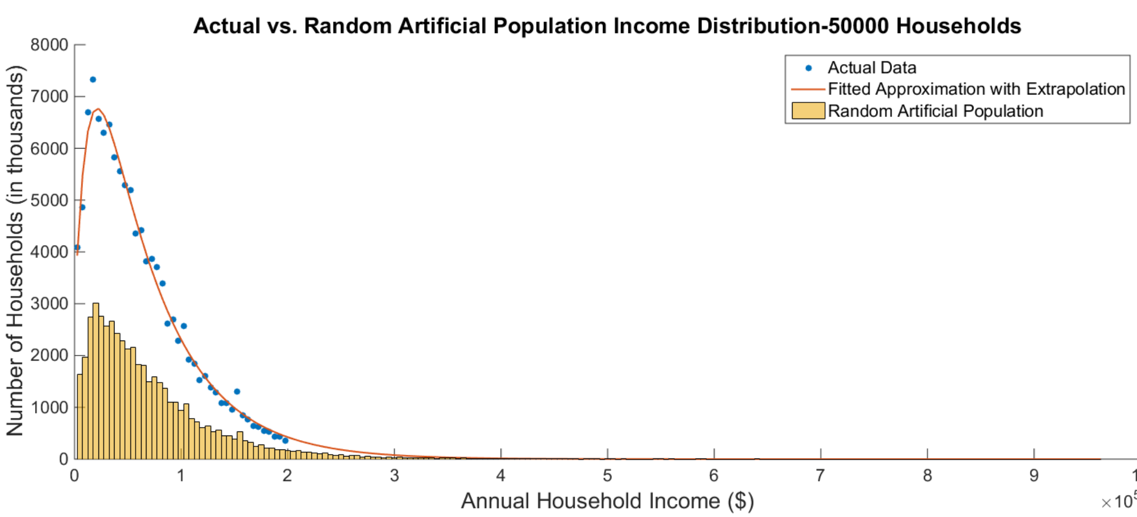

Figure III-11 Random Artificial Population of 50000 Households

The silhouette of the distribution is observed to be converging to the general distribution even when using congested data bins. This sample size might be enough to mimic the actual population. For comparison purposes a sample size of 100,000 households is run and seen in Figure III-12.

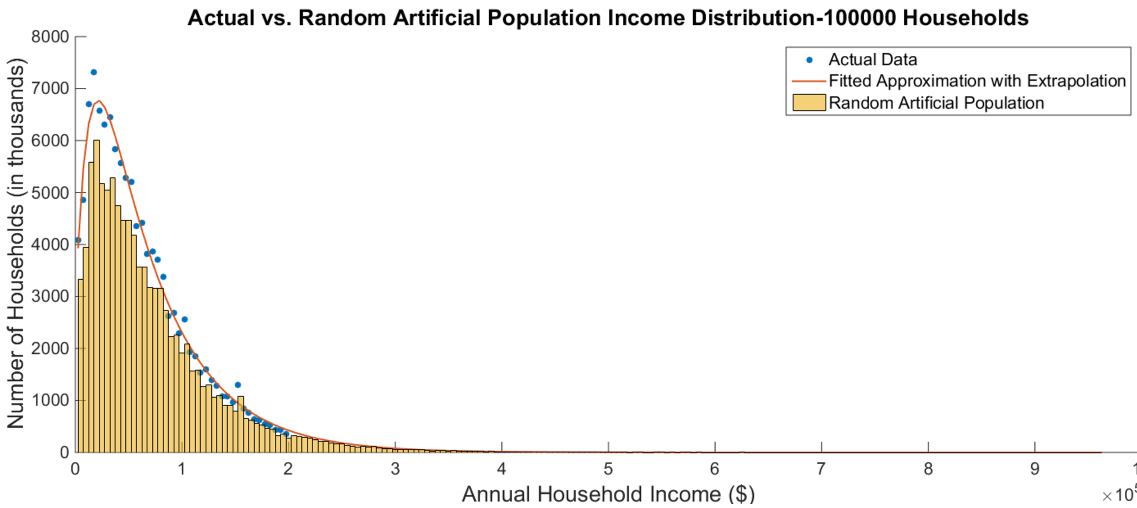

Figure III-12 Random Artificial Population of 100000 Households

Considering this population size is almost as big as the general population, the resemblance is as accurate as expected. It also shows that the mathematical expression that generates the population is accurate, therefore 10,000 households will be used to generate the random willingness to pay for each household.

Once the sample size is determined, randomized willingness to pay for each household in the sample subset is generated. This is done in a similar manner as the electricity cost uncertainties, through employment of triangular distributions. Assigning willingness to pay of each household generates a 10,000 x 2 matrix with the rows representing households and the columns representing their annual income and willingness to pay. This matrix is then used to calculate the eligible population that could afford the product as described in the consider-then choose based demand model section.

There are no guidelines for assigning willingness to pay for EV customers. A brief literature survey yields only website articles discussing the percentage of the annual income a person should allocate to purchase a vehicle. General discussion is usually around 10% to 20% of the person's annual income [120]. Considering the subjectivity of the personal willingness to pay, this distribution may not be linear. For example people with higher annual income may allocate higher percentages of their annual income with respect to people who make less, as the rich would have enough money left to make a living or, depending on their circumstances and preferences, they may not. Various assumptions can be made in order to approximate this relationship between the annual income and the willingness to pay. For the sake of this study it will be assumed that the willingness to pay does not change with respect to annual household income. It will be treated as an uncertain parameter that only depends on the personal preferences of the customer. Therefore the same triangular distribution will be employed to generate willingness to pay for each customer. Parameters representing the triangular distribution are a minimum of 8%, mode of 15% and maximum of 30% of the annual household income. These parameters, while partially based on the previous subjective reference [118], are a formulation of the beliefs of the commercial or government stakeholder regarding the customer's willingness to pay. These parameters will be different for each stakeholder. As such there is no universal set of parameters that would capture the beliefs of all possible stakeholders. The parameter values used in this thesis are therefore chosen understanding the subjective nature of beliefs. The beliefs used are assigned in accordance with the author's opinion on budget allocation. A use of such an analysis in industry would involve a capturing of stakeholder beliefs to ensure the analysis was in line with the stakeholder's preference and beliefs. Furthermore, this distribution represents the beliefs of the commercial or government entity on the population. The distribution used in this paper is seen in Figure III-13.

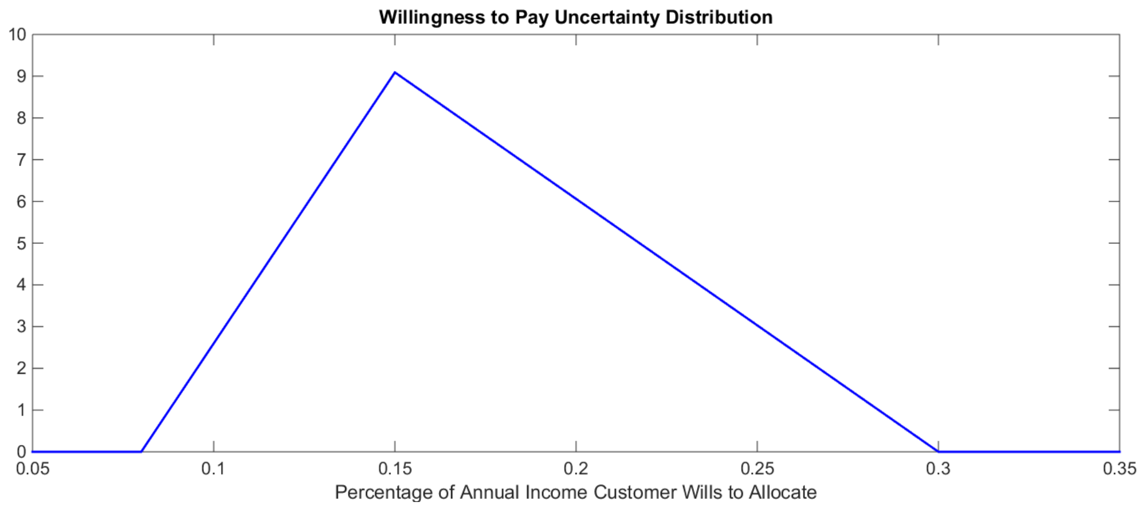

Figure III-13 Individual Willingness to Pay Triangular Distribution

Uncertainty associated with willingness to pay is incorporated by calculating the customer demand through assigning random willingness to pay for each individual of the artificial population that has been generated. Personal willingness to pay is be assigned by the Monte Carlo simulation module in accordance with the triangular distribution given above. Once individual income and willingness to pay values are assigned the amount that specific individual is willing to allocate can be calculated. This will be used in the consider-then choose demand model and total product demand can be evaluated.

