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Visualization-based decision support for value-driven system design

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Visualization-based decision support for value-driven system design

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NOMENCLATURE

VDD	Value-Driven Design
MDO	Multidisciplinary Design Optimization
TSE	Trade Space Exploration
DM	Decision Maker
NPV	Net Present Value
GSE	Global Sensitivity Method
PDF	Probability Density Function
DSM	Design Structure Matrix
VDSM	Virtual Design Structure Matrix

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ABSTRACT

In the past 50 years, the military, communication, and transportation systems that permeate our world, have grown exponentially in size and complexity. The development and production of these systems has seen ballooning costs and increased risk. This is particularly critical for the aerospace industry. The inability to deal with growing system complexity is a crippling force in the advancement of engineered systems. Value-Driven Design represents a paradigm shift in the field of design engineering that has potential to help counteract this trend. The philosophy of Value-Driven Design places the desires of the stakeholder at the forefront of the design process to capture true preferences and reveal system alternatives that were never previously thought possible.

Modern aerospace engineering design problems are large, complex, and involve multiple levels of decision-making. To find the best design, the decision-maker is often required to analyze hundreds or thousands of combinations of design variables and attributes. Visualization can be used to support these decisions, by communicating large amounts of data in a meaningful way. Understanding the design space, the subsystem relationships, and the design uncertainties is vital to the advancement of Value-Driven Design as an accepted process for the development of more effective, efficient, robust, and elegant aerospace systems.

This research investigates the use of multi-dimensional data visualization tools to support decision-making under uncertainty during the Value-Driven Design process. A satellite design system comprising a satellite, ground station, and launch vehicle is used to demonstrate effectiveness of new visualization methods to aid in decision support during complex aerospace system design. These methods are used to facilitate the exploration of the feasible design space by representing the value impact of system attribute changes and

comparing the results of multi-objective optimization formulations with a Value-Driven Design formulation. The visualization methods are also used to assist in the decomposition of a value function, by representing attribute sensitivities to aid with trade-off studies. Lastly, visualization is used to enable greater understanding of the subsystem relationships, by displaying derivative-based couplings, and the design uncertainties, through implementation of utility theory. The use of these visualization methods is shown to enhance the decision-making capabilities of the designer by granting them a more holistic view of the complex design space.

CHAPTER 1

INTRODUCTION

Engineering design is a decision-making process that involves analyzing candidate solutions to find the best design. Optimization can be used to facilitate this process, although the scale and scope of modern complex, engineered systems is immense.[1, 2] This is particularly true of aerospace systems. Several recent NASA and NSF workshops have been conducted specifically to focus on the challenges of designing complex, engineered systems.[3-5] The resulting optimization trade space, or feasible design space, is defined by hundreds to thousands of variables, objectives, and solutions. Visualization tools are therefore necessary to provide decision support to the designer by simplifying data and presenting it in a meaningful way to enable rigorous and informed decision making.

The primary goal of this thesis work is to develop new methodologies for Trade Space Exploration of large-scale complex aerospace systems, that support the new paradigm of Value-Driven Design (VDD) [6]. VDD seeks to improve the design process through the use of an understandable objective function that can be communicated clearly throughout the design hierarchy in order to achieve a unity in design intent.[7] The objective function represents the preference of the stakeholder and can be decomposed and distributed to the design participants. The design of complex systems, from idea to finished product, is a multi-stage process. It includes research, conceptual design, preliminary design, detailed design, and production.[8] VDD is generally associated with the preliminary design phase, after the design team has a conceptual idea of what they want to build (aircraft, vehicle, infrastructure). However, its usefulness beyond the preliminary design phase has substantial potential. VDD simplifies the trade space by combining the system's attributes into one coherent value function that captures the inherent trades. This can lead to more simple and meaningful visualizations, which can be used to create unified frameworks for complex systems design.

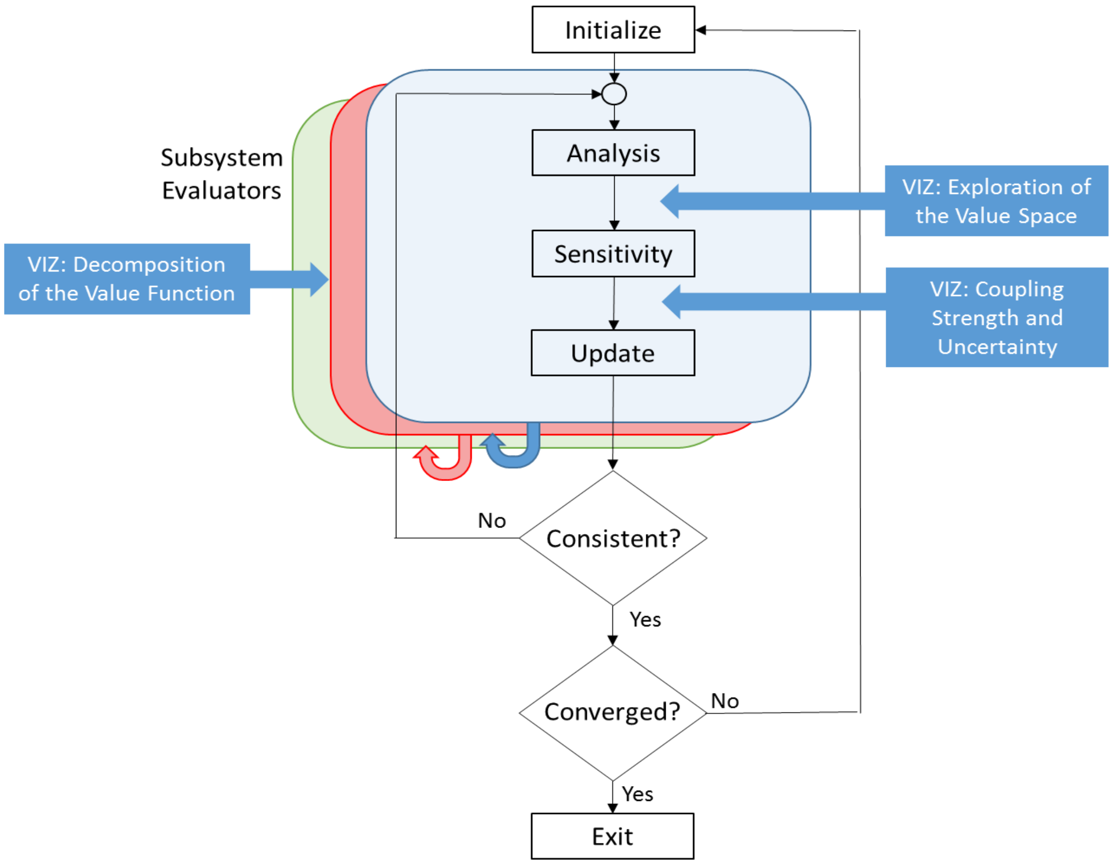

Figure 1: *VDD Flowchart with Visualization Components*

Figure 1 represents a general flowchart for the VDD process after the system-level value function has been created. A design is initialized and then evaluated for each subsystem level. Each colored box represents an evaluator at a different level of the system. Within each box, the value function is evaluated and sensitivities obtained for both attributes and design variables. After the evaluation has cycled through all levels of the system, the value function is checked for consistency. Then optimization is implemented on the value function until it converges. The result of this process is a singular value point that represents the optimal design, including design variables, attributes, and sensitivities. Visualization can be used to support decision-making at different points in this process. The adoption of VDD necessitates a new understanding and representation of the design data produced so as to better facilitate informed decision making under uncertainty. The blue boxes in Figure 1 represent three visualization methods, which correlate to the three main research sections of this thesis.

Chapter 2 provides a background on relevant foundational disciplines, including VDD, multi-objective optimization, and engineering Trade Space Exploration. Chapter 3 provides a description of the satellite system used in this work for demonstration of feasibility of the visualization methods presented. Chapter 4 will explain the exploration of the value space using traditional Trade Space Exploration (TSE) tools. Existing TSE paradigms and multi-dimensional data visualization tools are used to present the attributes of the system, which result from the analysis of the value function. These tools are also used to compare VDD with multi-objective optimization processes. Chapter 5 addresses how visualization can be used during the decomposition of the value function. After the development and evaluation of a system-level value function, the next step in the process is to decompose that function into subsystem-level value functions. New visualization methods are used during this process to support the formation of these subsystem-level value functions and identify how different lower-level attributes affect the system as a whole. This allows the designer to better understand the trade-offs that occur between subsystems. Visualization is also used to delve deeper into a particular subsystem, to explore design alternatives, identify problems, and prioritize or allocate resources. Chapter 6, explores how new visualization methods can be used to present the uncertainty that propagates from the design variables to the final value solution, and the strength of couplings between subsystems. Utility theory is used to demonstrate the impact of risk preferences on the final design selection.

CHAPTER 2

BACKGROUND

Multi-Objective Optimization

Optimization is the process of finding the best design. This process involves the use of an objective function, formed from multiple attributes, that represents the preferences of a decision maker and then uses computational means to generate alternatives.[9-11] A traditional optimization process also involves constraints, typically on performance attributes of the system, which restrict the feasible design space. Optimization constraints are generally derived from design requirements – a means of communicating preferences in requirement-based design that is a foundation of the current system engineering practice.[12] These requirements do not necessarily have to be concrete, but can be fluid. This fluidity is often restricted due to the administrative process of changing requirements and reflecting them through contracts or agreements.

A traditional objective function in multi-objective optimization is an aggregation function that forms from many lower-level attribute functions. For example, Physical Programming aggregates objectives based on attainment of physically meaningful levels. [13] In single objective optimization, this process results in a single design alternative that reflects the performance metrics of the underlying search algorithm. In multi-objective optimization, this process results in a set of alternatives, specifically Pareto optimal solutions (a feasible alternative in the trade space that has at least one objective optimized when compared to another alternative without being worse in a competing objective), which creates new challenges for designers who must then select a single design alternative.[14, 15] Navigating the trade space becomes a challenge in terms of tradeoffs and negotiating variable relationships since the dimensionality from which a decision must be made is often large. The number of viable design alternatives present in most multi-objective optimization problems makes the final decision even more difficult.

The organizational hierarchy used in the design of complex engineered systems typically consists of numerous groups of designers responsible for different aspects of the system.[2] Each of these groups, which can be viewed as subsystems, typically strives to optimize an objective function related to each designer's assigned subsystem. These independent subsystem optimizations typically are competitive, in which optimizing in terms of one subsystem's preferences will likely limit or hinder the optimum of another. Likewise, difficult or strict design constraints often greatly constrain the feasible design space and require greater attention in the search space. In order to determine the true system optimum, a negotiation process occurs between the competing subsystems that can be captured in a Multidisciplinary Design Optimization (MDO) framework.[16-20] However, competition between subsystems may steer the optimization algorithm towards highly constrained regions. Defining a coherent, system-level objective function to enable a system optimization requires understanding the impacts of various performance attributes on the system attribute that is most preferred by the stakeholder. It is this approach that this forms the basis of the value function, which is central to Value-Driven Design.

Value-Driven Design

Value-Driven Design (VDD) [6] is not a specific method or process, but rather an approach that emphasizes optimization of a value function that represents the true preference of the stakeholder. Figure 2 shows the VDD process from start to finish. Similar to traditional design methods, design variables are chosen and through the definition phase, they lead to a system configuration. Physical models then define what attributes will be measured. The top half of the arc is where the VDD process differs from traditional optimization approaches. VDD involves the development of a system level objective function (now called a value function), which is flowed down to each component of the system. The designers use this value function to evaluate the status of the component attributes and the collective status of the system as design changes are made, so that they can take appropriate actions to sustain the design goal.[21] Instead of checking requirements, the system value at the top of the arc is what is then used for comparison and optimization. Requirements cannot necessarily be eliminated, but VDD moves the focus away from requirements, which are often artificially imposed on designs.[22-24] Requirements inherently limit the design space. By reducing the number of requirements, more of the design space is open for exploration.

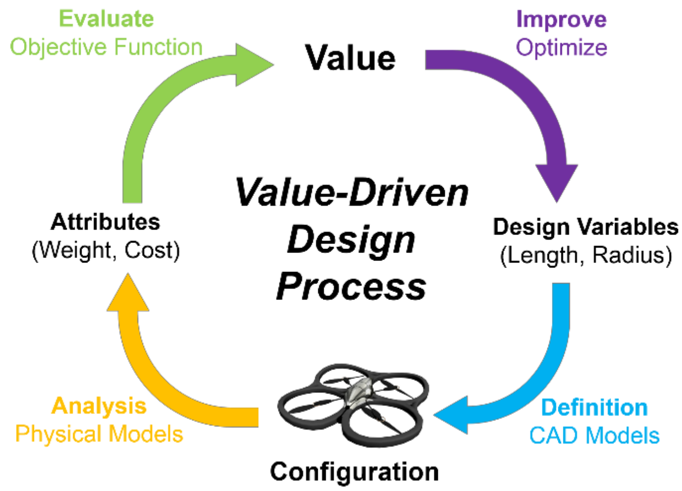

Figure 2. *The Value-Driven Design Process* [6]

VDD captures the true preference of the system designer and represents it in the value function. A typical preference in a commercial engineering setting is often company profit. This differs from economic decision-making as value is an intrinsic property of the engineering system related to an organization's philosophical or technological model and may consist of more than simple economic metrics (such as cost). The value of the system is determined through highly coupled system and subsystem models that capture the worth of performance attributes that are typically not captured in economic models. VDD also allows for better comparison between choices since the value function converts everything to a specific one-dimensional metric (generally net present profit for profit-seeking enterprises), enabling distinct contrast between design alternatives. VDD uses information about the problem to form a common objective function among disciplines to promote understanding of an individual subsystem's value to the design as a whole. This methodology differs from traditional system design because it moves the focus away from requirements that are often artificially imposed on designers and subsystems.[22] Requirements inherently limit the design space, defining regions that are unattainable to the designer. By reducing the number of requirements, more of the design space is open for exploration.

