An Early-Stage Set-Based Design Reduction Decision Support Framework Utilizing Design Space Mapping and a Graph Theoretic Markov Decision Process Formulation

by

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Dedication

To my parents,

who support and encourage me in all my endeavors.

Acknowledgements

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Table of Contents

List of Figures

List of Tables

Abstract

A novel set reduction decision support framework for large-scale, team-based design efforts is presented. The framework provides a design manager with valuable and easy-to-understand information that is used to make better informed reduction decisions within a set-based design (SBD) environment. SBD is a convergent design method that uses dominance and infeasibility to consider multiple design alternatives in parallel while accommodating separate groups of specialists within a concurrent engineering approach. Based on the limitations of current SBD research and the completion of extensive design experiments, three major set reduction considerations are identified: time-dependent design relationships, the impact of reduction decisions, and identifying robust reduction decisions. Design relationships change as the fidelity of analysis increases, variable set-ranges are reduced, or requirement changes are instituted. Due to these changing conditions, the impact of reduction decisions can be difficult to determine. Although SBD has proven resilient to changing circumstances, the reduction process can still be impact the design process to the point of potential failure. Identifying robust reduction decisions avoids situations where changes lead to a design failure.

Each of the three considerations set forth is addressed by a specific component of the overall decision support framework used to analyze a specific function of interest. Design space mapping is used to determine relationships between variable and function spaces. The Longest Path Problem (LPP) formulated as a Markov Decision Process (MDP) is used as a structure for the reduction decision-making process and the identification of optimal decision paths. Through simulation, robust decision paths are identified. Since the developed LPP MDP formulation has never been used to analyze set reduction problems, multiple metrics and representations are developed using the MDP and simulation results.

Based on a series of studies, the MDP LPP framework is able to better handle situations with changing conditions, as well as better accommodate constrained problems, compared to a method based solely on current in-state knowledge. As part of a ship design case study, the framework's ability to handle multiple and more complicated functions is shown. Also, how the framework fits into a more realistic reduction scenario is presented.

Chapter 1: Introduction

Nothing endures but change.

–Heraclitus (535BC – 475BC)

There are a number of complexities associated with early-stage ship design, particularly for naval combatants, including the lack of design knowledge, the unavailability of adequate analysis tools, unknown and changing requirements, and diverse teams of designers working together. Additionally, early-stage design decisions significantly impact the size, performance, and cost of the final product. Designers are aware of the importance of early-stage decisions; therefore, emphasis is placed on making the best decisions possible. However, as Heraclitus describes, the only thing that is constant is change, and ignoring the likelihood of changes occurring can lead to a failed design effort.

Organizations such as the U.S. Navy have struggled with management of complexities and changes that arise during early-stage design. Much of the challenge is related to the ambiguity between what are considered design methods and tools. Tools are supposed to support and enable design methods, but they often restrict design when viewed as a method. Currently within the Naval ship design community, there is a conflicting effort to define the preferred design method. Due to its complex nature, the design process requires concurrent engineering (i.e. large teams of designers), but the community desires automated physics-based modeling and synthesis (i.e. no people). This conflict stems from the belief that physics-based models are design *tools*, not methods in and of themselves.

In an attempt to mitigate this conflict, the set-based design (SBD) method has recently been employed within the U.S. Navy (Kassel, Cooper, & Mackenna, 2010; Eccles 2010; Doerry, 2009; Sullivan, 2008). SBD provides a framework for large-scale, team-based design activities, while maintaining the flexibility to properly use various types and forms of tools throughout the design process. The execution of SBD principles within the U.S. Navy, however, has proved challenging, mainly due to its unique culture and a lack of supportive tools (Doerry, 2010; Singer, Doerry, & Buckley, 2009; Mebane et al., 2011).

This dissertation focuses on a particular aspect of SBD execution, design solution reduction decision making, which deals with the identification of solutions that are eliminated from consideration. Through the use of design space mapping (DM) and a graph theoretic Markov Decision Process (MDP) formulation, the developed framework is able to understand dynamically changing design relationships and provide guidance on the reduction of design solutions by identifying robust decision paths. This introduction first discusses, in greater detail, the SBD method and the U.S. Navy's interest in applying it for early-stage design activities. The motivation and scope of the research presented in this dissertation is then defined. Finally, the contributions of this dissertation to both the general design and SBD fields, as well as the structure of the dissertation, are outlined.