An important discussion is the underlying assumptions made for generating the random population. This artificial population is formed by generating a random subset rather than settling on a deterministic scaled down portion of the actual population. This is done to capture the randomness of the customer base. It can also be used as a basis for future studies investigating other aspects of the population uncertainty. The population seen today will not be the population seen tomorrow, and the randomness in the population determination reflects this. Another remark to make is that this random subset does not capture the entirety of unknowns related to the population income data. Possible drastic changes that may alter the characteristics of the income distribution such as a possible economic crisis or a war is neglected.

III.6.6. Stakeholder Risk Preferences

In order to establish a normative decision making framework for the stakeholder, a proper quantitative definition of the stakeholder risk preference is necessary. A mathematical representation of the stakeholder risk preference enables proper assessment of the value distribution of the system to be designed by collapsing the expected utility of the design under uncertainty to a single, rankable, number. Similar to value preferences, risk preferences are highly subjective and dependent on the circumstances of the decision maker.

A general mathematical representation of risk preference can be defined through a description of the risk tolerance (ρ). Information regarding risk preference was given in the background section. Referring back to that; risk attitude is represented by the shape of the monotonically increasing utility (u) vs. worth (w) curve which is defined by the risk tolerance. Risk tolerance, also known as the reciprocal of the risk aversion coefficient (r) by Howard[121], is defined mathematically in Equation III-23.

$$\rho = -\frac{\frac{\delta u}{dw}}{\frac{\delta^2 u}{\delta w^2}} \tag{III -23}$$

For the scope of this thesis it will be assumed that ρ is constant and dependent on the stakeholder's annual revenue. If r is equal to zero, then the shape of the curve is linear representing a risk neutral preference. Risk tolerance can be a constant or a variable that changes with respect to the worth of the risked amount. For the scope of this study it will be assumed that the stakeholders have constant risk tolerance. Therefore a possible stakeholder risk preference can be in the exponential form of constant absolute risk aversion. Mathematically the utility of an uncertain lottery for a risk averse decision maker is seen in Equation III-24.

$$u = 1 - e^{-\frac{w}{\rho}} \tag{III -24}$$

Determining risk tolerance therefore is an important aspect of defining risk attitude and is highly subjective. An approximation of 15% of the annual revenue of the company for risk tolerance will be used for this thesis. The risk tolerance of the company is subjective in nature, similar to the stakeholder's belief of customer willingness to pay. The value of the risk tolerance used in this thesis is therefore arbitrary, formed from the risk tolerance believed by the author. In an application of this method in industry the risk tolerance would be determined for the stakeholder. The normative approach for decision making under uncertainty for complex engineered systems can be defined in a single equation once the risk tolerance is determined. Under uncertainty, the expected utility of the design $E(u)$ is seen in Equation III-25.

$$E(u) = \sum_{w \in W} p(w) * \left(1 - e^{-\frac{w}{\rho}}\right) \qquad \text{(III -25)}$$

In the Monte Carlo simulation the probability of occurrence is equal for each outcome and it is equivalent to reciprocal of number of runs. The formula given above holds true for exponential constant absolute risk attitudes. Once the expected utility of the distribution of designs are obtained, it can be collapsed by reverse transformation of the utility-certainty equivalent relationship by the equation seen in Equation III-26.

$$Certainty\ Equivalent(u) = -\rho * \ln\big(1 - E(u)\big) \qquad \text{(III -26)}$$

For this thesis, decision making scenarios for constant absolute risk averse and risk neutral stakeholder risk attitudes will be evaluated for external uncertainties.

III.7. Summary

In this section, appropriate methodology that will be applied in order to resolve the research questions declared in the introduction section is presented. This methodology will be used as a starting point for an investigation into the larger question of "How do various stakeholders impact the design of a system." The topics that were covered in the chapter are summarized below according to the related research question they are addressing.

Proposed method for Q1.1: A novel definition of value of an EV for the customer was defined. Important components of the customer value were identified through the total life time costs occurring to the customer, passenger capacity, engine power of the vehicle, and the down time suffered due to immature battery capacity. Underlying assumptions and necessary mathematical relationships were presented.

Proposed method for Q1.2: The value function for the industry was identified as maximizing net present profit of the company. Relationships linking the company profit to the costs of the design and development of the system, customer demand for the EV, and perceived customer value were derived.

Proposed method for Q1.3: Two possible value functions were identified for fictional government stakeholders. One value function had an economical focus that aims to maximize the change in the gross domestic product. The second value function was formed with the purpose of minimizing environmental impact focus through maximizing the quantity of EVs to be sold. Underlying relationships were established through mathematical representations.

Proposed method for Q2.1: Sources of uncertainty in systems design with a comparative discussion were presented. Major sources of uncertainty were identified through a data access taxonomy. Electricity cost and uncertainty in the customer demand were discussed and incorporated in to the deterministic design framework.

Proposed method for Q2.2: Possible risk preferences for the stakeholders were discussed. A method to evaluate resulting designs in accordance with the stakeholder risk preferences was presented.

The following section will present the results obtained for the research questions described in the introduction section by applying the methodology discussed in this section. The results section will also include a detailed evaluation of the results obtained and their possible implications to systems design.

CHAPTER IV

RESULTS & DISCUSSIONS

This section is a summary of the results obtained by the mathematical models that are developed for this thesis. Value functions are tested with several alternative scenarios and design specification of the optimal systems are presented with a comprehensive discussion. Results are presented in the same order of appearance as presented in the methodology section.

IV.1. Model Comparison

In order to check the credibility of the results obtained throughout this thesis, the generic mathematical EV model that constitutes the foundation of the study is compared to actual vehicles. The EV model takes in design variables as inputs and outputs design attributes and the stakeholder value. The design variables used are the system's physical dimensions, engine power and battery capacity. For comparison purposes, competitor design variables are used as a test case and the resulting system attributes are compared to the competitor's true attributes. Required data is obtained from the market. Observed model deviation from the actual data for two separate competitors is given below in Table IV-1.

Table IV-1 Model Validation Data – Competitor 1

Tesla Model S 65	Model Prediction	Actual Data	Model Deviation
Customer Value ($)	71,791.13	-	-
Commercial Value ($)	526,305,140.84	-	-
Governmental Value ($)	3,686,015,327.07	-	-
Range (km)	376.68	335	+12.24%
Passenger Capacity (people)	6	5	-
Purchase Cost ($)	63,859.93	71,070	-9.86%
Engine Power (hp)	421.12	416	1.2%
Annual Charging Cost ($)	461.41	540	%14.63
Mass (kg)	2,044.47	2,108	%3.03

Table IV-2 Model Validation Data - Competitor 2

Nissan Leaf	Model Prediction	Actual Data	Model Deviation
Customer Value ($)	33,055.01	-	-
Commercial Value ($)	63,797,975.50	-	-
Governmental Value ($)	908,517,807.01	-	-
Range (km)	184.13	200	-8.00%
Passenger Capacity (people)	4	5	-
Purchase Cost ($)	32,015.53	30,000	+6.72%
Engine Power (hp)	196.525	110	+78%
Annual Charging Cost ($)	377.57	550	-31.45%
Mass (kg)	1,456.836	1,493	-2.48%

To ensure that the correct magnitudes for values were generated by the mathematical model, two current electric vehicle specifications were examined, the Tesla Model S and the Nissan Leaf. The predicted selling prices of the vehicles are within 10%

of the actual selling prices. The system attributes (weight, charge time, etc.) outputted from the model were within 15% of Tesla Model S's related attributes. The model's outputs for Nissan Leaf were within 32%, with the exception of engine power which had an error of 78%. This error is due to Tesla Model S's data being used for the majority of the model formation, and the engine technologies being different between companies.

The model used in this study is a low fidelity, conceptual level model. Such a model will not capture all of the nuances and interactions that are present in an actual electric vehicle; therefore errors are expected. The low fidelity model that was formed in this thesis was partially based on the Tesla Model S and very little of the model was formed using information from the Nissan Leaf. Due to the assumptions in the model, it is anticipated to be biased towards the strengths and weaknesses of the Tesla Company. Such an anticipated result is seen when examining the engine power of the vehicles. We see that for the Nissan Leaf the anticipated vehicle power is 78% higher than the actual data, suggesting that the Tesla Company is more likely to design the vehicle with a more powerful engine. The model itself is subjective, as each commercial organization will have their own strengths and weaknesses. For example, one company may have a strong engineering focus on aerodynamics and another company may have a strong focus on battery technology. The model used in this thesis, while based partially off of the Tesla Company, is a fictitious organization. The comparisons performed in Table IV-1 and Table IV-2 are only used for performance magnitude checks and are not designed to validate the model, as the model is only valid for the company using it.