The first step in VDD is the creation of a value function. The system level value function is an objective function that takes into account extensive attributes of a system to produce a singular value.[25] At the conceptual design stages, designers typically have a clear understanding of the higher level attributes of a system. For example, high level attributes (such as cargo, power system, and communication) would be naturally included in the value function for a land transportation system. As the design progresses, decisions are made that lead to formation of subsystems with other secondary sets of attributes, which are input to the higher level attributes and functions of lower level attributes as well as design variables, thus forming a complex system. In the case of truly innovative system design, it is more difficult to define attributes intuitively. However, use of Trade Space Exploration has the potential to help guide the designer to identify appropriate attributes for value function creation across different level of a system hierarchy.

After the system-level value function has been created, it is decomposed to component-level value functions, which are distributed throughout various lower-level teams in order to guide their designs decisions [21]. No matter what method of decomposition is applied, the status of component attributes are monitored and flowed back up to the system-level value function. This is idealized in Figure 3, which shows the proposed VDD/MDO design method framework upon which this research is built.

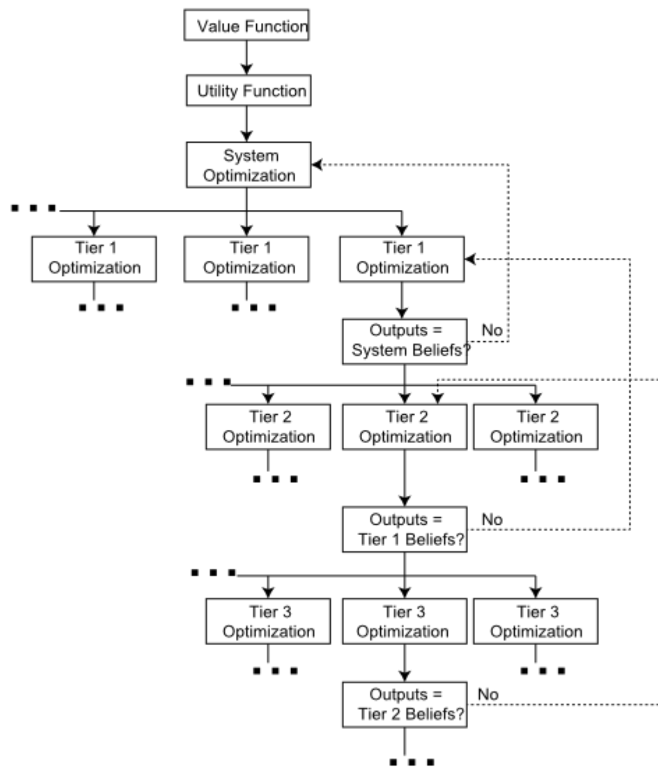

Figure 3. *Proposed VDD/MDO system design method framework*

The component attributes that are flowed up to higher hierarchical tiers are compared to the beliefs of those attributes held by the tier above the component. This action allows for a verification of the validity of the beliefs and may result in the realization that a design is not feasible, and therefore changes must be made. These changes might be in the design itself, in the beliefs held, in the modeling used, or in the formation of the value function.

The last step in VDD involves making decisions to balance the value of the system. The value function provides guidance to the designers as they reflect the preferences of the system designer. Understanding the trade environment allows designers to make more informed decisions regarding the trade-offs of value in the system. The key challenge for this work, however, is that the nature of the trades will change in the context of VDD.

Traditional Trade Space Exploration

Traditional Trade Space Exploration (TSE) was developed to help decision makers explore and analyze large sets of design data to understand relationships between variables so as to enable informed decision making in alternative selection.[26-28] The need for TSE is continually growing due to the ever-increasing complexity of large-scale engineered systems. The “space” in TSE represents the visualization of tradeoff behaviors that can be represented through different methods graphically or contextually. Many tools produce simplified data visualizations to reduce information and represent the data in manageable portions so that non-experts can understand and make decisions using the information from the space.[29-31] The “exploration” in TSE involves combining the data visualization tools and the intuition of designers to navigate to and identify the best design.

Traditional optimization operates under the assumption that preferences can be captured and modeled beforehand. [10, 32] Research has shown that this assumption does not hold in general and that simply optimizing a problem does not provide sufficient detail for choice in a multi-objective problem.[33, 34] Generating Pareto frontiers affords inherent designer feedback in selecting designs [15]. "Shopping" [33, 34] in the trade space using visual steering helps decision-makers (DMs) form their individual preferences, focus in on regions/points of interest, and sharpen their affinity for a design alternative as well as learn about the priorities and trades necessary to produce feasible/optimal solutions.

Decision aides help DMs analyze, interrogate, explore, and learn from large and complex data sets [32] with visualization serving this role in TSE. A TSE approach helps DMs to understand relationships between variables and of limitations of the space. Multi-dimensional data visualization tools, such as those found in the *Applied Research Laboratory (ARL) Trade Space Visualizer* (ATSV), have been designed to support just such an approach by providing interactive data visualization capabilities.[34] ATSV offers 3D glyph plots, 2D scatter plots, 2D scatter matrices, parallel coordinates, and histogram plots to visualize and link data. Designers are encouraged to explore and interrogate the space via dynamic filtering based on user-defined limits, preferences, and to produce Pareto frontiers easily as a means of developing a choice set. Individual designs can be selected, viewed in detailed, and compared with other alternatives.

In this research, new multi-dimensional data visualization tools are demonstrated to be useful to evaluate and describe the effect that a VDD problem formulation has on the design space. A VDD satellite system application previously examined in an MDO context [35] is used in this research as a case study. The following section is a summary of the VDD application of a satellite system that is used here.

CHAPTER 3

SATELLITE SYSTEM

Satellite Description

A commercial satellite system has been developed [35] as a test case. The system includes a geo-stationary communication satellite for TV broadcasting, a set of ground stations for signal transmitting, and a launch vehicle to get the satellite into orbit. The mission objective of the satellite is to re-transmit the signals received from one ground station antenna to another ground station antenna efficiently and effectively. This example is a conceptual design that is simplified for the purposes of optimization. The number of subsystems, typically in the hundreds for a satellite system, is reduced to eight broader subsystems here. These subsystems are: Payload, Ground, Propulsion, Attitude Determination and Control, Thermal, Structures, and Launch Vehicle.

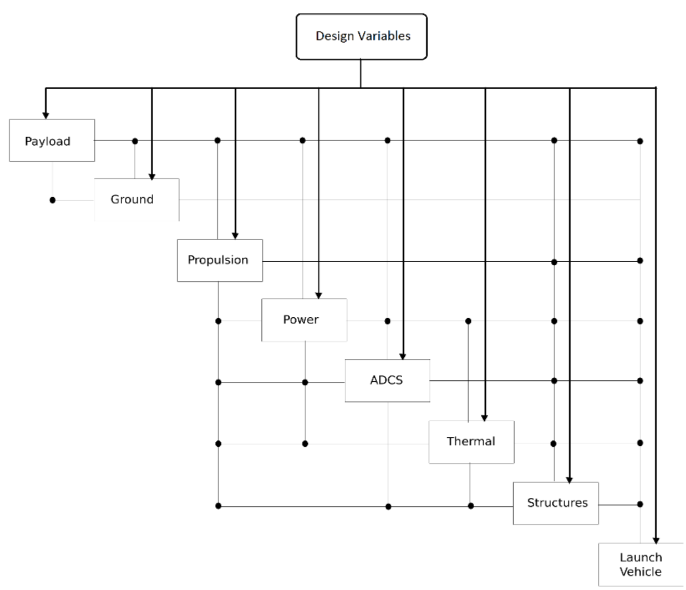

Figure 4. *Design Structure Matrix of a Satellite System*

The subsystem interactions in the satellite example are given in Figure 4. In the figure, the arrows that input into each subsystem are design variables. There are 36 design variables (continuous and discrete) that define the system. Examples include: diameters of the antennas, frequencies of the signals, numbers of transponders, etc. A full table of these design variables is shown in Table A in the appendix. The circles in figure 4 that connect the lines between subsystems are couplings. These couplings represent behavior variables that are outputs of one subsystem and that are necessary to design another subsystem. An example of such a coupling is between the Thermal and Propulsion subsystems. In order to properly design the Propulsion subsystem, the mass of the Thermal subsystem is required (i.e., to determine the proper amount of propellant necessary, the mass of all the subsystems must be determined). Table A in the appendix shows the attributes of the system. Attributes are also critical here, as VDD promotes a value function that comprises relationships of attributes. These attribute might be behavior variables or may themselves be functions of behavior variables. The couplings and attribute of the system do not occur on one level. There are lower tiers to the satellite system, which are shown in Figure 5. This three level decomposition provides the framework for the optimization, but also increases the complexity and challenges in visualization. Capturing the design variable and attribute interplay between levels so as to better inform the decision maker is a primary goal of this research.

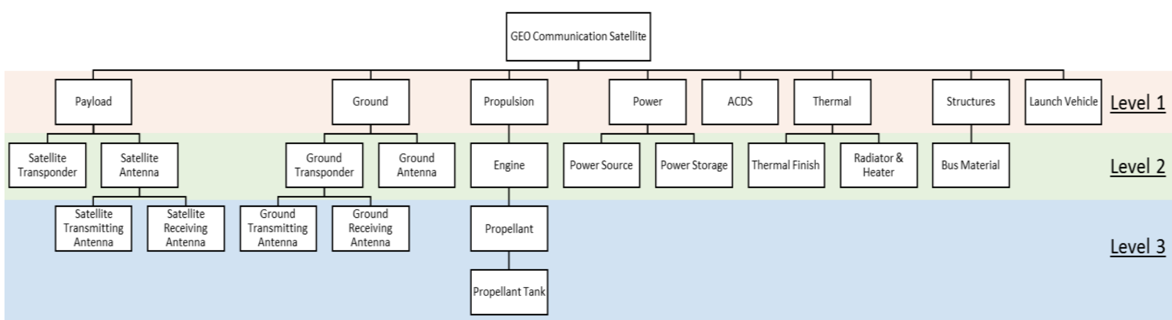

Figure 5. *Hierarchical Decomposition of a Satellite System*

Three common optimization formulations used in the design of a satellite system are to minimize mass [36-38], minimize cost, and a multi-objective formulation. Mass is a typical objective function for space vehicles due to the substantial cost of transporting each pound into orbit.[39] This function is often used as a surrogate for cost (and often therefore for profit), since reducing the mass of the objects propelled into space reduces overall system cost. While this objective function offers a simple formulation (the summation of the part masses that are being transported), it fails to capture all of the costs associated with the system or to enable understanding of the value proposition as it related to mass. The mass formulation used in this application is defined in Eq. (1). The attributes from the inequality constraints (*g1* through *g5*) and design variables from the bounds can all be found in Table A.

$$
\begin{gathered}
find\ \boldsymbol{X} \\
= \left[f_{down}, f_{up}, P_t, P_{gt}, D_{sat,trans}, D_{sat,rec}, D_{ground,rec}, D_{ground,trans}, \varepsilon\right]^T \\
Min\ \ f(\boldsymbol{X}, \boldsymbol{y}) = M_{total} \\
s.t.\quad g_1: 10dB - SNR_{composite} \leq 0 \\
g_2: M_{total} - 1000 \leq 0 \\
g_3: ArraySize - 40m^2 \leq 0 \\
g_4: L_{structures} - 5m \leq 0 \\
g_5: r_{structures} - 2.5m \leq 0 \\
1\ GHz \leq f_{down} \leq 100\ GHz \\
1\ GHz \leq f_{up} \leq 100\ GHz \\
300\ W \leq P_t \leq 3000\ W \\
300\ W \leq P_{gt} \leq 30000\ W \\
0.5m \leq D_{sat,trans} \leq 2.5m \\
0.5m \leq D_{sat,rec} \leq 2.5m \\
2\ m \leq D_{ground.rec} \leq 20m \\
2\ m \leq D_{ground,trans} \leq 20\ m \\
35\frac{W-hr}{kg} \leq \varepsilon \leq 200\frac{W-hr}{kg}
\end{gathered}
\tag{1}
$$

The cost objective function embodies the logic of the previous argument to minimize mass in a direct form. The cost of the system is determined by taking into account the costs of all of the subsystems, instead of using mass as the surrogate for cost. This formulation includes the costs of such system entities as the ground station parameters (e.g., manufacture and maintenance cost of the ground antennas) as well as vehicle parameters (e.g., manufacturing and development cost of battery technology) that are not captured in the mass formulation. The cost formulation for the satellite system is given in Eq. (2), with the same attribute and design variables from the Eq. (1).

$$
\begin{gathered}
find\ \boldsymbol{X} \\
= [f_{down}, f_{up}, P_t, P_{gt}, D_{sat,trans}, D_{sat,rec}, D_{ground,rec}, D_{ground,trans}, \varepsilon]^T \\
Min\ \ f(\boldsymbol{X},\boldsymbol{y}) = Total\ Cost \\
s.t.\quad g_1: 10dB - SNR_{composite} \leq 0 \\
g_2: M_{total} - 1000 \leq 0 \\
g_3: ArraySize - 40m^2 \leq 0 \\
g_4: L_{structures} - 5m \leq 0 \\
g_5: r_{structures} - 2.5m \leq 0 \\
1\ GHz\ \leq f_{down}\ \leq 100\ GHz \\
1\ GHz\ \leq f_{up}\ \leq 100\ GHz \\
300\ W\ \leq P_t\ \leq 3000\ W \\
300\ W\ \leq P_{gt}\ \leq 30000\ W \\
0.5m\ \leq D_{sat,trans}\ \leq 2.5m \\
0.5m\ \leq D_{sat,rec}\ \leq 2.5m \\
2\ m\ \leq D_{ground.rec}\ \leq 20m \\
2\ m\ \leq D_{ground,trans}\ \leq 20\ m \\
35\frac{W-hr}{kg}\ \leq \varepsilon\ \leq 200\frac{W-hr}{kg}
\end{gathered} \tag{2}
$$

The motivation for using mass and cost objective functions is to reduce the amount of money spent to produce a product. The natural optimum of these objective functions is 0 – a product that has no mass and costs nothing to create. To restrain the optimization process from reaching this optimum, constraints (both physics- and systems-based) are imposed to meet some expectations of the system, e.g., the satellite must function within some frequency band or that the antenna diameters are within a certain range.