1.1 Background

SBD is a design method developed in the automotive industry by Toyota, formalized by Ward, Sobek, Christiano, and Liker (1995). This concurrent engineering method provides a theoretical framework for large-scale, team-based design activities that uses set-ranges of design variables, focusing on eliminating infeasible or dominated solutions versus searching for an optimal solution. There are many advantages of using SBD, which include:

- Having a thorough understanding of the design space,
- The use of set-ranges to provide flexibility in handling uncertainties,
- The ability to track design decisions, and

- The ability to delay decisions until more information is known and design tradeoffs are more fully understood (McKenney, Kemink, & Singer, 2011; Sobek, 1997; Liker, Sobek, Ward, & Christiano, 1996; Ward, Liker, Christiano, & Sobek, 1995).

Given these advantages, the U.S. Navy has recently shown a desire to execute the SBD method for the ship design process (Kassel, Cooper, & Mackenna, 2010; Eccles 2010; Doerry, 2009; Sullivan, 2008). In 2007, the Ship to Shore Connector (SSC) Program began Preliminary Design using SBD as a novel approach to consider more alternatives in less time, during the early stages of the three year target schedule (Mebane et al., 2011). The SSC Program marks the first application of the SBD method for a U.S. Navy design. After completion of the SBD effort in September 2008, advantages were identified and most SSC team members saw value in the method (Doerry, 2010). Along with its successful execution, there were a number of lessons learned, including the difficulty of extending the method to larger-scale programs and more complex design processes.

One of the major challenges associated with SBD execution is the set reduction decision making process (McKenney & Singer, 2012; Doerry, 2010; Malak, Aughenbaugh, & Paredis, 2009; Nahm & Ishikawa, 2006; Ford & Sobek, 2005). As variable set-ranges are modified and the design progresses, analysis tools and design relationships change. These temporal dynamics make it more difficult to fully understand the implications of modifying set-ranges, and in what order. Determining when and by how much to reduce or expand a set-range is currently a more heuristic process, decided by a chief engineer or design manager. Additionally, unlike the extensive databases on acceptable automotive set-ranges and interactions between variables developed at Toyota, the U.S. Navy has yet to develop these resources. The processes that designers use to arrive at the final solution, as well as the actual design decisions executed, are just as important as the evaluation of solutions for this reason. The human designer has control over when and what decisions to make during a design process; therefore, providing the designer with the best information at all times becomes essential.

The world-renowned reputation of Toyota for quality, safety, and value has been one way to highlight the effectiveness and success of the SBD practices established based on Toyota's product development process. However, since the beginning of 2008, there have been a series of public criticisms and recalls that damaged Toyota's reputation. Liker and Ogden (2011) provide a detailed account of the recall crises in their book *Toyota Under Fire*. To summarize, Toyota's recalls stemmed from technical issues caused by a small number of engineering design errors, not the manufacturing process. While the technical issues were considered minor, Toyota management in Japan did not fully appreciate the seriousness of American perceptions of Toyota's products, and the implications of their nonchalant reactions to the issues. The main conclusions to draw from this example are that communication between headquarters and its regional organizations were limited, there was little understanding or appreciation of American perceptions, and that regional organizational management had little control to act within the timeframe that the public desired. The Toyota recall crises identified the challenge of executing the principles that had made them successful in the past. Toyota's management did not identify their methods as failures, however, instead concluding that Toyota needed to stay true to their core values, and most importantly, their emphasis on learning from their mistakes.

1.2 Motivation

Principles observed at Toyota provide a framework for SBD execution in other fields, but a textbook execution based on their process is not practical. Toyota has spent decades developing and modifying extensive documents and databases of the process, identifying lessons learned, and fostering a culture around its guiding principles. In organizations such as the U.S. Navy, SBD can provide the framework to achieve the requirement for concurrent engineering, where complex design is completed by large teams of designers. The relatively unstructured execution process used for the SSC Program presents challenges in larger-scale programs, and Toyota's detailed process cannot be replicated. While a heuristic approach can be used for smaller design activities with understandable design relationships, large-scale efforts have much more complex relationships that a designer cannot fully understand. Related SBD research has been in two major areas. One area focuses on related problems – not directly addressed in this dissertation – using optimization techniques, multi-objective Pareto fronts, design space exploration, and automated convergence approaches (Avigad & Moshaiov, 2010; Shahan & Seepersad, 2009; Panchal, Gero Fernandez, Paredis, Allen, & Mistree, 2007). The second area focuses on team dynamics, but is limited when dealing with guiding set reduction (Gray, 2011, Singer, 2003). Therefore, there is a significant part of SBD execution for large-scale, team-based design activities that is missing.

If there is a requirement to conduct team-based design, which most large organizations demand, a method that enables understanding of design relationships and guiding design convergence is needed. Focus needs to be placed on design decisions as the process evolves and how changes in design relationships affect designer preferences and the design direction. Without a structured approach to large-scale, team-based concurrent engineering, execution would not be possible.