IV.2. Optimizer Parameters

The generic EV design space is optimized using a PSO algorithm that uses value functions as the objective function. Parameters for the PSO algorithm were set manually in accordance with common practice. Common practice for the number of particles is 10 times the design variables; however, this parameter is highly dependent on the type of problem being examined. The number of particles used was determined from trial and error, trading off performance with efficiency. Considering the non-linear design space the number of particles were set to 100 for deterministic runs, 20 times the number of design variables. Another parameter that effects the computation time is the convergence criteria. The convergence criteria was set to 1.e-06 for deterministic runs and 1.e-03 for runs that evaluate design under uncertainty. The convergence criteria was also adjusted based on trial and error, examining the tradeoff between performance and efficiency. The number of particles were also increased to 150 for uncertainty analyses. If this study were being done at a high fidelity, the optimization parameters could have been evaluated extensively through a parametric study to determine the set most likely to result in the optimal system with the optimal computation time. To ensure a higher likelihood of obtaining the optimum system a genetic algorithm was also used during the determination of optimization parameters and obtained similar optimal results. The PSO algorithm was chosen for the optimization due to its efficiency in exploring complex design spaces.

IV.3. Examination of Value Functions

IV.3.1. Deterministic Designs with Value Linear Demand Model

The value linear demand model was employed for commercial and governmental EV configurations. It should be noted that the commercial stakeholder is assumed to have a 50% profit margin and the government designers have 20%. The profit margin can be incorporated as a design variable to evaluate its impact on the system value. The results presented in Table IV-3 displays EV configurations for various stakeholder preferences when a 482.8 km performance requirement on vehicle range was introduced as an inequality constraint on the system. A simple sketch that visualizes vehicle dimensions is provided in Figure IV -1.

Table IV-3 Examination of Value Functions with Value Linear Demand Model - Constraint on Range

	Max Customer Value	Max Commercial Profit	Max GDP
Consumer Value ($)	118,511.08	71,572.99	72,502.77
Commercial Value ($)	-	713,577,734.41	-
Governmental Value ($)	-	-	6,260,268,510.93
Range (km)	482.8	482.7	482.8
Capacity (people)	4	6	12
Purchase Cost ($)	23,581.12	84,004.45	86,647.22
Engine Power (hp)	98.6	539.8	717.0
Length (m)	5.50	5.25	5.70
Width (m)	0.95	1.54	2.08
Height (m)	1.30	2.05	1.64
Battery Capacity (kW)	43.80	89.95	111.09
Annual Charging Cost ($)	262.82	539.78	666.57
Mass (kg)	1,309.63	2,469.44	3,288.28

Configuration of the EV that is obtained by maximizing consumer value is unexpected, resulting in a slender vehicle. In this design, four individuals are seated one behind another. While the design is counterintuitive, it does reflect the consumer value function defined in this paper. In the customer value model there is no benefit given to social interactions that are enabled through row seating. Instead the consumer desire focuses on reducing selling price, and on maximizing benefits such as range, which are improved with low air resistance (enabled through a small cross section). The optimal consumer vehicle has a relatively low selling price and annual cost. The optimal design with respect to the consumer's value function illustrates the importance of properly capturing the preferences of the stakeholder. If certain attributes are not captured or there interactions are not modeled properly, such as the desire to want to sit in rows, then the preference will not properly be reflected in the design process. It is also important to consider the functionality of a vehicle. For example, this model and value function do not consider the possibility of rollovers, which could greatly diminish the value of such a long, narrow vehicle. The consumer value function also highlights the possibility of value functions leading designers to counterintuitive designs. When given the task of designing a vehicle, a designer will often revert back to what is the traditional design template (4 tires, 2 axles, 3 or 2.5 seats across). By keeping the design space unrestricted (by reducing the amount of constraints and by keeping the value function non-specific to a vehicle type) the optimization routine is free to explore a much larger design space. The value function used here may be valid for some individuals, making this type of vehicle the most preferred.

The optimal designs with respect to the commercial net present profit and government GDP value functions are more reminiscent of traditional vehicle designs. The commercial design, producing the most profit, has a 6 person capacity seating 2 people across. This is due to the assumption that since there is no need for a gear shifting mechanism, the front seat can accommodate as many people as its physical dimensions allow. We see a departure from the extremely efficient consumer vehicle due to the preference of profit maximization, which does not coincide precisely with the desires of the consumer (although they do factor into the quantity sold). This is an important observation, showing that stakeholder preferences of a company do not have to align with the consumer, but that the consumer preferences must be taken into account to maximize the company's value.

The government design, producing the highest increase in GDP, is very large, seating 12 people with 3 seats across. This design is reminiscent of an extended van. This is due to the GDP being a function of not only the desire of the consumer (captured in quantity sold), but also the cost of the vehicle captured in the selling price and in the investment costs. It is obvious from these two value functions (commercial and government) that even though both have similar value function attributes, the stakeholders may have very different preferences concerning those attributes (combining the attributes in different ways in the function) that will drive their decision-making process. It is important to recognize in these results that the optimal consumer design and the predicted market demand (quantity sold) are dependent on a specific consumer profile chosen. It also employs the value linear demand model therefore affordability of the vehicle is neglected.

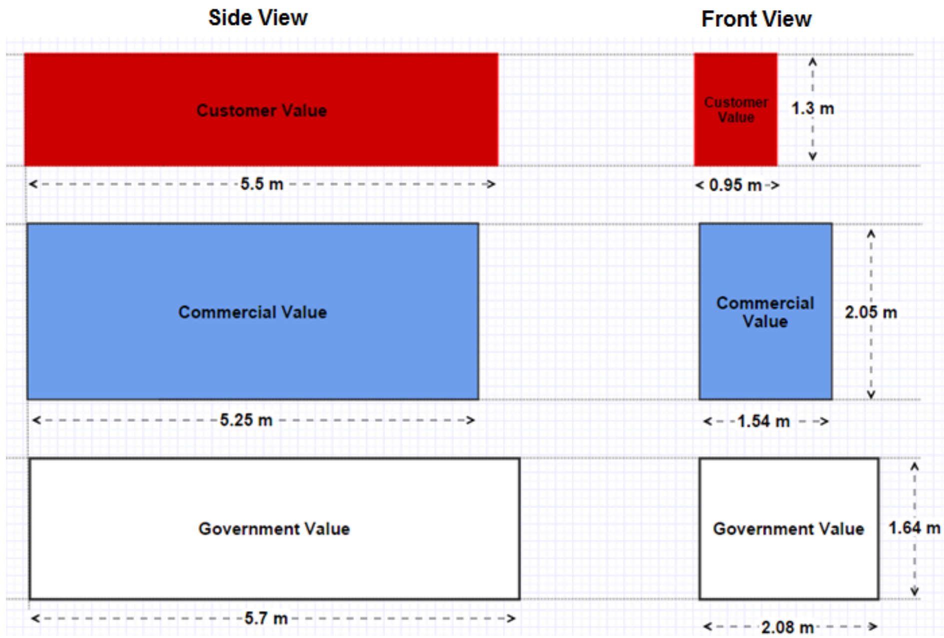

Figure IV -1 Vehicle Dimensions

In order to evaluate the effects of defining premature requirements on the system, the design process can be repeated by removing the inequality constraint on the range. Other aspects of the mathematical model such as the design parameters, the demand model, and the optimization algorithm are kept constant to accommodate a fair comparison between results. Referring back to the discussions in the methodology section, an increase on the stakeholder value is expected. The results are seen in Table IV-4.

Table IV-4 Examination of Value Functions with Value Linear Demand Model - Constraint on Range Removed

	Max Customer Value	Max Commercial Profit	Max GDP
Consumer Value ($)	126,466.66	73,399.00	75,824.55
Commercial Value ($)	-	2,164,757,175.31	-
Governmental Value ($)	-	-	17,9826,617,916.61
Range (km)	755.37	1,344.68	1,287.06
Capacity (people)	4	15	15
Purchase Cost ($)	27,536.89	170,462.01	314,037.51
Engine Power (hp)	103.17	506.05	899.59
Length (m)	5.5	6.5	7
Width (m)	0.95	2.5908	2.5908
Height (m)	0.9	0.9	2.32
Battery Capacity (kW)	64.44	492.78	887,736.3
Annual Charging Cost ($)	247.14	1,061.58	1,998.04
Mass (kg)	1,370.69	6,722.85	11,947.84

Even though the maximum customer value vehicle has the same physical dimensions, there is significant improvement on the vehicle range. This is achieved through a nearly 50% increase in the battery capacity. There is also a slight improvement on the engine power. These improvements on the range and engine power was balanced by the system with a 17.3% in the purchase cost. The customer value is slightly improved by less than 10%.