Multi-objective functions are typically created for complex engineered systems to enable further preferences of the designers. A multi-objective function can be formed with the objectives of system mass and transmitter power [35] for the satellite example, as seen in Eq. (3), with the same attributes and design the previous two equations. The transmitter power objective is a surrogate objective for the revenue possible for the system. As the power increases more transponders can be accommodated in the satellite because transmitter power is directly proportional to the number of transponders onboard the satellite.[40] An increase in the number of transponder results in an increase in the revenue. The multi-objective function formulation allows the system designer to explore the tradeoffs between a surrogate objective for cost (i.e., mass) and a surrogate objective for revenue (i.e., transmitter power).

$$\begin{gathered}
find\ \boldsymbol{X} \\
= [f_{down}, f_{up}, P_t, P_{gt}, D_{sat,trans}, D_{sat,rec}, D_{ground,rec}, D_{ground,trans}, \varepsilon]^T \\
Min\ \ f(\boldsymbol{X}, \boldsymbol{y}) = w_1 \times M_{total} - w_2 \times P_t \\
s.t.\quad g_1: 10dB - SNR_{composite} \le 0 \\
g_2: M_{total} - 1000 \le 0 \\
g_3: ArraySize - 40m^2 \le 0 \\
g_4: L_{structures} - 5m \le 0 \\
g_5: r_{structures} - 2.5m \le 0 \\
1\ GHz \le f_{down} \le 100\ GHz \\
1\ GHz \le f_{up} \le 100\ GHz \\
300\ W \le P_t \le 3000\ W \\
300\ W \le P_{gt} \le 30000\ W \\
0.5m \le D_{sat,trans} \le 2.5m \\
0.5m \le D_{sat,rec} \le 2.5m \\
2\ m \le D_{ground.rec} \le 20m \\
2\ m \le D_{ground,trans} \le 20\ m \\
35 \frac{W - hr}{kg} \le \varepsilon \le 200 \frac{W - hr}{kg}
\end{gathered} \tag{3}$$

For this example, it is assumed that a commercial organization is designing the satellite, which translates into maximizing the profit of the company. Such profit is typically a reoccurring amount dependent on the performance of the system. The impact of time must be taken into account due to the value function being formed on the profit of the system. The value function used captures both the true preference of the designer (the profit of the product over its operational lifetime), as well as the designer's time preference on when the product's profits are received, through a discount rate.[41] The value function is seen in Eqs. 4 and 5, with further detail in [35]. The total yearly revenues and cost, while complex to determine, enable an optimization process involving a meaningful objective function (profit) based on the true preference of the system designer.

$$Profit = \sum_{y=1}^{OL} Revenue_y - Total\ Cost \tag{4}$$

$$Net\ present\ value\ (NPV) = -Total\ Cost + \sum_{y=1}^{OL} \frac{Revenue_y}{(1 + r_d)^y} \tag{5}$$

$where:$
$r_d: discount\ factor = 10\%$
$OL: Operational\ Lifetime = 10\ years$
$y: year$

It has been shown in previous work that drastically different designs will be produced for the satellite example, with varying profits, depending on the objective function used.[35] These results are expected as different objective functions will result in different optima. Hence, a designer must choose the objective function carefully, with the understanding that while a value function is typically more complex than traditional objective functions, it has the benefit of finding the optimum that best meets the system designer's desires. In this research, mass, cost, transmitter power, and net present profit are represented as attribute or, in the case of profit, the value function itself.

Visualization Data Generation

For this research, the commercial program ModeFrontier, a software platform for multi-objective and multi-disciplinary optimization developed by ESTECO (http://www.esteco.com/), is used to generate the data produced for the satellite system to be subsequently used in the visualization methods. While it also includes a number of visualization tools, it was used primarily used as a tool for optimization and data collection.

The satellite system code, created in MatLab, was integrated into ModeFrontier to develop the design points which were subsequently used to populate the visualizations. Within ModeFrontier, 360 random design points were created (100 times the number of design variables in the satellite application), which follows a common rule for the implementation of Particle Swarm Optimization [42].

Particle Swarm Optimization (PSO) [43] is a heuristic optimization method which was originally based on the natural phenomena of animal swarms, such as bird flocks and fish schools. A numerical value is calculated for the initial points and then each point moves a random amount towards the global best point in the population. This process is iteratively repeated until a desired convergence criteria is met. PSO is advantageous because of its simplicity and because the calculation of gradients and derivatives is not required, reducing the computational cost of each iteration. For the satellite example, PSO was applied for 1000 generations, resulting in 360,000 design points subsequently used for the visualization. Two sets of design points were created, one which was optimized for the mass/power multi-objective function and the other was optimized for net present profit.

CHAPTER 4

EXPLORATION OF THE VALUE SPACE

Interactive and multi-dimensional data visualization with traditional objective functions is useful but does not sufficiently aid designers in forming their preferences or in aligning their preferences with that of the organization. This research focus of this chapter is on mapping VDD to conventional interactive data visualization tools used in TSE. It must be recognized here that traditional TSE in design has traditionally focused on multi-objective optimization formulations, with the trades being amongst alternatives with variations in the objective functions. The VDD formulation necessarily changes this TSE, given that a singular function exists (i.e. the value function). Each visualization can be tied to the overall value of the system, which is consistent with the designer's true preferences and facilitates alignment with the organization's preference. The design alternatives can therefore be easily ranked for comparison.

In this formulation, value was captured as the NPV of the satellite. Here, it is proposed that the addition of this metric presents several possible modifications to the trade space. Value can be used as an additional criteria, simply added to the multi-objective space. Value can used as a selection criteria within that multi-objective space. Lastly, value can be used as the primary formulation, creating a new design space. Each of these modifications changes how TSE is used. They are detailed in the following subsections.

Value is used as an additional criteria

The design space is not reduced but is instead increased via the introduction of an additional discerning criteria, in this case the NPV of the design. This leads to a higher-order multi-objective problem. The data used in these visualizations is representative of the constrained formulation of the satellite system [35], , as described in the previous chapter.

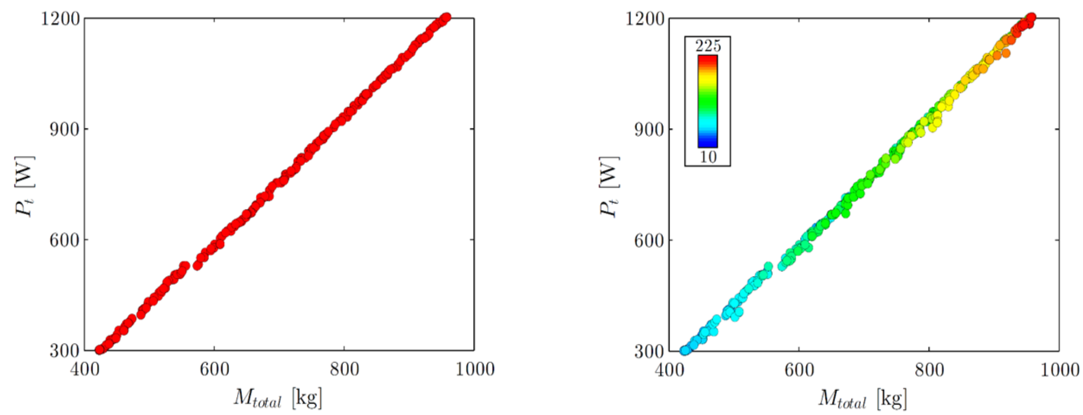

Figure 6. *(Left) Subset of a multi-objective space (Right) Value added to that space*

Figure 6 shows a subset of the multi-objective space on the left, and the addition of value to that space on the right. It is clear that the simple addition of value can help the designer to better understand the design space, and deal with competing objective functions and possibly arbitrary weights.

Value is used as a filter

Filtering can be as simple as enforcing a constraint on the space or as complex as introducing specific components of a design into the organization's economic plan. Designers could use the value metric to further differentiate designs selected from the optimal design set when performing point-wise comparison.

The non-dominant set of alternatives from the objective space can be projected onto various visualizations such as a parallel coordinate plot, as shown in Figure 7. This figure demonstrates a “roadmap” for how the input variables (the first nine columns, which are design variables) affect output variables (the last two columns, which includes a system attribute and the net present profit). Parallel coordinate plots are also important for decomposition, which will be explained in the following chapter. The numbers on the top and bottom represent the range of input and output values in a given number of design alternatives. Mapped onto these alternatives is the result of the multi-objective optimization routine, which is represented by the dashed line. Interestingly, if value is used to select a design in the same trade space, then the result is the solid line, which leads to a completely different set of design decisions. The final column (NPV) represents the net present value of the design sets. It is clear that using a VDD approach affects not only the selection process for the design variables, but also results in a vastly different design with a much higher NPV.

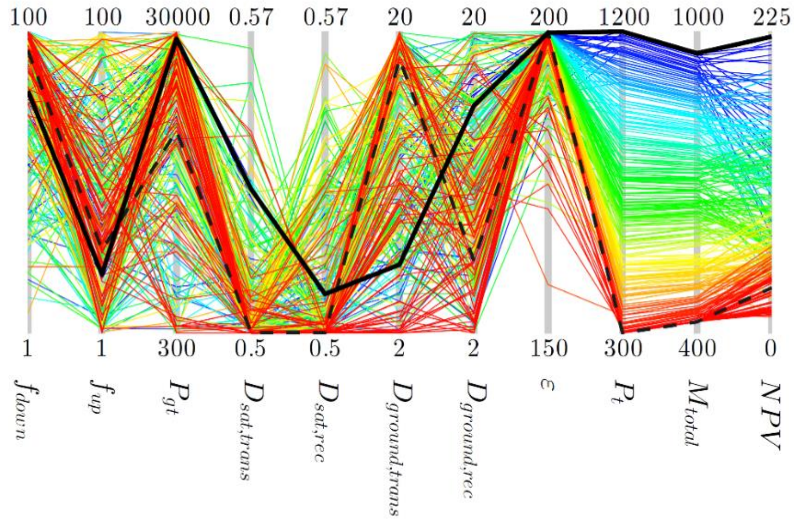

Figure 7. *Parallel coordinate plot showing the effect of input parameters on preferred output variables. The variables are colored by the multiobjective function, where red is a more “preferred” design*

When value is used as a selection criteria, it changes the nature of the multi-objective space and enables the designer to better understand and prioritize their objectives. Two-dimensional scatter plots are a traditional trade space exploration tool which can be used to present the design space with the addition of value. Figure 8 shows the solution (or outcome of a certain set of design variables) with respect to a group of objectives. The figure illustrates some of the tradeoffs that must be made to select one solution from the set of Pareto, or optimal, solutions. In this instance, the objective is to minimize mass and maximize transmitter power indicating that the best point is in the upper-left corner of the figure (greatest power but lowest mass). The color mapping relates to value, with red being the highest value. Hence, if value were not provided as a unifying concept, there would be no real guidance as to which of these designs might be considered 'best'.

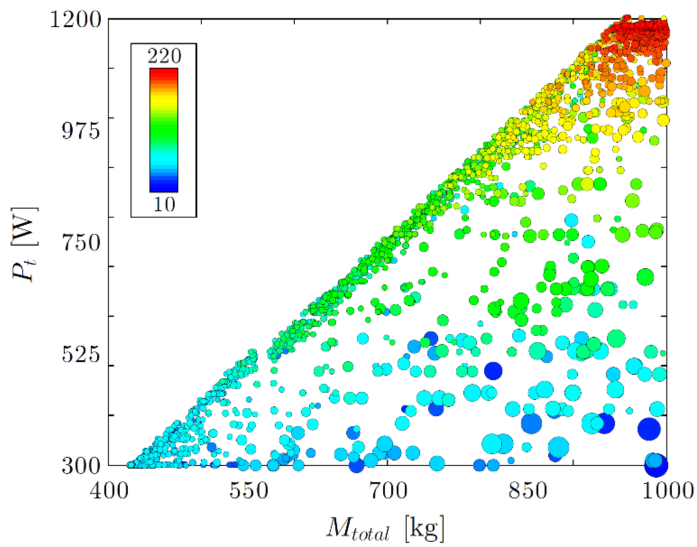

Figure 8. *Scatter plot showing Objective 1 (Mass), which is to be minimized, Objective 2 (Transmitter Power), which is to maximized, colored by NPV, and sized by the diameter of the satellite antenna*

Value is used as the primary formulation

When a complex engineered systems is evaluated in the organizational context of VDD, the result is a single-objective function, with a vastly different design space. Using this single-objective formulation may necessitate a reimagining of traditional approaches to TSE.

The three different modifications (value added, value as selection criteria, and value as the primary formulation) present interesting questions of how VDD enhances TSE and vice versa. Multi-dimensional data visualization tools can support VDD through understanding the relationships between system attributes and design parameter values, as illustrated in Figure 7. In the VDD approach, subsystem impacts on system attributes can be determined using a singular metric. This value function is representative of the stakeholder preference instead of an aggregated set of preferences (i.e., multi-objective formulation). Each subsystem monitors the status of its component attributes to sustain the design goal of the system.