1.3 Research Scope

There are many aspects of SBD execution, such as managing a large-scale, team-based approach, communication of sets, and facilitation of preference generation. There has been successful research in some of these areas, while others remain mostly untouched. One aspect that remains an open research area is the guidance of set reductions through the integration of designer preferences during the design process. This knowledge gap is the focus of this dissertation. As part of the set reduction guidance research, three major considerations are directly addressed: time-dependent design relationships, the impact of reduction decisions, and identifying robust design decisions. Each consideration is discussed briefly below.

1.3.1 Time-Dependent Design Relationships

Regardless of the design method used, dividing a design into manageable components can be difficult, and there will always be interdependencies to consider (Jones, 1992). The SBD method can reduce interdependencies of a complex design process by using feasible set-ranges that are communicated and negotiated between designers (Liker, Sobek, Ward, & Cristiano, 1996). However, when dealing with multiple designers and set-ranges, there is a need for tools that facilitate the exchange of information, as well as the need to identify other factors involved (Liker, Sobek, Ward, & Cristiano, 1996).

While some interdependencies are captured through the negotiated sets, additional dependencies can arise due to set reductions, the use of higher fidelity analysis tools, and changes in requirements. Reducing a set-range associated with one variable can impact the relationship between that variable and another variable or function of interest. Switching to a higher fidelity tool typically adds variables and design relationships. Also, requirement changes can shift the feasibility of an entire set-range significantly, depending on its degree. The key component of all the potential dependencies – the issue this dissertation addresses – is that they change through time.

1.3.2 Impact of Reduction Decisions

Smith (2007) warns that, although the areas of the design space that are likely to be eliminated are both numerous and obvious in the design's outset, weak spots are not often as clear later in the process. Thus, set reduction should be completed carefully. Rapid reduction can lead to eliminating feasible options, while slow reduction could prolong selection of a solution (Smith, 2007; Ford & Sobek, 2005). The best option for overall design reduction may mean keeping certain set-ranges open, even if feasibility or dominance says otherwise. Keeping an infeasible region of the current design space could maintain flexibility and ensure set-range expansion is not required later.

The responsibility of understanding the impacts of decisions and guiding set reduction is placed on the chief engineer or design manager in charge of the design process. Many agree that using the SBD method requires considerable experience to manage effectively (Smith, 2007; Panchal, Fernandez, Allen, Paredis, & Mistree, 2005; Sobek, 1997). Others have stated that significant work in guiding set reduction needs to be completed (Malak, Aughenbaugh, & Paredis, 2009; Nahm & Ishikawa, 2006; Ford & Sobek, 2005). While experienced managers are always desired, a method to determine the impact of reduction decisions used to aid managers in guiding set reduction would prove beneficial in all design circumstances. The ideal method balances the risk and reward of reducing certain areas of the design space, and determines the impact of these decisions on the overall design process.

1.3.3 Identification of Robust Decision Paths

One of the major SBD principles developed by Toyota is a strong desire to stay within the initially defined sets, hence avoiding divergence. Sobek (1997) stated that this principle was mainly due to the fact that "downstream sets are subsets of upstream ones, thus any work or communication based on upstream sets is also valid for all downstream sets, including the final solution." Additional work must be completed in order to fully understand the design space if set-ranges are reopened. McKenney, Gray, Madrid, and Singer (2012) also identified the desire to avoid what they define as a failure opportunity, which occurs when the given set-ranges are not able to handle a design change.

As part of the set reduction decision making process, there is a desire to avoid situations where set-ranges are not able to handle changes and/or have to be reopened. By identifying potential decision paths that are more robust to changing design conditions, unfavorable situations can be avoided. Through the identification of robust decision paths, the designer is equipped with further information that can be used to make informed set reduction decisions.

1.4 Contributions

This dissertation presents a framework that can be utilized as a decision support tool by designers making set reduction decisions within a SBD environment. Leading up to the formulation of this framework, a number of important conclusions were formed that aided in its development. Also, a series of methods to better understand the SBD reduction process were developed. Specific contributions presented in this dissertation are as follows:

1. Aided in the development of a rigor standard that can be used to evaluate a design activity and determine the degree of adherence to five major SBD elements. Standards enable proper and repeatable execution of SBD principles.
2. Developed a design facilitation tool that aids in understanding design relationships at the functional design level, thereby, improving the preference generation process for designers.
3. Conducted a series of experiments with human designers that validated the ability of the SBD method to handle changes, and identified two elements, reduction path and reduction rate, as key factors in successful reduction efforts.
4. Developed a novel approach to generate automatically set reduction graph structures. This approach avoids the need to manually generate a graph for every problem.
5. Developed an MDP formulation of the longest path problem for SBD reduction decision making, providing both a structure for the problem and a method for analysis.
6. Created novel visual representations of the support framework results in simple and understandable formats so that SBD reduction decisions are presented to the designer.
7. Developed a series of DM reduction metrics utilized within the support framework to describe quantitatively the impact of reducing certain regions of the design space.
8. Through simulation, demonstrated the advantage of considering potential future outcomes versus the use of current in-state knowledge.