Roughly 300% improvements in the stakeholder value is achieved for both the commercial and government stakeholders. Both vehicles have a passenger capacity of 15 people. The Commercial vehicle is observed to be trying to maximize the passenger capacity with minimum material cost. The design optimized for government preferences is observed to be pushing for the largest vehicle possible. This vehicle also has 15% more engine power than the constrained design. This is because when maximizing the change in the GDP, increasing system costs are evaluated as an investment for the domestic economy, therefore increasing the stakeholder value. Both the industrial and governmental designs are evocative of public transportation vehicles rather than personal transportation vehicles.

An important observation of this analysis is the positive impact of removing the prematurely defined range constraint on the stakeholder value. There is an increase in the value for all three stakeholders. This demonstrates the drawback of the traditional system engineering approach of defining requirements on the systems level. Considering this is achieved by removing a single requirement, possible implications of having multiple immaturely defined requirements and their propagating effects by cascading them down to the subsystems can be envisioned. This matches and contributes to the critiques presented in the background section.

Another significant remark is the extremely expansive purchase and operating costs for both industrial and government designs. This is a reflection of the demand model being employed. Value linear demand model does not take the affordability of the products into account and assumes that only the customer value of the product represents the quantity of vehicles that will be sold. This assumption violates the traditional linear cost and demand relationship by ignoring affordability.

IV.3.2. Deterministic Designs with Consider-Then Choose Demand Model

As discussed in the methodology section a realistic demand model was developed in order to capture the affordability of the product. This consider-then choose based demand model employs both the customer value and the affordability of the product for an approximation of the market demand. Replacing the value linear demand model with the consider-then choose model with a constant willingness to pay of 25% results in the vehicle configurations seen in Table IV-5.

Table IV-5 Examination of Value Functions with Consider-Then Choose Demand Model Constant Willingness to Pay 25%

	Max Commercial Profit	Max GDP
Customer Value ($)	115,670.78	127,511.26
Commercial Value ($)	8,114,792,834	-
Governmental Value ($)	-	49,880,273,687
Range (km)	366.07	526.64
Passenger Capacity (people)	5	5
Purchase Cost ($)	18,750	18,806.85
Annual Charging Cost ($)	223.33	242.85
Total Cost to Own ($)	21,155.82	21,346.67
Length (m)	7	7
Width (m)	0.95	0.95
Height (m)	0.9	0.9
Battery Capacity (kW)	28.22	44.15
Engine Power (hp)	89.90	101.51
Mass (kg)	1,194.09	1,338.88
0-60 Acceleration Time(s)	9.3	9.23
55mph Climbable Angle(degrees)	19.243	19.436
Eligible Population (thousands)	41,408.06	41,408.06
Projected Demand	1,310,366	1,444,500

Incorporating the consider-then choose demand model results in smaller, low performance vehicles for both the government and the industry. Both vehicles resemble the maximum customer value vehicle in terms of the physical dimensions. It is observed that both designs are driven towards more affordable vehicles with lower purchase costs. This is due to the nature of the consider-then choose demand model. A slight decrease in the purchase cost of the vehicle significantly increases the eligible population that could afford the product due to the household wealth distribution characteristics of US. This steep increase in the eligible population translates into an increase in the demand because of the linear relationship. Since this demand model is based on the eligible population rather than the competitor's market data, it allows more units to be sold compared to the value linear model by increasing the customer value and decreasing in the purchase cost with respect to the competitor by allowing larger numbers of people to afford the product. Therefore incorporating the consider-then choose demand model and re-optimizing the designs results in significant improvements on both stakeholder values when compared to the value linear value model. This reveals the fact that the system's stakeholder value is highly dependent on the quantity of vehicles to be sold therefore it is highly dependent on the employed demand model and its prediction accuracy. It can be stated that developing accurate demand models should be an integral part of the value driven design framework. Moreover, results presented in this study should not be evaluated separately from the proposed demand model.

Evaluating the system attributes, it is seen that the 9.3 second inequality constraint on the 0-60 acceleration time is active for both vehicles. This can be explained by the structure of the customer value function as vehicle characteristics such as acceleration and maneuverability are not captured holistically. Designs are observed to be satisfying the transportation need in accordance with the defined customer value function and ignoring rest of the system attributes such as the acceleration time, as expected. These attributes, not represented in the value function but are constrained, will be driven to the point that maximizes the value function, typically on the constraint. This predicted behavior of the model is a result of the incompleteness of the value model. There should be an ideal value model that captures every single meaningful attribute regarding the system. The customer value model defined in this thesis is just a simple, subjective abstraction of such an ideal model and the resulting system configurations should be evaluated in accordance with this fact. In order to evaluate the behavior of the consider-then choose demand model, another run with higher willingness to pay allocation is necessary. Given in Table IV-6 is the resulting designs for 50% population willingness to pay.

Table IV-6 Examination of Value Functions with Consider-Then Choose Demand Model

Constant Willingness to Pay 50%

	Max Commercial Profit	**Max GDP**
Customer Value ($)	126,209.59	132,075.66
Commercial Value ($)	2,013,626,121	-
Governmental Value ($)	-	13,178,171,823
Range (km)	793.67	942.40
Passenger Capacity (people)	5	5
Purchase Cost ($)	32,500	32,497.78
Annual Charging Cost ($)	278.90	313.921
Total Cost to Own ($)	34,545.59	34,789.46
Length (m)	6.5	7
Width (m)	0.95	0.95
Height (m)	0.9	0.9
Battery Capacity (kW)	76.41	102.12
Engine Power (hp)	120.94	141.69
Mass (kg)	1,606.29	1,866.00
0-60 Acceleration Time(s)	9.3	9.22
55mph Climbable Angle(degrees)	19.349	19.573
Eligible Population (thousands)	49,098.06	53,520.06
Projected Demand	192,796	219,928

Comparing system attributes to the 25% willingness to pay designs show that both stakeholders are pushing for higher customer value vehicles given that the population is willing to allocate higher percentages of their annual income. Resulting systems are also observed to have more range on single battery charge and more horse power. Vehicle dimensions are observed to be not sensitive to increases in the willingness to pay. Projected demands are observed to be decreasing due to the increase in the purchase cost.

Another remark is that government designed vehicles are observed to offer more range and performance for lower prices. This is because the government profit margin is significantly less than the commercial profit margin. The relationship between the profit margin, projected demand, and the stakeholder value can be analyzed explicitly for deriving optimal market strategies. For comparison purposes, the analysis cycle is repeated by decreasing the willingness to pay to 5%, with results seen in Table IV-7.

Table IV-7 Examination of Value Functions with Consider-Then Choose Demand Model Constant Willingness to Pay 5%

	Max Commercial Profit	**Max GDP**
Customer Value ($)	71,978.56	91,245.12
Commercial Value ($)	1.01428E+18	-
Governmental Value ($)	-	8.48905E+18
Range (km)	141.69	204.77
Passenger Capacity (people)	2	2
Purchase Cost ($)	7,750	7,000
Annual Charging Cost ($)	142.51	146.68
Total Cost to Own ($)	10,188.64	9,508.82
Length (m)	3.5	3.5
Width (m)	0.95	0.95
Height (m)	0.9	0.9
Battery Capacity (kW)	6.97	10.36
Engine Power (hp)	44.77	47.09
Mass (kg)	594.63	625.52
0-60 Acceleration Time(s)	9.3	9.3
55mph Climbable Angle(degrees)	18.82	18.86
Eligible Population (thousands)	10,157.06	13,499.06
Projected Demand	3.92625E+14	6.61485E+14

In this scenario, the customer value of the vehicles decrease drastically with decreasing willingness to pay. Also, the government design is observed to be offering more than 25% customer value compared to industrial design due to lower profit margins. This can be used as an indication for stakeholders that are evaluating to enter markets with lower population willingness to pay. Design of the system has to evolve with the percentage of annual income the customers are willing to allocate for a personal transportation vehicle. It is also observed that for the coefficients of customers that would purchase the vehicle based on customer value employed in the demand model, for 5% willingness to pay, the projected demand diverges. This is because of the reverse engineering methods applied when forming the model. The competitor used for estimating the coefficient is a luxury class sedan and therefore yields irrational results when employed for willingness to pay values that represent destitute populations. The coefficient exhibits drastically increasing behavior with decreasing willingness to pay due to the high purchase cost of the competitor only enabling a very limited amount of household to afford the product due to the income distribution characteristics. When coefficient obtained by 5% willingness to pay is employed, resulting product demand is exceeding the number of households in the population, therefore these results can be deemed not acceptable. It can be concluded that the proposed consider-then choose based demand model is not applicable for unrealistically low willingness to pay percentages due to the method in which the coefficients are determined. Therefore the coefficient of customers that would purchase the vehicle based on customer value has to be modified in order to overcome the problems described. This modification is left for future work.