This value-based trade environment may have clusters of optima that represent focal points for future designs, or may help the designer eliminate design alternatives to simplify the trade space. TSE and VDD, then, are complimentary and compatible techniques that represent trades intrinsically and visually through both the design space and the organizational hierarchical value structure that manages the complete system. A tool that combines the two, can enable a "human in the loop" optimization methodology which can help to provide the extensive decision support that many companies seek.[4]

In a VDD framework, one of the goals is to move away from constraint-based problem formulation resulting from arbitrarily "flowing down" requirements to the subsystems. When this goal can be realized, the trade space changes significantly. Value functions map the system's attributes into a singular dimension, which can be visualized using 1D visualization as shown in the top of Figure 9. A simple sort can then find the maximum value in this map that

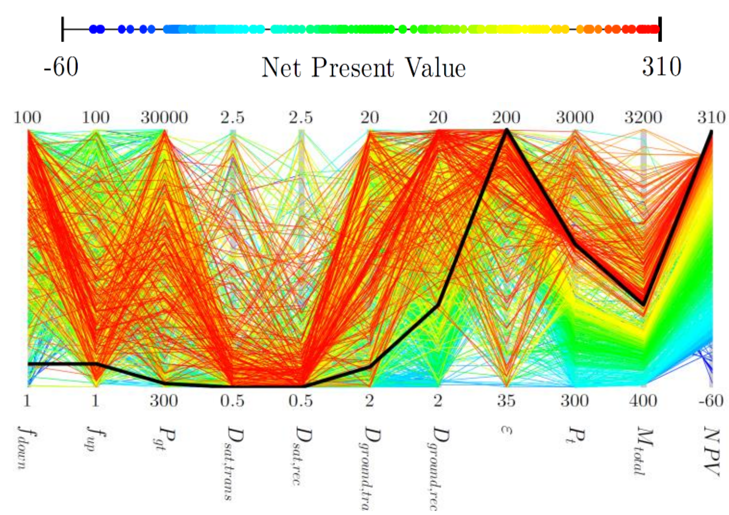

***Figure 9**. (Top) mappings of designs into a 2-D plot of NPV and (Bottom) parallel coordinates of a subset of designs with high NPV, the black line represents the most profitable design*

may then be presented to the designer. However, this 1-D visualization does not represent the related values of the design variables. Nor does it provide insight into attribute relationships. Again, parallel coordinate plots can be used to relieve this issue, as shown in the bottom of Figure 9. Similar to multi-dimensional data visualization, this new value mapping represents aggregation and attribute interplay.

At this stage, parallel coordinate plots enable the designer to visually explore the design space and understand the underlying physical relationships between input variables and attributes. This capability can help the designer to alter, advance, or simplify the value function as they see fit. Simple TSE techniques can also be used as comparison tools for MO and VDD.

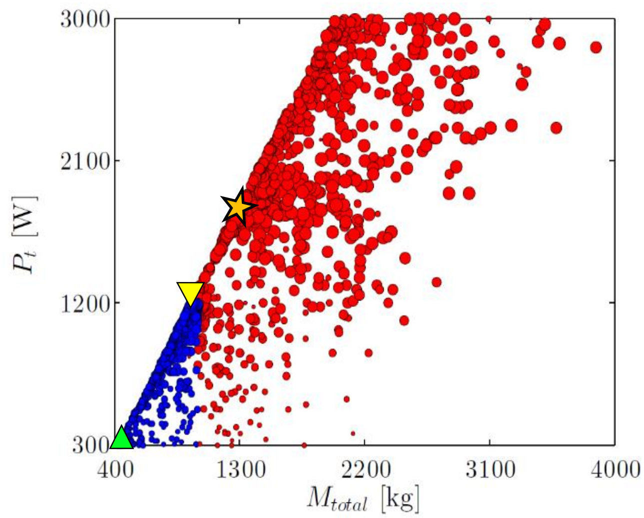

Figure 10. *Extent of the traditional requirements-driven trade space (in blue) versus VDD approach (in red and blue)*

Table 1. *Results of a design selection process in the satellite trade space using three different objective function formulations*

Attribute	MO (▲)	MO w/NPV (▼)	NPV (★)
f_{down}	93.9	80.5	10.0
f_{up}	28.3	20.2	10.0
P_t	300.0	1201.2	1799.1
P_{gt}	20244.0	29279.4	721.2
$D_{sat,trans}$	0.5	0.5	0.5
$D_{sat,rec}$	0.5	0.5	0.5
$D_{ground,trans}$	18.4	6.1	3.4
$D_{ground,rec}$	6.3	15.6	7.8
Energy Density	200.0	199.8	200.0
Spacecraft Mass	423.2	510.3	605.3
Total Cost	10.9	22.2	28.5
Net Present Value	33.8	221.5	318.1

Figure 10 shows a comparison between the traditional requirements-driven design space (blue dots) and the value design space (blue and red dots). This demonstrates that when arbitrary "flow-down" requirements are removed from the problem formulation, the trade space increases correspondingly. The NPV (size of the dots) has also increased from a maximum of ~$220M in the constrained formulation to nearly $310M in the VDD formulation. This significant change in value to the system is realized by having a slightly larger vehicle that can support more transponders—a design option that was ruled out by early “flow-down” requirements.

Accordingly, the modification of value in the trade space will likely result in differences in the selection process. For instance, Table 1 lists three designs that can be generated from this satellite design problem depending on the objective function that is optimized. A typical multi-objective (MO) aggregate function using a linear weighted sum on the constrained space would lead to the design listed in the MO column associated with the green triangle in Figure 10. When NPV is used as a selection criterion among the Pareto designs, the result is shown in the MO w/NPV column associated with the yellow triangle in Figure 10. The results of the value function [35] are shown in the last (NPV) column and with

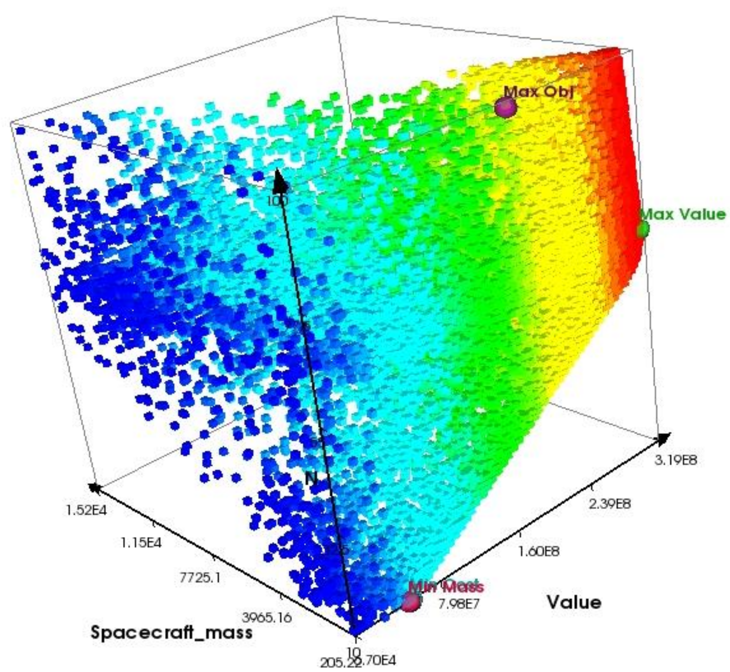

Figure 11. *3D glyph plot of Spacecraft Mass (left axis), Value (right axis), and Power (central axis)*

the orange star in Figure 10. The three designs have significantly different attributes, specifically their mass and power, which result in vastly different values. To help simplify the comparison between the three designs, a 3D glyph plot can be used.

Figure 11 is a 3D representation of the value space. Each square is a different design and the color scheme is based on NPV (red means higher profit). There are 4 indicators on the graph which show the relative positions of different optimum points. The green point at the far right is the maximum of the value function (the NPV column value from Table 1). The purple point at the top is a maximum of the multi-objective function (the MO w/NPV column value). The two overlapping points at the bottom are the minimize cost and minimize mass optimum points, which were discussed as alternatives in the satellite design chapter and both represent the results of the MO column value.

The designs in Table 1 and the glyph plot in Figure 11 help to differentiate VDD from MO and identify some of the advantages of using VDD, but it also introduces some challenges. On one hand, a VDD framework presents a unified coherent organizational value function that can be passed to subsystem designers with the expectation of directed search. On the other hand, the final design selected may differ significantly from conventional multi-objective formulations and selection processes. Multi-dimensional data visualization tools present a way of teaching and analyzing the interaction of the value function with each system as well as to present information to designers. Traditional TSE techniques can easily integrate VDD results and designers can use this information in many ways such as a filter mechanism, a new problem formulation, to improve subsystem interactions, gain new insight into the system, and help develop and advance the system value function.

Chapter Conclusion

This chapter has investigated the integration of multi-dimensional data visualization tools used to support traditional TSE for multi-objective optimization with a value-based trade environment, to provide improved decision support for decision makers during the design of complex engineered systems. The TSE visualization techniques, paired with VDD, enable a stronger "human in the loop" methodology for optimization by capturing and flowing-down preferences that reflect those of the organization. The multi-dimensional visualization tools have also illustrated the differences between traditional MDO functions and optimization in a VDD environment. The results in Table 1, as well as the visualizations in Figures 10 and 11, showcase the benefits of incorporating value functions in the design process and their impact on design selection. The TSE techniques are also shown to be useful when developing the system level value function. The explorative capacity of the tools enables the designer to better understand the underlying variable and attribute relationships that define the system, and enables them to "shop"[33] through the design space to find local and global optima. However, to have a representative value function, the designer must understand not only the system-level attributes, but those that exist at the subsystem level as well.

The driving principle of VDD is to form a value function that captures the true preference of the stakeholder, replacing the traditional multi-objective functions. One of the main hindrances with using VDD is the potentially large overhead involved in the formation of the value function. The system level value function may be simple, utilizing any available high level models for revenue and cost, but to create a detailed and accurate value function, a decomposition of the system is required. The next chapter presents an approach that addresses how the TSE techniques introduced in this chapter can be used in the decomposition process.

CHAPTER 5

DECOMPOSITION OF THE VALUE FUNCTION

After the development of a system-level value function, the next step in VDD is to decompose that function into subsystem-level value functions. The primary research focus in this chapter is to identify how novel visualization methods can support the formation of subsystem-level value functions and identify how different lower-level attributes affect the overall system value. These visualization techniques can be used as a decision support tool for this analysis, because they provide a simple mechanism for the designer to understand the correlation and trade-offs that occur between subsystem and system attributes. Once a particular subsystem has been chosen for analysis, other visualization tools can be used to observe the pairwise comparisons between subsystem attributes, the behavior of the system, or even the design variables, the parameters that define the system. This pairwise visualization tool enables decision-makers to delve deeper into design alternatives, identify new questions and hypotheses, and explore the trade space further.

Decomposition Visualization Tools

As shown in the previous chapter, parallel coordinate plots are used to show the aggregation of value and attribute interplay.With respect to decomposition, parallel coordinate plots are a valuable tool for analysis and examination of the value space as it depends on the attributes. During the conceptual design phase, the parallel coordinate plot gives the designer a general idea of where the value function is driving each of the system attributes, in order to maximize or minimize the value function.

During the preliminary design phase, the parallel coordinate plot is useful for the formation of subsystem value functions. Areas in the graph that have very collapsed regions of value may be sensitive to changes in a parameter, whereas areas in the graph that have scattered regions of value may be insensitive to changes in a parameter. This “value variability” or visual sensitivity, can help the designer indicate what design attributes or variables are most important, or could possibly be eliminated, in the value function decomposition. Figure 12 shows a high level parallel coordinate plot. The left most variable, power, shows a great deal of value variability compared to other attributes of the system.

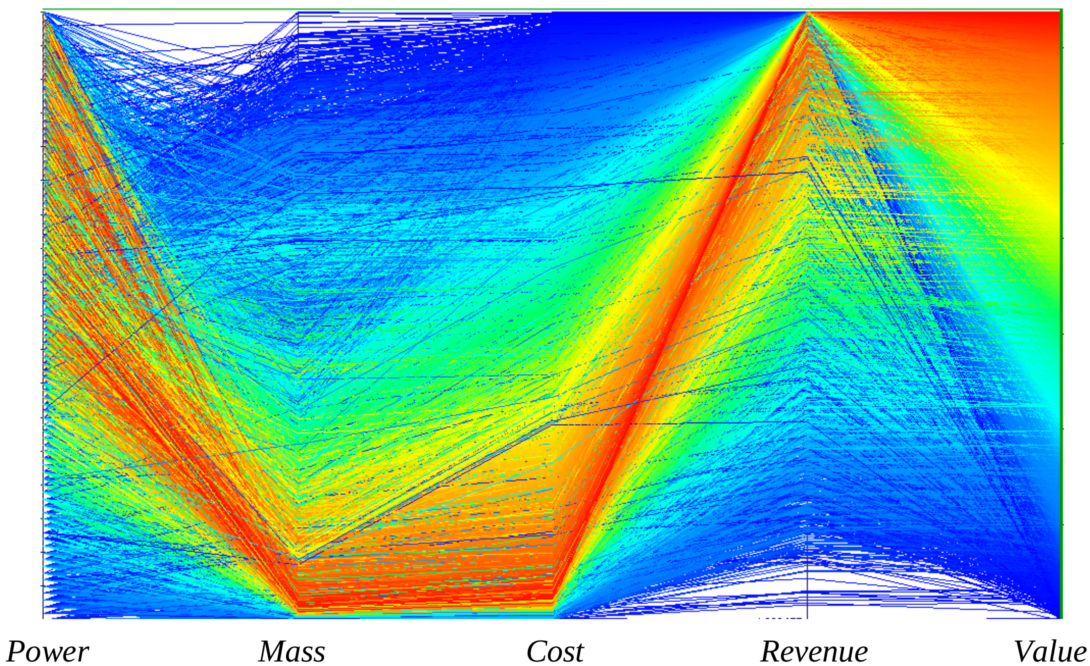

Figure 12. *High level parallel coordinate plot*

The value of a system is driven by the relationships of the subsystems that contribute to it. In traditional MDO, subsystems are in competition to meet requirements and to further their own agenda. In a VDD framework, a common value function enables the subsystems to collaborate and achieve the collective goal for the entire system. The intensity of competition/collaboration is directly correlated with the relationship each subsystem has with one another – competing subsystems tend to trade their contributions. Pairwise visualizations can enable the designer to understand how each subsystem affects the system as a whole.