Besides the demand model related issues, both commercial and government vehicle configurations for a 5% willingness to pay resemble an elongated motorcycle. When compared to the nominal 25% willingness to pay designs, battery capacities and engine powers are reduced by 75% and 50% respectfully. As a result of these changes both vehicles result in a light weight configuration with extremely low purchase costs, around $7K. In order to compare and evaluate the effect of willingness to pay on system design attributes and system variables, a deterministic sensitivity analysis is used. Seen in Figure IV-2 is a tornado diagram that uses the 25% willingness to pay designs as the origin and plots design sensitivity with changes in willingness to pay.

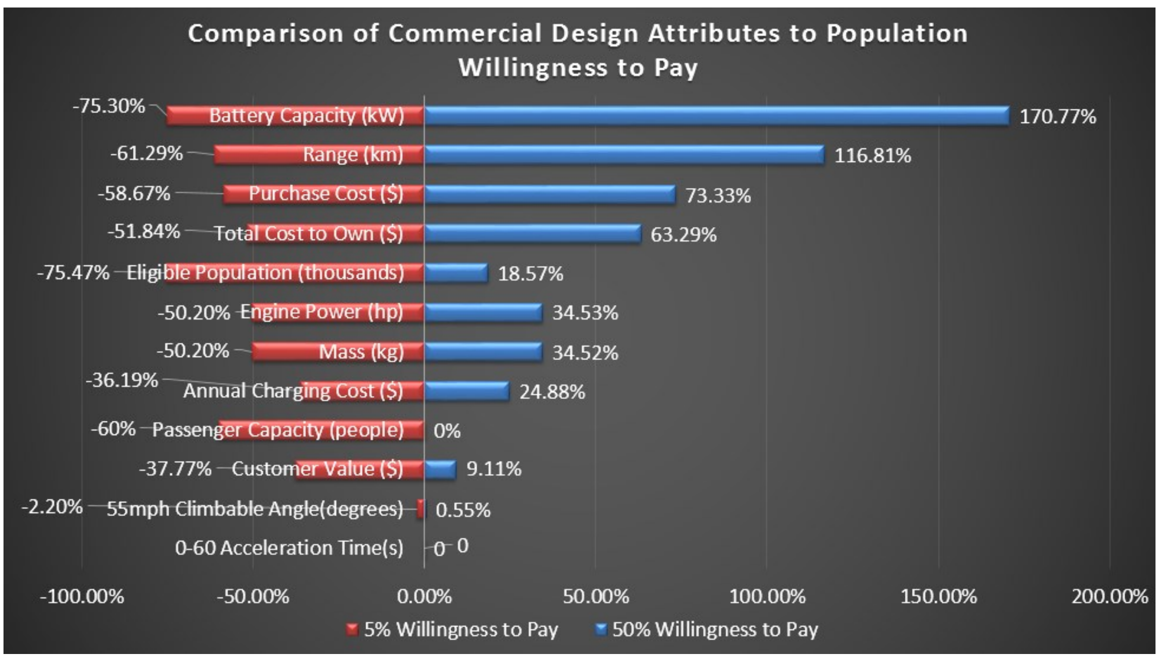

Figure IV-2 Tornado Graph - Commercial Design Sensitivity to Willingness to Pay

Figure IV-2 visualizes the changes on design as the willingness to pay of the population is perturbed to 5% and 50% from the nominal value of 25%. Vehicle dimensions are not included in the graph since they remain unchanged. The figure clearly shows that the 0-60 acceleration time of the vehicles remained constant. This may hint that the preferences towards acceleration are not captured properly. A slight sensitivity in gradeability of the vehicle is observed. The gradeability attributes are significantly off the 6° constraint, therefore the gradeability constraint is not active. This does not mean that the constraint is not a factor in determining the global optimum, as a global optimum may still lie behind the constraint in the infeasible region. Decrease in the population willingness to pay is observed to be pulling down system performance characteristics such as the range, engine power, and the battery capacity resulting in a low cost system. Exactly the opposite system behavior is observed when population willingness to pay is increased. Increasing willingness to pay is observed to be increasing the battery capacity of the vehicle drastically. Customer value of the product is decreasing proportionally with willingness to pay but the same statement does not hold true for willingness to pay increases from 25% to 50%. A similar tornado graph can be plotted for government design for a visualization of system response, seen in Figure IV-3.

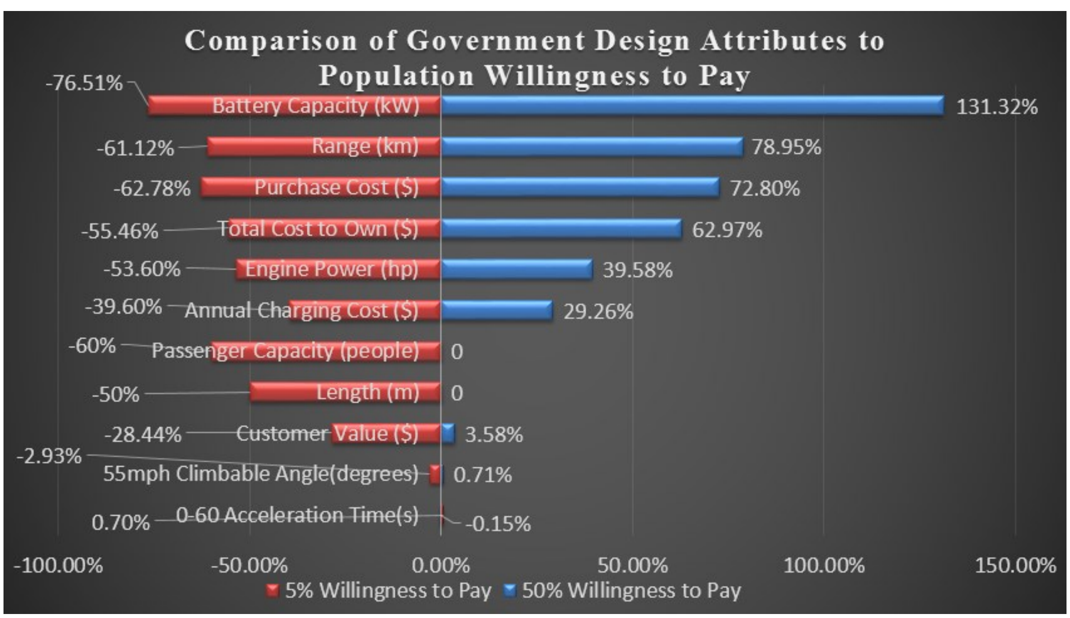

Figure IV-3 Tornado Graph – Comparison of Government Design Attributes to Willingness to Pay

Gradeability and 0-60 acceleration times are observed to be relatively insensitive to willingness to pay changes. This can be explained by the abstraction of the value model as discussed previously. Similar to the commercial design, battery capacity is observed to be changing drastically. Decrease in willingness to pay results in a decreasing effect on the vehicle length and passenger capacity. Other physical design variables such as the width and the height remains unchanged and therefore not represented on the graph. Increase from 25% to 50% willingness to pay does not appear to impact the customer value of the product even though there is a sharp increase in the purchase cost. This behavior shows a scenario where the stakeholder takes advantage of the increased customer desire to purchase. For decreasing willingness to pay from 25% to 5% the customer value decreases along with the range, passenger capacity, and engine power.

The analysis shows a trend of decreasing willingness to pay leading to decreasing system performance and customer value. This does not reflect on the stakeholder value due to decreasing purchase costs resulting in more demand. As mentioned several times, this is a result of US household income distribution. Data shows a large accumulation households on the lower portion of annual income. As the annual income increases number of households diminish. Therefore, analyses show that producing vehicles that can be afforded by more of the population leads to higher stakeholder value. This statement is made under the assumption that even the poorest people are making enough for a living and would consider purchasing a vehicle, if the purchase cost is below that individual's annual income times the willingness to pay assigned by the demand model. In addition to that, results presented up to this point in this section are obtained deterministically. Introducing specific sources of uncertainty into the design would provide additional insight on system behavior. In the following subsection, results of incorporating uncertainty in the deterministic system design framework will be presented.

IV.3.3. Effects of Incorporating Uncertainty to Design

Resulting system configurations by introducing uncertainty will be presented in the same order as presented in the methodology section. Shown in Table IV-8 are the resulting designs for introducing electricity cost uncertainty to both the industrial and governmental stakeholders with neutral risk attitudes and a willingness to pay of 25%.

Table IV-8 Risk Neutral Designs with Electricity Cost Uncertainty- Constant Willingness to Pay 25%

	Max Commercial Profit	Max GDP
Customer Value ($)	121,607.73	128,076.67
Commercial Value ($)	9,453,349,959	-
Governmental Value ($)	-	55,943,292,191
Range (km)	524.36	532.00
Passenger Capacity (people)	3	4
Purchase Cost ($)	17,499.63	16,249.98
Annual Charging Cost ($)	194.22	217.07
Total Cost to Own ($)	19,769.25	18,748.30
Length (m)	4.51	5.50
Width (m)	0.95	0.95
Height (m)	0.9	0.9
Battery Capacity (kW)	35.16	39.86
Engine Power (hp)	73.74	86.43
Mass (kg)	978.07	1,147.45
0-60 Acceleration Time(s)	9.28	9.29
55mph Climbable Angle(degrees)	19.18	19.23
Eligible Population (thousands)	49,098.06	53,520.06
Projected Demand	1,633,465	1,875,301

The commercial design is observed to be driven towards a smaller vehicle with higher range and engine power when compared to the deterministic design configurations. Passenger capacity is decreased to three people by shortening the vehicle length to 4.5m, decreasing the vehicle mass. Combined with 10 kW of increase in the battery capacity these design changes allow the vehicle to cover longer distances. Because of the accumulation in the lower portion of the household income distribution, one thousand dollars decrease in purchase cost allows the vehicle to be affordable by 20% more people. With a slight improvement in the customer value this results in $1.5B increase in the commercial value of the product. The government design displays similar characteristics to the commercial design. It is slightly longer allowing for additional passenger capacity. The government design allows the customers to have a better vehicle in terms of value with lower purchase price due to lower stakeholder profit margin. Both stakeholders are observed to be compromising on passenger capacity but this allows for lower cost vehicles that are higher in demand, therefore increasing the stakeholder value. Compared to the deterministic designs, both stakeholders systems are getting more compact even with a risk neutral attitude. Incorporating uncertainties associated to the population willingness to pay reflects on the designs as seen in Table IV-9.

Table IV-9 Risk Neutral Designs with Electricity Cost and Willingness to Pay Uncertainty

	Max Commercial Profit	**Max GDP**
Customer Value ($)	117,905.71	122,930.51
Commercial Value ($)	16,521,682,067	-
Governmental Value ($)	-	1.00314E+11
Range (km)	412.95	460.98
Passenger Capacity (people)	3	3
Purchase Cost ($)	15,099.80	12,758.24
Annual Charging Cost ($)	183.08	187.70
Total Cost to Own ($)	17,422.20	15,240.85
Length (m)	4.50	4.50
Width (m)	0.95	0.95
Height (m)	0.9	0.9
Battery Capacity (kW)	26.10	29.87
Engine Power (hp)	70.19	70.19
Mass (kg)	895.48	929.74
0-60 Acceleration Time(s)	8.93	9.27
55mph Climbable Angle(degrees)	19.98	19.18
Eligible Population (thousands)	33,923.73	42,287.46
Projected Demand	3,297,396	4.285,525

Both vehicles in Table IV-9 are observed to be driving towards a lower cost vehicle than the deterministic population vehicles. This might be interpreted as a tendency to minimize risk. Both vehicles have considerably less range and engine power. Range is observed to be slightly more than a traditional GPV's. This is a reflection of the downtime penalty function component of the customer value. If the vehicle range is less than 480kms than this penalty function becomes active and penalizes the customer value of the product. Another major change from the deterministic vehicle configurations is the slight perturbations on the vehicle dimensions that is not displayed on the tables due to the number of significant digits chosen. This occurs as a tendency to put a safety margin between the boundary and the design variable because of the introduced uncertainties. Dimensions are exactly the same for first 2 significant digits allowing for a slender vehicle with 3 passenger capacity. Due to the low purchase costs, both vehicles are projected to have very high demand. Similar to the previous vehicle configurations, this is a result of the characteristics of the income distribution and the proposed demand model. To evaluate effect of risk preferences better, a non-neutral stakeholder risk attitude well next be examined.

In order to explore the design behavior associated with a risk avoiding stakeholder risk attitude, the CARA utility function defined in the methodology section is incorporated. Risk tolerance of the commercial industry is represented with 15% of Tesla Motor Industry's revenue in 2014 which is $480M [122]. For the government stakeholder, ten times the industrial tolerance will be used. Resulting designs are seen in Table IV-10.

Table IV-10 Constant Absolute Risk Averse Designs with Electricity Cost and Willingness to Pay Uncertainty

	Max Commercial Profit	Max GDP
Customer Value ($)	117,664.77	121,732.49
Commercial Value ($)	16,449,588,742	-
Governmental Value ($)	-	1.00853E+11
Range (km)	408.92	433.82
Passenger Capacity (people)	3	3
Purchase Cost ($)	15,065.00	12,399.62
Annual Charging Cost ($)	183.16	185.48
Total Cost to Own ($)	17,389.79	14,886.24
Length (m)	4.53	4.54
Width (m)	0.95	0.95
Height (m)	0.9	0.90
Battery Capacity (kW)	25.86	27.78
Engine Power (hp)	70.18	70.19
Mass (kg)	895.49	913.18
0-60 Acceleration Time(s)	8.93	9.11
55mph Climbable Angle(degrees)	19.98	19.56
Eligible Population (thousands)	33,923.725	44,174.86
Projected Demand	3,290,657	4,433,169

Table IV-10 shows a decrease in stakeholder values when compared to the neutral risk attitude designs. This is an expected consequence of introducing risk preferences. A slight decrease in the customer value of vehicles is also observed. This might be caused by deviations from design boundaries that are caused by the utility function inherently introducing safety factors, especially on the physical dimensions of the vehicle. For example vehicle length of 4.53 or 4.54 does not offer any additional benefits than having a 4.50 vehicle length for a deterministic system; however when under uncertainty such lengths are desired by risk averse entities in order to ensure an extremely low value design (when length is less than 4.50) is not possible. Passenger capacity is unaffected but the 0.04 additional length requires more material cost therefore decreases the value of the product. Another reaction of the system attributes is the decrease in purchase cost. Introducing the concept of risk pushes stakeholders to design lower cost vehicles. Both vehicles are small 3 passenger slender vehicles similar to the risk neutral designs. Vehicle ranges are again reminiscent of neutral risk attitude designs, although slightly higher to avoid the penalty function but not high enough to generate additional value due to increased range. Similar to previous results government design vehicle is observed to have higher customer value than the industrial design, emphasizing the difference on profit margins.

The uncertainty results for a specific set of design variables (commercial and government optimum systems from Table IV-9) were obtained by running the optimizer on a 100 iteration Monte Carlo simulator that reflects the uncertainty in electric cost and customer willingness to pay. Value distribution for both stakeholders are given in Figure IV -4 and Figure IV-5.