The pairwise comparison visualization used in this research is a scatter matrix plot, which provides a visual representation of the relationships between system attributes or design variables plotted against one another to form a grid of 2D scatter plots. Figure 13 shows an example of this type of plot which compares: transmitter power, spacecraft mass, total cost of the system, and NPV. The black dot in each of the scatter plots represents the highest value design. The plot enables greater understanding of how design variable, like power (*Pt*), and attributes, like mass (*Mspacecraft*) affect the total cost or total profit that can be gained from a certain design. For example, the total cost has a very linear relationship with spacecraft mass because of the underlying influence of launching the spacecraft. Whereas the power of the transmitter has a much more variable relationship with the cost function, and might allow for more creativity in the final design.

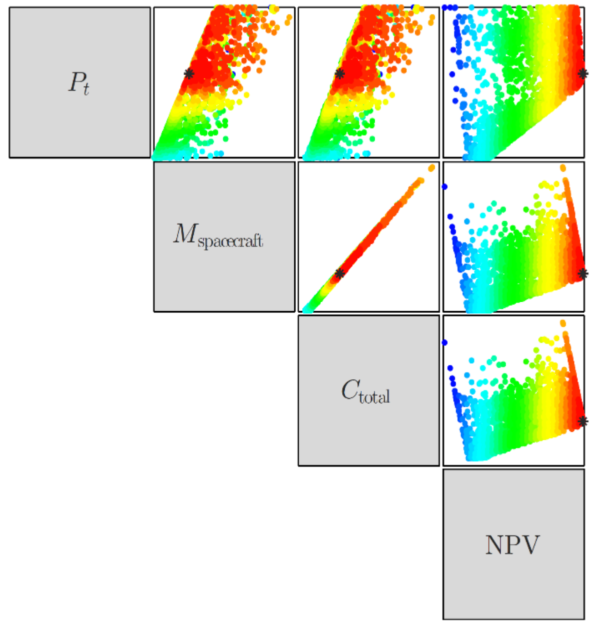

Figure 13. *Scatter matrix plot of power, spacecraft mass, system total cost and NPV.*

The attribute relationships also offer greater insight into each subsystem's impact on the overall value. Mathematically, these relationships are driven from Pearson correlations [44] of the value model of the system, i.e., the flowdown or decomposition of the value model. Visually, these formulations provide immediate feedback and context for each subsystem in the total system hierarchy. For example, in Figure 13, spacecraft mass, which is an attribute at the system level, has a linear relationship to cost, which is relatively simple. When the spacecraft mass increases, the cost increases. Transmitter power however, is a design variable in the payload subsystem. Its relationship to cost is visibly more complex, because transmitter power affects multiple other subsystems. The scatter matrix plot allows the designer to quickly indicate the optimum transmitter power (the black dot) and have a better understanding of how that component of the payload subsystem is affecting the overall system value.

The scatter matrix plot also facilitates the measuring of relationships between subsystems. This provides valuable information to designers in the preliminary design phases. The notion of “give-and-take” promotes discussion, compromise, and understanding of the decision impacts that are consequent of each system.

System Analysis

As previously desribed, the satellite design example used in this research has eight subsystems and 36 design variables.[35] Visualization of the first level of analysis involves creating parallel coordinate plots for the total system. Visualization of the lower levels involves creating parallel coordinate plots with subsystem attributes and inputs. Figure 14 shows a parallel coordinate plot of different attributes from each subsystem. The yellow boxes indicate the eight different subsystems. The color scale is based on NPV from red lines, portraying high value designs, to blue lines, portraying low value designs. The decomposition of the system is not taken into account during this analysis. Instead, the most important attributes of each subsystem are included. However, this plot may help enable the decomposition process in VDD. To develop lower-level value functions, the designer must understand how attributes

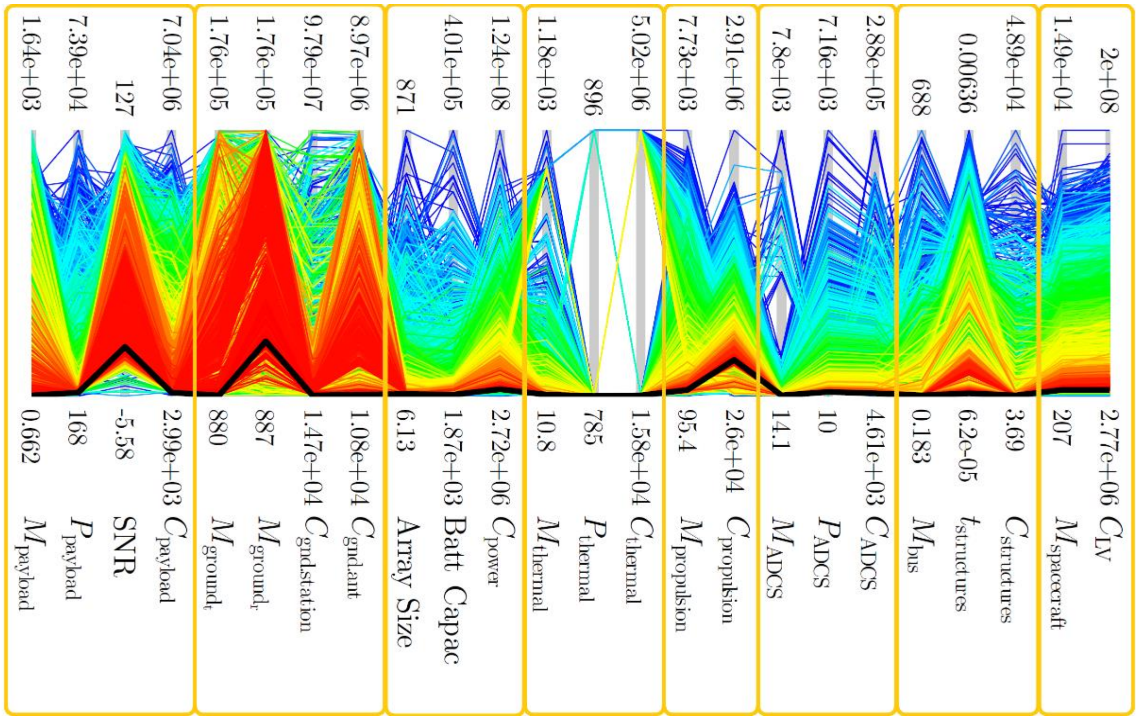

Figure 14. *Parallel coordinate plot of overall system space broken down by subsystems and colored by NPV*

and design variables affect each subsystem. For a designer, this plot is a good initial view of the system because it shows the variability of value for the most important components of each subsystem. Having a dynamic parallel coordinate plot would allow the designer to quickly compare different configurations of subsystem attributes to facilitate the appropriate divisions of labor/energy among contractors or design teams. For instance, the ADCS subsystem (the yellow box third from the right) has very linear gradients of value for all of its attributes. This means that the subsystem is sensitive to the value function and therefore there are only a few “best” design options for that subsystem. The designer could choose to reduce the energy spent on designing the ADCS subsystem or make the final decision on that subsystem earlier in the design process. This would free up labor/energy to be implemented in other subsystems, like the payload (left most yellow box) which has some attributes with high value variability, or large regions of red (high value) design space. This is a possible “indicator” for the designer to conduct further analysis on the payload subsystem, which is described in the following section.

One other interesting aspect of the system analysis parallel coordinate plot is that the value function tends to push towards the bottom constraint bound for many of the subsystem attributes. At first glance, the designer could look to question some of the bounds and explore the space beyond them, to see if there may be even more profitable design options. This visualization “shopping” or searching technique could also be applied to traditional or multi-objective design processes.

System Decomposition

Once the system-level value function is created, the next step in VDD is to decompose that function into subsystem-level value functions. Visualization can facilitate this process in two ways: (1) by providing enhanced decision support at each level of the system decomposition, and (2) by showing the relationships between the subsystems at each level. Parallel coordinate plots can be used during decomposition to show the relative importance of design variables and attributes. These concepts are demonstrated in the following two subsections.

Two-Level Subsystem Decomposition

To provide decision support at different levels of the system, two different examples of two-level decomposition are presented. Figure 15 shows a two level decomposition using parallel coordinate plots. The upper plot represents a few selected attributes from the level 1 subsystems of the satellite. This is the first decomposition of the value function, from the basic revenue and cost function, down into the eight subsystems. Each purple box in the top plot represents a different subsystem and its associated level 1 attributes. The bottom level plot represents the second level of decomposition, from the level 1 subsystems to the level 2 subsystems. This visualization follows the same paths as the satellite hierarchy, Figure 4 in Chapter 2. There is a lot that a designer can gain from this first decomposition visualization. The top level plot shows areas of value variability, specifically which subsystems have high value variability and which subsystems are defined by discrete decisions. This is critically important for decomposition of the value function. For example, the designer can see from the bottom plot that many of the attributes that affect the level 1 Thermal subsystem are discrete decisions, and therefore the value variability in the total Thermal subsystem is not very large. Another interesting aspect of the visualization is that two subsystems, ADCS and the Launch Vehicle (LV), are not decomposed further. This offers insight to the designer regarding the validity of the value function. The calculation of value for those two subsystems may be oversimplified and may cause error in the result. The visualization indicates that the high variability subsystems, such as Payload, can be analyzed further using the same plots and the same technique.

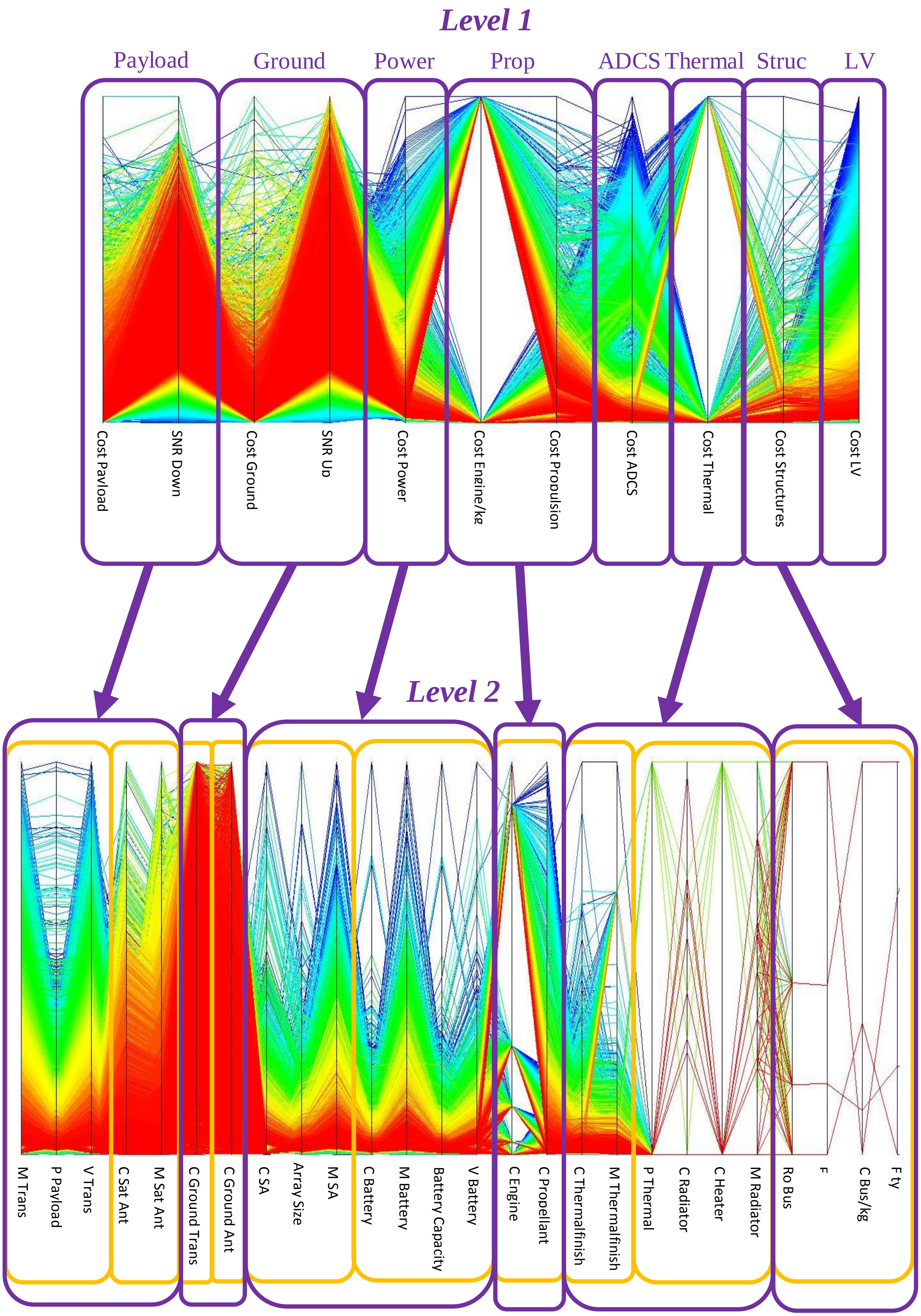

Figure 15. *Two-level decomposition of the satellite subsystems, from Subsystem level 1 to level 2*

The decomposition of the payload subsystem is shown in Figure 16. This is another two-tiered decomposition using parallel coordinate plots, with different attributes of the system. The system level plot on the top left is very simple. From left to right it only includes total cost, total revenue and NPV. The next plot shows all of the design variables and attributes at level one of the decomposition, with boxes around each subsystem. This plot demonstrates how the visualization of the multi-level dependencies can provide insight on which subsystems require further analysis.

Once a subsystem is chosen, the designer can use the final plot, the level two subsystem parallel coordinate plots, to essentially "drill-down" into the details. The Payload subsystem has low value variability associated with its power and high value variability associated with the signal-to-noise ratio. The decomposed parallel coordinate plots for the payload subsystem, shown on the bottom of Figure 16, allows the designer to better understand what the relationships are among the attribute and variables and, specifically, where those results are originating. The figure shows that the power of the payload is insensitive to change. This is because of its dependency on the power of the satellite transponders (Pst). The payload design team could therefore treat the Pst variable as a constant or near constant value, freeing up energy to work on other aspects of the design. The signal-to-noise ratio is sensitive to change because it relies on many of the design variables in the payload subsystem, including the frequencies, antenna diameters, and ground station locations. This is an aspect of the subsystem that requires further analysis and should be a main point of focus for the design team. The visualization highlights these dependencies for the designer.

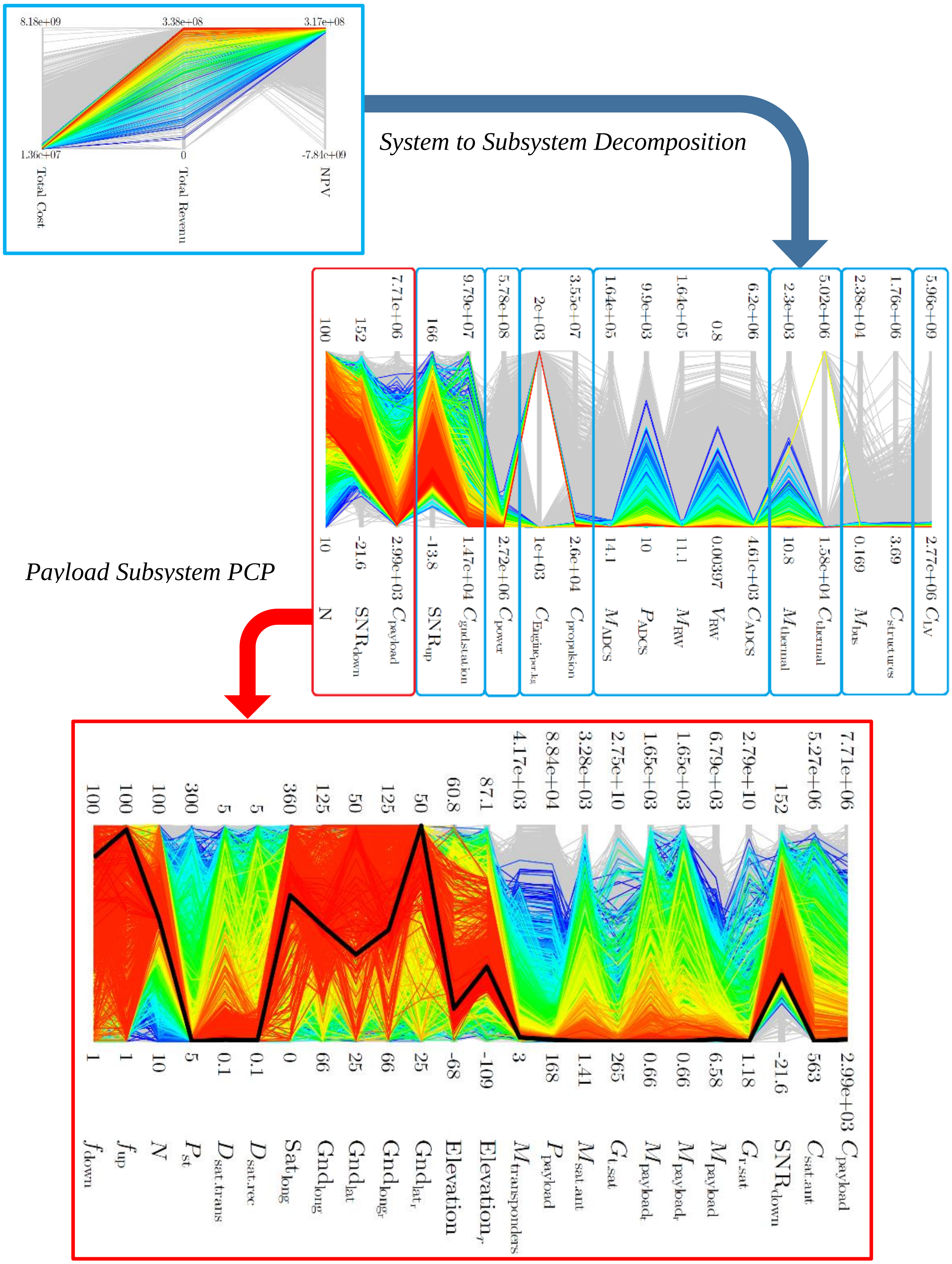

Figure 16. *Decomposition using parallel coordinate plots; Top left is the system-level value function; Top right is the first level of decomposition; Bottom is a payload subsystem parallel coordinate plot; All plots colored by NPV; gray lines <$0, blue ($0) to red ($317M)*

There are a number of important research questions that can be answered by using this two-level decomposition visualization technique. Chapter 4 showed the capabilities of visualization to expand the VDD design space, from a 1-D value solution, to a 2-D or even 3-D representation. However, these visualizations only show the highest level attributes of the system. The visualization of a decomposition that is presented in this section portrays the lower level attributes of the system. The value variability in the plots is a clear identifier of the attribute and design variable interplay. The plots can help a designer or organization decide where to allocate resources or what attributes or variables can be effectively ignored. While data alone could also demonstrate this, it would be virtually impossible for any designer to effectively understand all aspects of the 360,000 alternatives without visualization. These representations can also be used to compare different designs at multiple levels of the system. This affords the designer better communication tools for lower-level design teams. Instead of sending requirement specifications to the Payload team, the higher level design team can visually communicate how changes in the Payload subsystem will affect the system as a whole. This is a completely new approach to demonstrating these relationships. Understanding the nature of the design space more holistically is mutually beneficial to design and engineering teams. It allows for greater exploration of the design space because more people have access to the data, which can result in more innovative and creative solutions.

The visualization of a decomposition presented in this section is two-tiered, but that is only to simplify the examples in this thesis. This technique is easily extensible to multi-tiered systems, representing everything from the highest level value function, down to specific design variables of any particular subsystem. Within the organizational structure, this visualization technique represents the vertical flow of information, from the top level to the bottom level.

To analyze the lateral relationships between decomposed subsystems, different visualization tools are required.

Relationships between Subsystems

Using the two-level decomposition visualization allows the designer to indicate points of interest and understand the vertical relationships within the hierarchy, but other visualization tools are needed to analyze the horizontal relationships between the subsystems, the visual sensitivities. For this example, the scatter matrix plot in Figure 17 was created using subsystem level one attributes from the satellite.

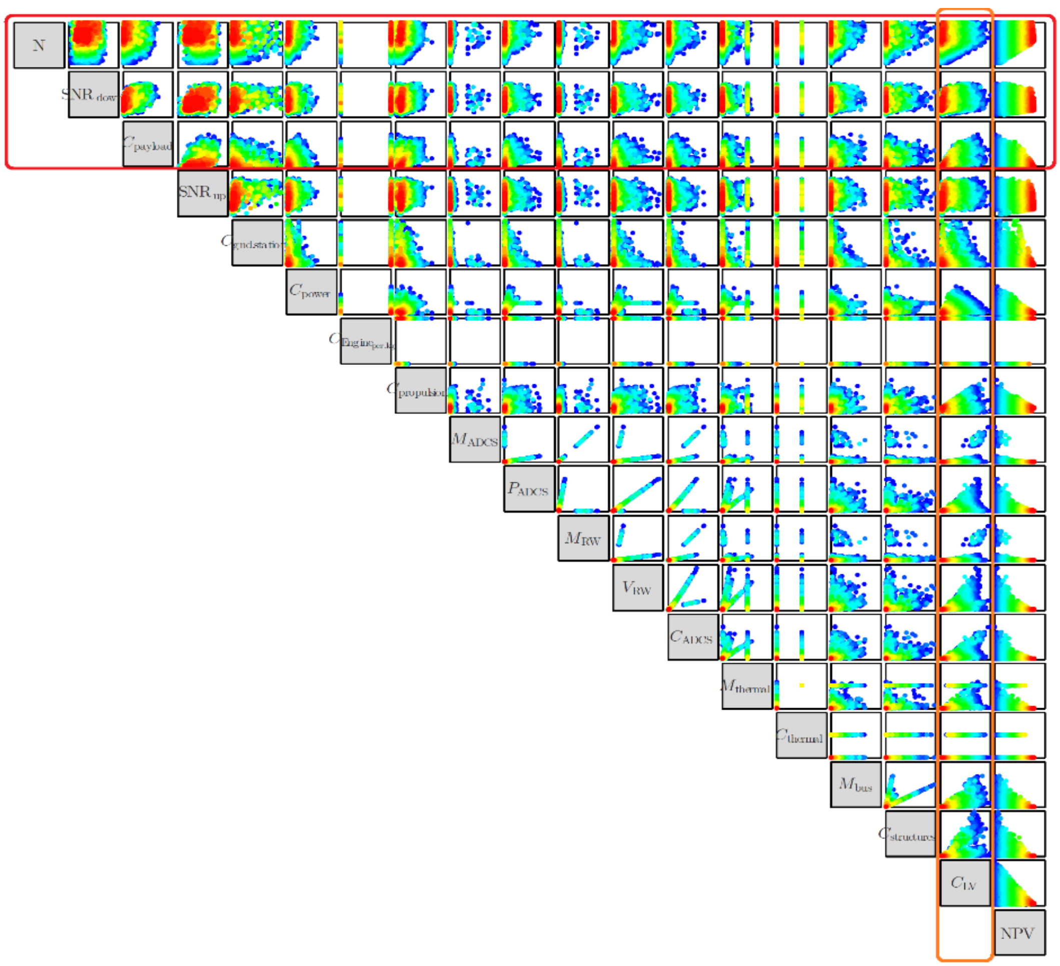

Figure 17. *Scatter matrix plot of subsystem level 1 attributes colored by NPV, blue ($0) to red ($317M)*

This visualization provides feedback in the form of heat maps for each subsystem as they work towards achieving an optimal design. The relationships between attributes are linear correlations and somewhat akin to couplings, although couplings will be further discussed in the following chapter. The purpose of the scatter matrix plot within the decomposition of the system is that it provides an ordering of the space and the sensitivity of each subsystem to the whole. For instance, the first 3 variables in the scatter matrix plot (highlighted by a red box) represent the payload subsystem and the range of attributes that that this system could provide to support the entire system. However, the payload system is not independent and therefore influences the other system attributes. This is evident with the launch vehicle subsystem (highlighted by a yellow box) which, in turn, has a small range of highly scoring designs with respect to system value. The scatter matrix plot provides feedback to the designer regarding the sensitivity of each subsystem to the system level value function. Since there is a sense of "give-and-take", system designers obtain a more vivid and concrete sense of the impact of how their decisions affect the performance of the other systems. Regions of design that are highlighted positively by the value model can provide goals and direction for the subsystem designers so that they may work and collaborate in a common frame.

The scatter matrix plots are interactive, allowing a designer to indicate specific relationships for analysis. An example decision-making scenario is presented in Figure 18. Both plots come from Figure 17. The left plot represents the signal-to-noise ratio versus the number of transponders. The right plot represents the launch vehicle cost function versus the number of transponders. The designer wants to inform the payload team regarding the optimal number of transponders for the satellite.

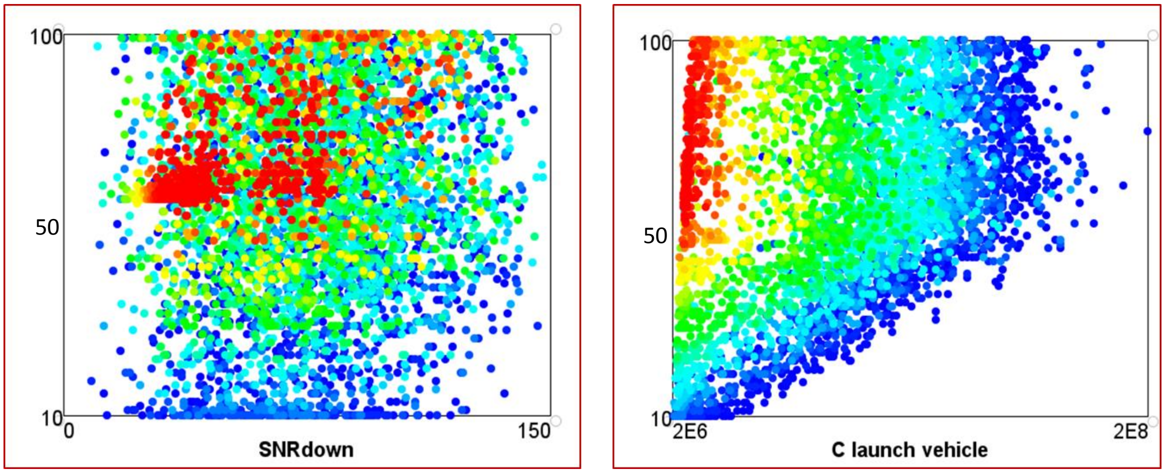

Figure 18. *(Left) Scatter plot of N vs SNRdown (Right) Scatter plot of N vs Cost LV*

Using these two heat maps, it can be seen that the clustering of optimal points is somewhere around 60 transponders. Checking the data reveals the number of the value function optimum to be 61. The decomposed attribute relationships provide a useful method for the designer to gain insight into the system.

The relationships between subsystems that are presented in the scatter matrix plots represent the visual sensitivities within the decomposition. The scatter matrix plots are simply a more detailed version of a Design Structure Matrix (DSM). The example shown in this chapter can be seen to correlate with the DSM in Figure 3 from Chapter 2. The scatter matrix plot facilitates communication between different engineering teams, and aids higher level decision makers by providing simple illustrations of the dependencies between subsystems.

Chapter Conclusion

This chapter has investigated how visualization tools including parallel coordinate plots and scatter matrix plots that capture relationships between attributes and variables as well as impacts on value, can be used to aid decision-making during the decomposition of a value function. The decision making that occurs during the design of large-scale systems is complex and involves information and data that exists at multiple levels of the organization and the system.[45] Within the decomposition of the value function, there are levels or tiers as well as subsystems within each level. Figure 19 shows the relationships transference of data vertically in the value space, from level to level, and horizontally at each level of the decomposition, in the form of a DSM.