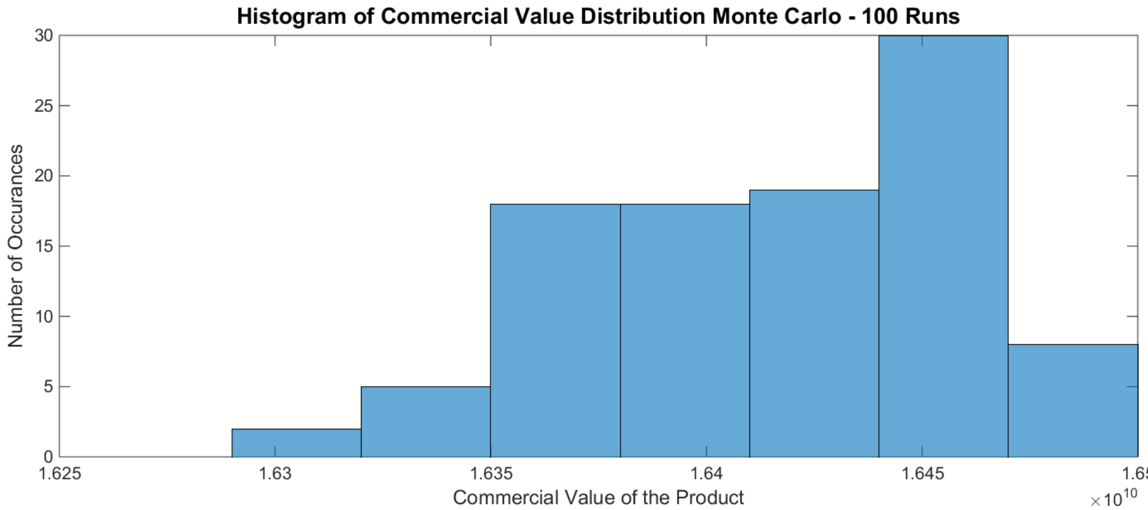

Figure IV -4 Risk Avoiding Commercial Value Distribution 100 Runs

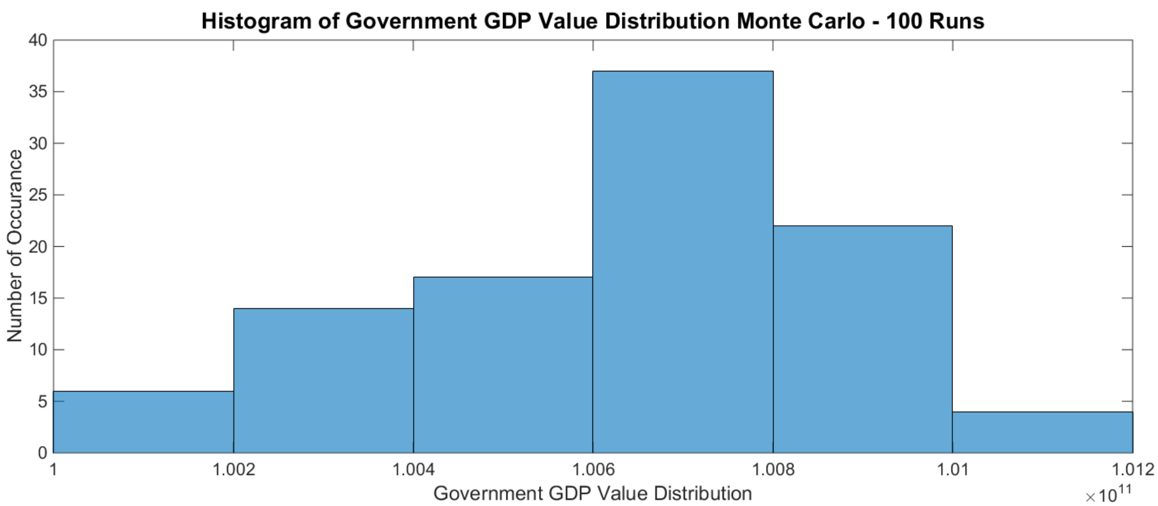

Figure IV-5 Risk Avoiding Government Value Distribution 100 Runs

The number of Monte Carlo iterations used to generate Figure IV -4 and Figure IV-5 was chosen after trading off performance and computational time. Given better computation power and more time these calculations could have been done with a higher number of iterations that would reflect the uncertainty more accurately. Sample value distributions for both stakeholders with 500 Monte Carlo iterations are given in Figure IV-6 and Figure IV-7 to illustrate the effect of increasing the number of iterations:

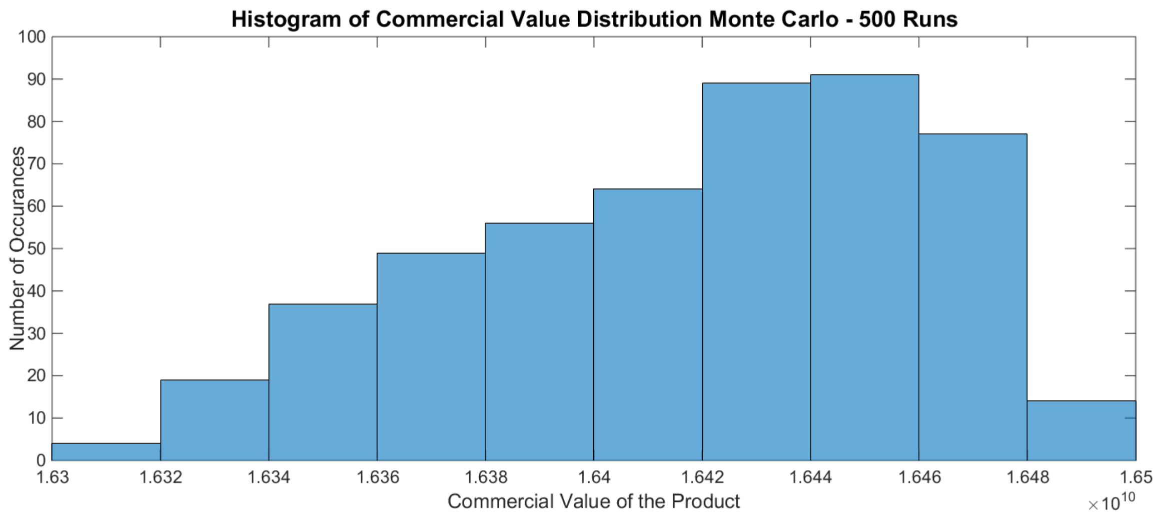

Figure IV-6 Risk Avoiding Commercial Value Distribution 500 Runs

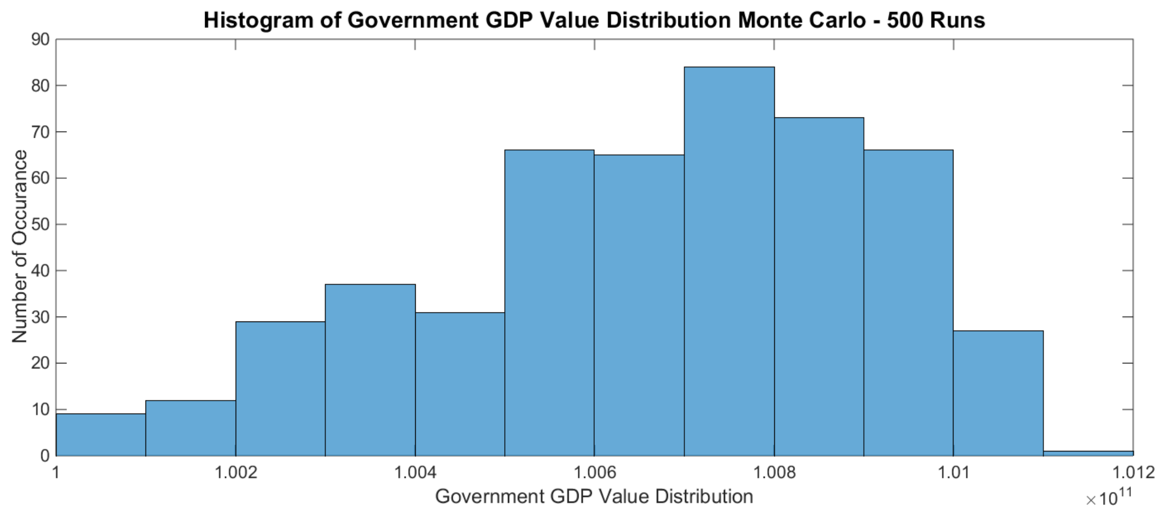

Figure IV-7 Risk Avoiding Government Value Distribution 500 Runs

Comparing distributions to each other, it is seen that even though the general characteristics of the distribution do not change, the number of bins are increased. It is important to note here that the code bins are not used in the calculations but are used here just for visualization of the data. The increase in number of bins due to the increase in runs is an indication of the ability to capturing value distributions better by increasing number of Monte Carlo runs. Limits of the distribution are observed to be unchanged with respect to the number of runs. This can be used as an indicator that 100 runs were sufficient to represent the general distribution characteristics.

IV.4. Summary

In this chapter, results obtained by applying the methodology offered for the research questions declared in the introduction section was presented. Some parts of the research questions remain not evaluated extensively. Government design with environmental concerns was not demonstrated due to the divergent behavior of the demand model with decreasing vehicle purchase cost. Another question that was not evaluated in detail was the effect of having various risk attitudes. Only risk neutral and constant absolute risk averse preferences were demonstrated however it is realized that there are many other possible risk preferences. Also a sensitivity analysis on design parameters was proposed in the methodology section but not presented in this thesis.