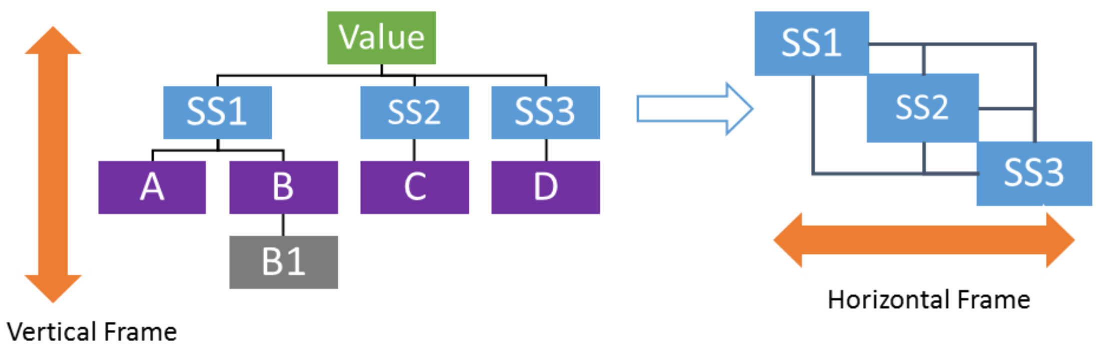

Figure 19. *Flow of data and information in a hierarchical decomposition*

In the vertical frame, visualization tools such as parallel coordinate plots can help design teams to focus in on variables and attributes that have the greatest effect on the system as a whole. In the satellite system, it was shown that attributes in the payload subsystem were insensitive to the system level value function and therefore required further analysis. Whereas attributes in the ADCS system were sensitive to the system level value function because the system was not decomposed any further. These insights can greatly aid decision making for the designer by highlighting optimal regions of the design space for each subsystem value function, as well as indicating potential problem areas.

In the horizontal frame, the subsystem relationships, represented in scatter matrix plots (similar to DSMs), show the horizontal dependencies between subsystems at the same level. The visual connections between subsystems show how the underlying value function defines the optimum regions of the design space. In Figure 17, the payload and launch vehicle subsystems were compared to show how each attribute affects the other, resulting in an optimum design space that actually minimizes the payload mass and power to lower the cost of the vehicle. However, the scatter matrix plot method is still complex. Figure 17 only includes a few attributes from the system level but it is large and difficult to understand at first glance. Visualization, as a tool for simplification, can still overload a designer. This observation affords new questions about how these tools should be used, and what methods can be developed to help a DM navigate complex design spaces. Future work in this field will address these questions, to enhance the efficiency of the visualization methods discussed in this research.

The combination of the horizontal and vertical visualization techniques provide decision support for designers and engineers, by representing the impact on value at every stage of the decomposition. However, there are two aspects of the system decomposition which are not covered using these techniques: the strength of derivative-based couplings between subsystems and the uncertainty that pervades all engineered systems.

CHAPTER 6

COUPLINGS AND UNCERTAINTY

Large-scale complex systems include multiple components and subsystems. As described in the previous chapter, the decomposition of the system involves analyzing the impact of the value function at each subsystem level. The new visualization methods used during the decomposition of a value function were shown to enable greater decision support, by identifying impactful regions of the design space and visually describing the behavior of the value function within different subsystems. However, these plots do not capture the mathematical relationships between attributes of the system (known as couplings). The primary research focus in this chapter is to check whether the underlying mathematical couplings correlate to the visual sensitivities that were identified in the satellite example, to introduce new tools for visualizing these mathematical couplings, and to implement a design under uncertainty approach to the satellite VDD process.

Coupling Analysis

In the satellite system example, the couplings are defined by derivatives. Within the VDD framework (shown in Figure 1 at the beginning of this thesis) between analysis and updating of the value function, there is a step labeled sensitivity. This box refers to the application of the Global Sensitivity Equation (GSE) method to the coupled subsystem analyses to obtain total system derivatives.[46, 47] The GSE method is an efficient approach for decoupling a large system into smaller subsystems in order to obtain the sensitivities between subsystems, and the sensitivity of one subsystem to the value function as a whole.[48] For the satellite example, two sets of total derivatives were used. The first set represents the sensitivity of the value function to the subsystem level one attributes (dV/dA), also known as a global derivative. The second set represents the sensitivity of the subsystem attributes to one another ($\partial A_i/\partial A_j$), also known as a local derivative. Two separate visualization techniques were developed to present these sensitivities.

Figure 18 is a combination of a bar chart and parallel coordinate plot from Figure 15. The bars represent the global derivative of the total value of the system with respect to each subsystem level 1 attribute. The parallel coordinate plot, as described in Chapter 5, shows how changes in these attributes affect the value function. Both plots describe sensitivity; one through the mathematical relationships that exist in the background equations and one through the visual results of the value function. Using these plots together affords the designer a more holistic understanding of the sensitivities of the value function to each attribute.

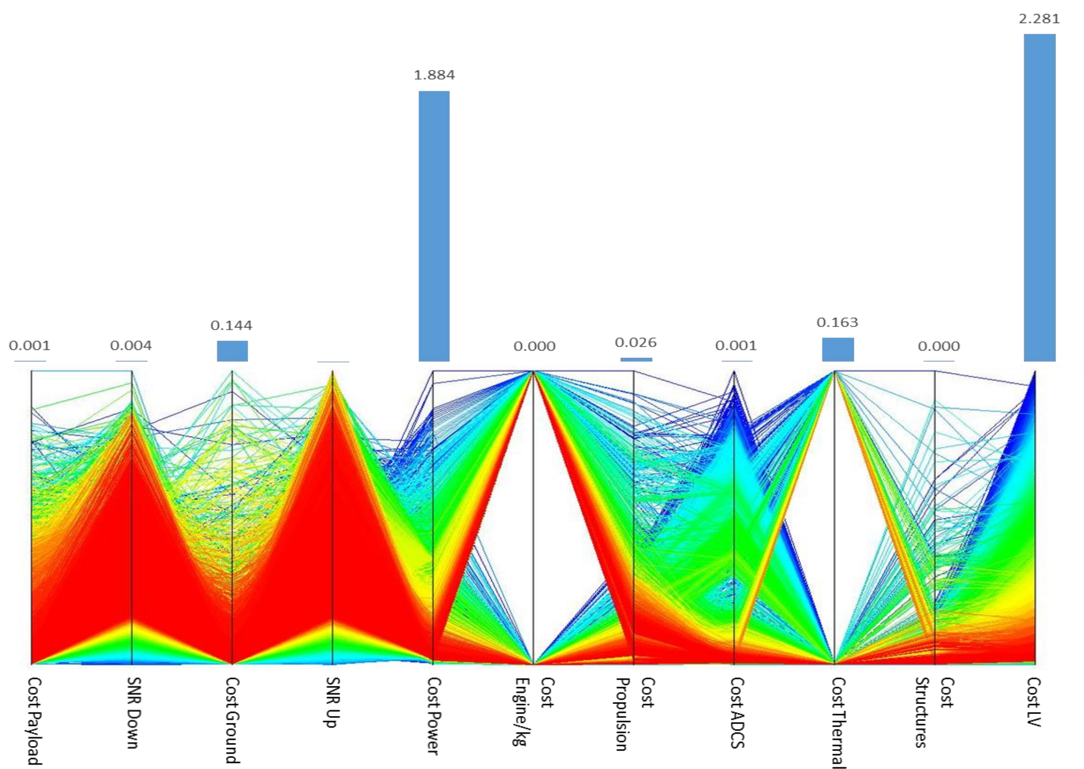

Figure 18. *(Top) global derivatives Value with respect to the SSL1 attributes (Bottom) Parallel coordinate plot of SSL1 Attributes*

It is clearly apparent from the derivative bar charts, that attributes associated with the power and launch vehicle subsystems have large global derivatives. In other words, the value changes substantially with small changes in these attributes. From the parallel coordinate plot, it can be seen that these attribute also have low value variability, or small gradients of value. Therefore, the value function is relatively sensitive to changes in the power and launch vehicle subsystems. Whereas, the signal-to-noise ratios (SNR Down and SNR Up) have small global derivative values and large value variability in the parallel coordinate plot. Therefore, the value function is relatively insensitive to changes in the signal-to-noise ratios. The numerical sensitivities associated with level 1 subsystems provide mathematical rigor and support to the visual sensitivities that were presented in Chapters 4 and 5.

These figures demonstrate a correlation between value variability and global derivatives at the system and first subsystem levels. However, some of the attributes do not correlate as well as others. For example, the ADCS and Structures attributes have almost zero global derivative values, but still contain some variability in the parallel coordinate plot. This could be due to the normalization of the derivative, the bounds of the parallel coordinate plot, or an unknown reason. The technique is valuable but requires further analysis. Also, this representation can not be used for lower levels because of the complexity of the derivatives at lower stages and the degree to which lateral couplings amongst subsystems exist. A lower level subsystem global derivative, its total effect on the system value function, is affected by many other subsystems and design variables, and it is therefore skewed by the local derivatives. An opportunity exists for future work to develop methods to capture all of the couplings throughout the system in a single visualization. This research provides a model for that visualization in the form of a Visual Design Structure Matrix (VDSM).

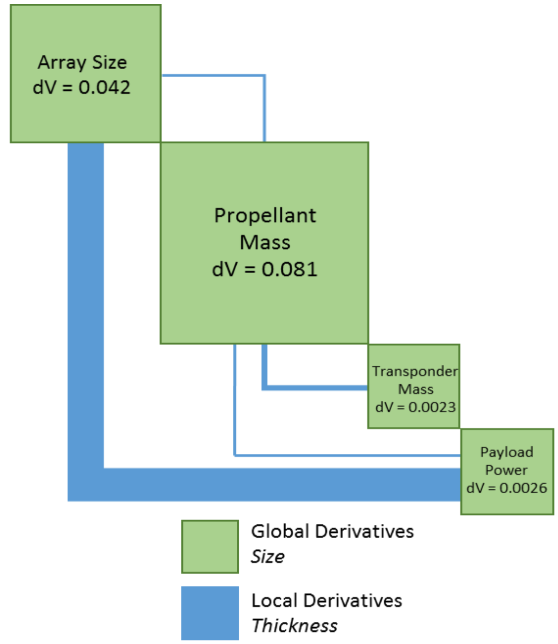

Figure 19. *VDSM of subsystem attributes*

The DSM, as described in previous chapters, is a simple tool for the analysis of a system. The VDSM is an interactive DSM that allows the designer to select which subsystem relationships they would like to analyze. Figure 19 shows a sample VDSM with four subsystem attributes: Array Size, Propellant Mass, Transponder Mass, and Payload Power. The global derivative of each attribute (the dV values) correlate to a change in the size of each box. The propellant mass has the greatest effect on the total value, and the transponder mass and payload power have the lowest impacts. This is due to the cost function which is greatly affected by the mass of the propellant. The lines that connect each attribute box represent their local derivatives. These lines change thickness based on the strength of the local coupling. The placement of the line, as a feedforward or feedback, represents the direction of the local coupling. For example, the thick line between array size and payload power corresponds to a strong local derivative. Within the value space, the output of the payload power has a strong effect on the array size, but a small effect on the propellant mass.

The VDSM provides the capability for a designer to quickly assess the impact and importance of all of the couplings within a system. The interactive nature of the VDSM allows the designer to target specific subsystems or disciplines and enhance their understanding of the sensitivities. Future work in this field will analyze the uncertainty in the system and how it is propagated from the design variables to the total value, and how this can be represented visually to quickly enable enhanced decision support. A foundation for this work is described in the following section.

Uncertainty Analysis

Uncertainty is inherent in all complex engineered systems.[49] The uncertainty represents an incompleteness in knowledge and inherent variability of the system and its environment.[50] Uncertainty is present in the models, the constraints, and the variables. Presently, value functions rarely include uncertainty. However, uncertainty must be addressed as the VDD field advances to make value functions more realistic and applicable to real world systems.

A visual representation can be used to convey the importance of including uncertainty in value functions and to support decision-making under uncertainty. Figure 20 shows a 'before and after' plot for the application of uncertainty.

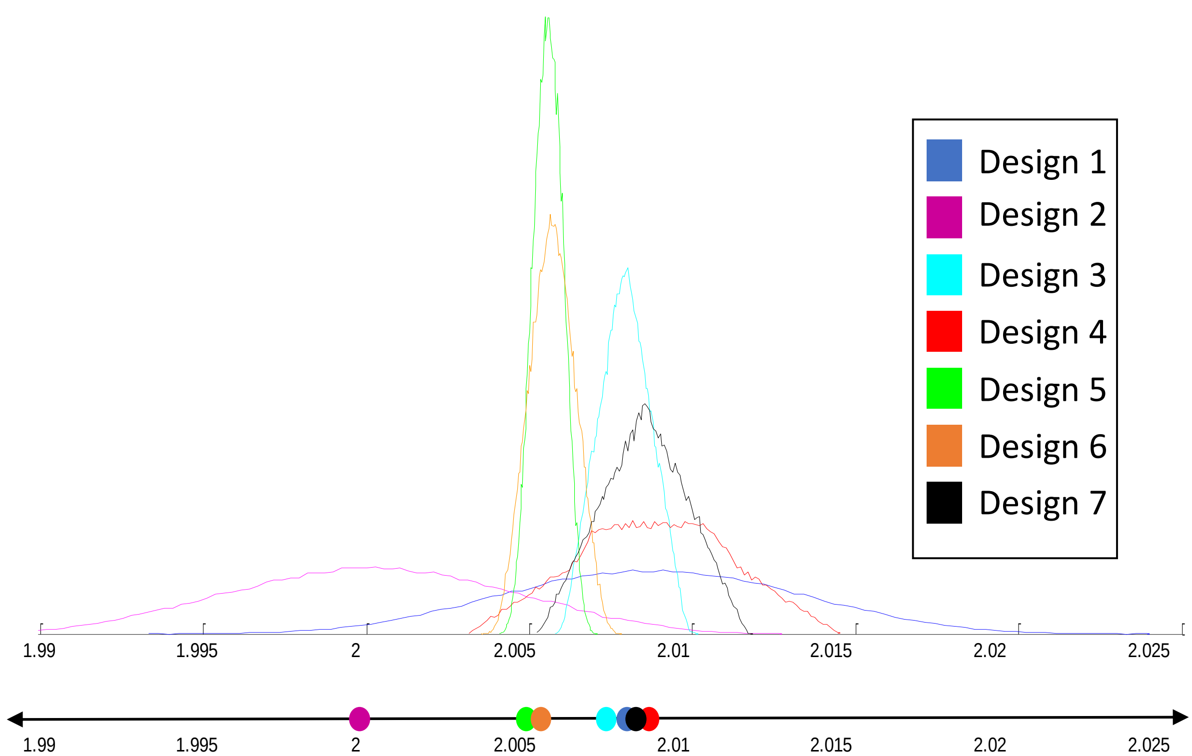

Figure 20. *(Bottom) 2-D line plot of 7 designs ranked by NPV (Top) PDF plots of 7 designs with uncertainty*

The bottom line represents the results of the satellite value function for seven separate design alternatives. This 2-D line plot provides the ranking of the designs by NPV. However, when uncertainty is included, the rankings change.