Referring back to the research questions that remained unanswered at Section III.7;

Summary of results for Q1: EV design space was optimized with respect to the comprehensive stakeholder value models that incorporate end user preferences. Resulting EV configurations was presented with a comparison of system design attributes and underlying reasoning was discussed extensively.

Summary of results for Q2: Sources of uncertainty in EV design were identified. Expected distribution characteristics of these uncertainties were defined in accordance to the stakeholder beliefs through employment of probability distribution functions. Expected uncertainty characteristics was incorporated into the Value-Driven Design framework through employment of Monte Carlo simulations. Possible stakeholder risk preferences were discussed and their impact on the EV design was evaluated.

CHAPTER V

CONCLUSION

This thesis is a first step in addressing the question: "How do various stakeholders impact the design of a system." This thesis has highlighted the need to identify the stakeholder, capture their desires, and communicate it to the designers in order to deliver a product that is most preferred to the stakeholder. Through the case study of an electric vehicle, three value functions were developed and their resulting optimal designs were compared. The designs illustrated the capability of value functions to open the design space to counterintuitive designs due to the reduced constraints and ability to transform generic system attributes to a useful value. In this manner value functions enable the designer to compare many different design alternatives. It is also recognized that it is critical that the designer understand the assumptions and simplifications made in the value function and the design model. Designs may be produced from value-driven design that are physically infeasible or undesired if interactions in the function and model are not captured appropriately.

This draws attention to the existence of a hypothetical ideal value function. Going back to the constraints defined in this study, it is recognized that these constraints should be replaced with the interactions that are currently missing (between attributes and in the value functions). This demonstrates just an observable missing relationship the abstract value models in the thesis fails to capture. Considering the entirety of the design space there may be many more attributes that would be represented in the ideal value function, such as ergonomics, social factors, etc. The value functions formed in this paper are simple predictive models with user imposed fidelity. Search for such an ideal value function can be based on abstract value functions such as the functions formed in this thesis through exploration and discovery.

Comparison of the resulting system configurations clearly highlighted the significance of demand modeling in VDD framework; especially for commercial products such as EVs. Customer preferences were captured through the definition of a consumer value model. This novel definition allowed forming of value centric demand models that incorporates income demographics as an alternative for simple cost & demand relationship curves. The demand model creation showed the need for forming interdisciplinary collaborations with cognitive scientist and marketing strategists in order to properly quantify customer preferences. It is also concluded that income demographics should be considered before the initiation of the design process for maximizing stakeholder value rather than being initially constrained to a specific market segment.

A probabilistic expansion to deterministic VDD framework was introduced and demonstrated through employment of stochastic descriptions of external uncertainties related to the system environment. Uncertainties were represented using triangular distributions that approximated the expected behavior of the associated uncertainty. It is important to note that when evaluating stakeholder value under uncertainty it was assumed that the uncertainties taken into account were the beliefs of the top level stakeholder and the customers know the variable with certainty, reacting accordingly during Monte Carlo runs. For example if a Monte Carlo run randomly chooses an electricity price of $.06/kWh, the customer behaves as that is the price for certain, and do not apply an uncertain belief of their own when making a decision within that world. For a more realistic approach these external uncertainties can also be modelled for the customers by integration of an additional Monte Carlo simulator.

This thesis investigated two major research questions through an application on EVs. The first question was how different stakeholder preferences effected the system design. A VDD framework was built by forming a simple EV design space and capturing artificial customer, commercial, and government stakeholder preferences. System behavior when maximizing stakeholder value was analyzed. The second question was how uncertainty impacted the design decisions. Two crucial sources of uncertainty in EV design was identified and incorporated into the deterministic VDD framework through employment of probability distributions and a Monte Carlo simulation. System design behavior was evaluated for commercial and governmental stakeholders with various risk attitudes.

V.1. Future Work

The future work associated with this thesis should focus on expandation and improvement of the electric vehicle model to capture more system attributes such as the risk of rolling over, variable widths along the length, and a range of different axle configurations. Government models other than economic growth (GDP) could be developed to allow for comparisons of alternatives related to environmental pollution. The consumer model could be improved by investigating such benefits as social desires (sitting next to a person rather than behind), aesthetics, and cargo space. Representations of desires other than the value of physical transportation could be explored. High fidelity relationships between the value models and market data could be formed and a sensitivity analysis could be performed. A sensitivity analysis should also be performed examining the relationship between the inequality constraints and the value function. In order to better understand the desires of the population a probabilistic model might be formed to capture a range of consumer models rather than the approximation presented in this thesis. This population model would then be used to improve the demand model used in the commercial and government value functions.

Risk preferences for stakeholders could be defined in detail and alternative risk mitigation scenarios could be studied through employment of the probabilistic VDD framework. Parallel design scenarios and their feasibility could be studied. This framework would be later utilized to evaluate risks associated to new technology products and market entrance scenarios. A game theoretic multi-player new market scenario would be explored for EVs. The described framework and the demand model in this thesis could be adapted to several other markets that demonstrate strongly different market conditions, such as a more equally distributed wealth and a less wealthy society to evaluate its reflection on design configurations. Multiple stakeholder scenarios for joint design projects could also be evaluated through theoretical evaluation of possible sub optimal aggregated value functions.

Stakeholder value functions defined in this thesis could be used in conceptual design of GPVs or other types of personal transportation vehicles. This would enable a value based comparison of design alternatives and could lead into an exploration of differences in detailed value functions. Another possible research area that might be based on this thesis could be an investigation of customer decision making relationship with respect to cultural changes. This could be done through incorporation of detailed end-user models that capture customer behavior with a game theoretic approach. Another possible research area that could be addressed by the Value-Driven Design community is the transition from the conceptual design to the detailed design. VDD applications in the academia investigate systems level value assessment but does not address major sources of complexity such as the design of interfaces within the system. A technique for transitioning from VDD to the requirements based design and characteristics of this integration could be investigated.

APPENDIX: List of Design Parameters

Parameters	Equivalent	Unit
Density of air	1.225	kg/m^3
Coefficient of Friction	0.013	dimensionless
Coefficient of Aerodynamic Friction	0.3	dimensionless
standard gravity	9.80665	m/s2
Seat width	0.55	m
radius of wheels	0.2032	m
Road angle of incline	6	degrees
Speed ratio of the engine	6	dimensionless
Vehicle base speed	8.33334	m/s
Mass constant	1.05	dimensionless
Battery specific energy	110	Wh/kg
Battery cost	0.15	$/Wh
Average passenger weight	75	kg
gear ratio of transmission	8	dimensionless
gear ratio of the final drive	1	dimensionless
efficiency of driveline to power	0.85	dimensionless
55 mph	25	m/s
100 km/hr	27.78	m/s
regeneration ratio	0.7	dimensionless
Average velocity	20	m/s
Auxiliary Power	200	W
Battery charge efficiency	0.94	dimensionless
empty vehicle density	71.26	kg/m^3
Engine + gearbox + driveshaft + cooling + misc. weight	200	kg
legroom	1	m
dead length of the car	1.5	m
dead width of the vehicle	0.4	m
degrees to radian	0.017453293	dimensionless
50 km/hr	13.8889	m/s
chassis cost	6.062705	$/kg
cost per shaft Hp	67.5	$/hp
Hp to watt	746	dimensionless
Cost per Watt	0.090482574	$/W
Max RPM of the motor	5000	rpm
rpm to rad/s	0.104719755	dimensionless
Average distance travelled by US citizen	24140.1	km

Profit Margin of company	0.5	dimensionless
Federal Tax incentive	-7500	$
State Tax	0	$
Joule to Wh	0.000277778	dimensionless
national average electricity rate	0.12	$/kWh
rental car cost per year	15600	$
Rental car insurance cost per year	3240	$
Average gas price	3	$/gl
Average gas consumption	25	mpg
1 year lease cost	5000	$
Average insurance cost per leased car per year	960	$
Battery energy density	200000	Wh/m^3
depreciation each year	0.2	/yr.
customer discount rate	0.07	dimensionless
Commercial discount rate	0.1	dimensionless
Maintenance cost wr.t regular car	0.5	dimensionless
maintenance cost per mile	0.0497	$/mile
owning period	10	years
average gasoline car range	482.8	km
average car room	5	people
Total EV market size	356000	quantity
Tesla Model S Share total	38555	quantity
Investment Costs to start up	75000000	$
Government Profit Margin	0.2	dimensionless
Charging rate	10	kw
median US income	22	$/hr
accord EX=L 185 hp	28,420	$
accord ex-l V-6 278 hp	30,495	$
dollar per hp	22.31182796	$/hp
Tesla Model S value through rent	71,791.13	$

CHAPTER VI

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