The uncertainty of NPV in this plot was propagated from 13 design variables including: antenna diameters, transmitter frequencies, satellite and ground station power measurements, and the GPS coordinates of the ground location. Each design variable was assigned a triangular distribution based on appropriate constaints, manufacturing tolerances, or typical errors. A monte carlo simulation was conducted using random design variables from within their distributions and a range of NPV was calculated. The NPV ranges are plotted as probability density functions (PDF). The propogation of triangular distributions in the design variables, results in relatively normal distributions of NPV, as seen in Figure 20. It is clear that the inclusion of uncertainty will have a durastic effects on the rankings of designs. Table 2 shows the original design rankings on the left, and on the right, the 95% certainty values of the PDFs. The 95% certainty interval is the most common assumption for statistically signifigant values in an uncertain range.[51] Even with relatively conservative design variable uncertainties, the design rankings change signifigantly.

Table 2. *(Left) Ranking of design by NPV w/o uncertainty (Right) Ranking of designs by NPV with %95 confidence*

Design	Value
4	2.00880E+08
1	2.00873E+08
7	2.00851E+08
3	2.00792E+08
6	2.00569E+08
5	2.00557E+08
2	2.00012E+08

Design	95% Confidence
3	2.00661E+08
7	2.00631E+08
4	2.00496E+08
5	2.00482E+08
6	2.00457E+08
1	2.00149E+08
2	1.99314E+08

The lowest ranked designs tend to stay the same, but the top of the rankings are completely different. The change in rank of design alterntaive #1 is particularly signifigant. Design #1 has one of the highest original NPV, but it also has the largest value range as a result of the uncertainty in relevant design variables. Therefore, when uncertainty is applied to the design, the designer can no longer be confident in its original top-3 ranking.

The uncertainty analysis that was conducted represented a small subset of the value space. In a real world application, the inclusion of uncertainty in a value function could be a multi-million dollar profit advantage. The simple 2D visualization of PDFs gives the designer a better understanding of how uncertainty propagates through the design space, allowing them to make more informed decisions. The visualization of probabilities also represents the robustness of a particular design.[52-54] In general, a robust system is one that is capable of operating under variations in the environment and in the system iteself. Robustness is one of the most important and desired aspects of a system, so the capability to quickly ascertain and compare uncertainty in design alternatives is extremely valuable to a designer.[55] After the intial analysis, one of the most important components of analyzing uncertainty in a design space, is the risk preference of the designer. This risk preference can be represented using utility functions.

Utility theory was developed by economists and mathematicions in the early 20th century to integrate risk preferences, and add mathematical rigor to the field of decision theory.[56, 57] The utility function assigns a ranking to members of a set based on the preference of the designer. A risk averse or “risk hating” designer is less inclined to choose a design that has a large amount of uncertainty or a broad probability range, whereas a risk proverse or “risk loving” designer would be more willing to take risks if it could result in a higher value design alternatives. The utility function that was used for the satellite example, shown in Eq 6., is a common exponential utility function [58] where c is the NPV of the satellite and a is the risk coefficient. A positive risk coefficient represents a risk averse designer, and a negative risk coefficient represents a risk proverse designer.

$$U = -\frac{1}{a} * e^{-a*c} \quad (6)$$

Table 3. *(Left) Ranking of designs by Utility for a Risk Averse Function (Right) Ranking of designs by Utility with Rise Proverse Function*

Design	Risk Averse
7	9.9484
4	9.9461
3	9.9414
1	9.9071
6	9.8930
5	9.8909
2	9.0249

Design	Risk Proverse
1	5.79537
4	3.62785
7	2.96439
3	2.40832
6	1.29489
5	1.23849
2	0.556661

Table 3 shows the results of the utility function with risk averse rankings on the left, and risk proverse rankings on the right. The actual utility scores, in units of utils, are meaningless. It is the design rankings that are important, and they change significantly between the two risk scenarios. The top-3 design choices are different but tracking the change in design alternative #1 provides the best comparison. In the risk averse scenario, the designer is risk hating, and because design alternative #1 has such a wide range of possible values, the utility function scores it lower in the rankings. In the risk proverse scenario, the designer is risk loving, and therefore design alternative #1 ranks first because there is a chance that the NPV will be high. The utility function provides a simple and effective way to communicate risk preferences when choosing designs. The initial NPV, the confidence values, and utility function results can be compared numerically, but the presentation of PDF plots provides additional information about the nature of the uncertainty, and how it propagates from design variables all the way up the hierarchy to the system level value function.

Chapter Conclusion

Couplings strengths and uncertainty are important components of effectively implementing VDD. Derivatives of the value function with respect to attributes and design variables, allow the designer to gain a heightened understanding of the relationships that exist within the system. The local derivatives represent the couplings between the many subsystems and components, and the global derivatives represent the affect each subsystem has on the total system value. These two sets of couplings can be displayed using TSE tools, as well as in interactive VDSMs, to enhance the designer's capability to conduct trade-off studies and sensitivity analysis. The work described in this thesis represents a foundation for future work in this field. This thesis demonstrated, the comparison of visual and numerical sensitivities using visualization, the development of a VDSM interface, and the integration of uncertainty in the visual design space, to enable more informed decision making.

Representation of uncertainty is a particularly important aspect of this work. Uncertainty exists in every system and every decision. Uncertainty occurs at the lowest level of the design process, in the manufacturing of components, in the models and subsystems, and it compounds into probabilities that must be addressed at the highest levels of design decision-making. Visualization can provide a means to present the propagation of uncertainty from design variables to the value function in a way that is simple and meaningful for designers. As the field of VDD advances, it will be imperative to include uncertainty in value functions to make them more accurate, realistic, and representative of actual systems.

CHAPTER 6

CONCLUSION

Value-Driven Design was developed as means to improve the design process by enabling and facilitating MDO, reducing the focus on the requirements, more accurately representing stakeholder preference, and expanding the feasible design space.[21, 59, 60] However, when the design space is essentially unconstrained, it becomes more complex to explore. Visualization tools are therefore necessary to provide decision support to the designer by simplifying the design process, and presenting data in meaningful ways. Further, the application of a value driven approach to design necessitates a rethinking of what a tradespace is for engineering design. There are a number of established TSE tools, as well as proposed visualization tools, that have been presented in this research to aid decision-makers during the design process. There are three important steps during the VDD process at which visualization tools are particularly useful: the development of the value function and exploration of the initial value space, the decomposition of the value function, and the propagation of uncertainty and coupling relationships.

The initial exploration of the value space can be useful to a designer when they are developing and improving value functions and during the initial optimization of the design space. Chapter 3 presented methods for visualizing the design space for a sample satellite system. TSE tools, including scatter plots and parallel coordinate plots, were used to compare MDO with VDD and demonstrate how these tools could be used to “shop”[33] through the design space, to specify regions of interest, and improve the value function.

Chapter 4 focused on an approach that uses TSE tools to provide assistance to the designer during the decomposition and flowdown of attributes. The satellite system has a hierarchical organization, with multiple tiers of subsystems and components. Visualization tools were used to analyze the decomposition in different ways. It was shown that multiple parallel coordinate plots can track the value function from the lower level design variables, vertically up the organization, to the system level value function. This allows the designer to conduct sensitivity analysis without calculating global derivatives, and gives them a better understanding of how the value propagates throughout the system. The scatter matrix plots were used to analyze a single tier of the decomposition. Similar to a DSM, the plot allows the designer to compare subsystems to one another through the attribute relationships. Combining these two tools gives the designer an enhanced understanding of the entire decomposed value space, which allows them to make more informed decisions regarding: the allocation of resources, the simplification of variables or subsystems, and the validity of the value function.

Chapter 5 focused on the propagation of uncertainty and the global and local derivatives. One of the advantages of using parallel coordinate plots with the value function, is that the designer does not need to calculate derivatives, which can be costly for large systems. However, if the derivatives are available, then visualization tools can be used to present them to the designer, as well. The VDSM that was developed and presented in this research can aid the designer after the value function has been established, to better understand attribute relationships and their relative importance in the design. The VDSM and the comparison plots from Chapter 5 are a foundation for future work in this field. An interactive VDSM will enable the designer to more accurately drill-down into the subsystem to understand the underlying physical relationships and sensitivities. The application of uncertainty in design variables and the way this uncertainty propagates through the system to impact the value function was the final research section of this thesis. It is clear that uncertainty must be included for value functions to be representative of real world systems. Visualization of uncertainty, through PDFs, allows the designer to better understand value rankings and also the robustness of the designs. Once a small set of designs is chosen, the uncertainty can be used to differentiate them for a final design alternative selection. Utility functions are also useful at this stage of the design process as a means to integrate preferences. The risk preference of the designer is important during decision-making and can again help to simplify the value space by eliminating unfeasible designs. The representations in Chapter 5 demonstrated clearly how uncertainty and risk preferences can significantly change alternative selection.

This research has focused on developing new visualization representations for attribute and value relationships as well as uncertainty propagation to aid decision-makers during the value-driven design process. The exploration of the design space, using traditional trade space exploration tools, can assist in value function formulation and initial system decisions. Visualization associated with value function decomposition help the designer to understand how subsystems interact within the value space. Designing under uncertainty and conducting derivative-based coupling analyses help to create more robust and accurate value functions. Future work on this project will expand on all three methods using a number of different example systems, including aerospace and transportation. Uncertainty will be a primary focus moving forward, so that the implementation of VDD can be more realistic. This research serves as a foundation for future work that will continue to advance Value-Driven Design as a desired and powerful process for design and systems engineering.

APPENDIX

***Table A:** Satellite Design Variables and Attributes*

Tiers				Attributes	Design variables
SYSTEM (Geo Communication Satellite)				Total cost, Revenue	Single satellite or satellite constellation?
Subsystem level 1	**(SS1)** Payload			$C_{payload}$, SNR_d	N,Type of HPA, Satellite longitude
	(SS2) Ground Station			C_{ground}, SNR_{up}	Ground $longitude_{rec}$, Ground $latitude_{rec}$ Ground $longitude_{trans}$, Ground $latitude_{trans}$
	(SS3) Power			C_{power}	Type of power source
	(SS4) Propulsion			$C_{Engine/kg}$, $C_{propulsion}$	Type of liquid propulsion system(mono/bi)
	(SS5) ADCS			C_{ADCS}	Type of controller
	(SS6) Thermal			$C_{thermal}$	Type of passive thermal control
	(SS7) Structures			$C_{structures}$	Configuration of bus
	(SS8) Launch vehicle			C_{LV}	Launch site/Type of vehicle
Subsystem level 2	Payload	**(SS1)** Satellite Transponders		M_{trans}, $P_{payload}$, V_{trans}	P_{st}
		(SS2) Satellite antennae		$C_{sat,ant}$, $M_{sat\ ant}$	Antenna type (Parabolic/Helical antenna)
	Ground station	**(SS1)** Ground transponder		$C_{g,transmitter}$	P_{gt}
		(SS2) Ground antennae		$C_{g,antennae}$	Antenna type (Parabolic/Helical antenna)
	Power	**(SS1)** Solar Array		C_{SA}, Array size, M_{SA}	SA_material
		(SS2) Battery		C_{Batt}, Battery mass, Battery capacity, V_{batt}	Battery type
	Propulsion	**(SS1)** Propellant		$M_{propellant}$, $V_{propellant}$, C_{Engine}, $C_{propellant}$	Propellant
	Thermal	**(SS1)** Surface Finish		$C_{thermalfinish}$	$\left(\frac{\alpha}{\varepsilon}\right)_{SA}, \left(\frac{\alpha}{\varepsilon}\right)_{sat,trans}, \left(\frac{\alpha}{\varepsilon}\right)_{sat,rec}, \left(\frac{\alpha}{\varepsilon}\right)_{bus}$
		(SS2) Radiator and Heater		$P_{thermal}$, $C_{radiator}$, C_{heater}, $M_{radiator}$	$\varepsilon_{rad_{battery}}, \varepsilon_{rad_{RW}}, \varepsilon_{rad_{proptan}}$
	Structures	**(SS1)** Bus		$C_{bus/kg}$,	Bus material
Subsystem level 3		Satellite antennae	**(SS1)** Satellite transmitting antenna	G_{st}, M_{st}	f_{down}, D_{st}
			(SS2) Satellite receiving antenna	G_{sr}, M_{sr}	D_{sr}
		Ground antennae	**(SS1)** Ground transmitting antenna	M_{gt},G_{gt}	D_{gt}, f_{up}
			(SS2) Ground receiving antenna	M_{gr},G_{gr}	D_{gr}
	Propulsion	Propellant	**(SS1)** Propellant tank	$M_{proptank}$, $V_{proptank}$,$C_{proptank}$	Propellant tank material

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