1.5 Dissertation Structure

There are two major phases of the research presented in this dissertation. The first phase, outlined in Chapters 2-5, provides an introduction to SBD and the work completed to form the important conclusions that were the impetus for the developed framework. The second phase, outlined in Chapters 6-8, presents the developed framework and metrics, and demonstrates their value through a series of studies and finally a ship design case study. The remainder of this section briefly describes each chapter individually.

Chapter 2, Early-Stage Design, discusses the landscape of design and defines the distinction between a design approach, process, method, and tool. Current design issues that have led to the inadequacy of traditional design methods are then presented. Finally, the ability of SBD to handle these design issues and its advantages over more traditional design methods is discussed.

Chapter 3, Set-Based Design Execution, presents both the successes and challenges associated with SBD executions. A detailed description of the SSC Program is used as an example of a successful SBD execution. Major SBD criticisms and execution challenges are also discussed to highlight the areas where improvement is needed. A SBD rigor standard is introduced to aid in the understanding and classification of a SBD effort. Current SBD execution methods and aids are then presented, and the limitations of current research are summarized.

Chapter 4, Initial Set-Based Design Research, first introduces the work completed by Singer (2003) and Gray (2011) that this dissertation is based on. An initial case study is then presented that provides insights on the set reduction process. Also, a design facilitation tool is discussed, as well as its shortcomings when applied to larger-scale design efforts.

Chapter 5, Detailed Design Experiment, presents an extensive study of how SBD handles changes through a series of experiments using human designers. A number of key conclusions were formed that help frame the problem and develop a framework that addresses several items, including the importance of reduction rate and path.

Chapter 6, Decision Support Framework, outlines the methods used as part of the unified decision support framework, which include DM, MDP, and sensitivity analysis. Various representations of the method's results are presented to demonstrate the types of information designers can use to make decisions.

Chapter 7, Evaluation and Comparison Studies, presents an evaluation of the developed reduction metrics used to integrate the DM method and the MDP formulation. The metrics are evaluated using the MDP formulation to identify distinguishable advantages. Finally, the MDP formulation is utilized to show the advantages of considering future outcomes over a method focused on only current in-state knowledge.

Chapter 8, Reduction Demonstration, uses a ship design case study to demonstrate the developed framework with multiple types of functions and representations. A complete reduction is discussed in detail.

Chapter 9, Conclusion, returns to the identified research problems and discusses the work presented throughout this dissertation to understand better how the developed framework addresses each problem with regard to the information designers can use to make reduction decisions. Alternative applications and future work are also discussed.

Chapter Citations

1. Doerry, N. (2010). *Transitioning Technology to Naval Ships* (NAVSEA Report 05T/17). Washington, D.C.
2. Doerry, N., & Steding, M. (2009, June 1). *Ship Design Manager Manual*. Naval Sea Systems Command.
3. Eccles, T.J. (2010, September 29). *Ship Design And Analysis Tool Goals* (COMNAVSEA memo 9000 Ser 05T/015). Washington, D.C.
4. Ford, D., & Sobek, D. (2005). Adapting Real Options to New Product Development by Modeling the Second Toyota Paradox. *IEEE Transactions on Engineering Management*, 52(2), pp. 175-185.
5. Gray, A.W., & Singer, D. J. (2011, October 25-27). *Applied Set-Based Communications and Negotiation System*. Paper presented at ASNE Human Systems Integration Symposium, Vienna, VA.
6. Jones, C. J. (1992). *Design Methods* (2nd ed.). New York: Van Nostrand Reinhold.
7. Kassel, B., Cooper, S., & Mackenna, A. (2010, April). *Rebuilding the NAVSEA Early Stage Ship Design Environment*. Paper presented at American Society of Naval Engineers Day 2010, Arlington, VA.
8. Liker, J. K., & Ogden, T. N. (2011). *Toyota Under Fire: How Toyota Faced the Challenges of the Recall and the Recession to Come Out Stronger*. New York: McGraw-Hill.
9. Liker, J. K., Sobek, D. K., Ward, A. C., & Cristiano, J. J. (1996, May). Involving Suppliers in Product Development in the United States and Japan: Evidence for Set-Based Concurrent Engineering. *IEEE Transactions on Engineering Management*, 43(2), pp. 165-178.
10. Malak, R., Aughenbaugh, J., & Paredis, C. (2009). Multi-Attribute Utility Analysis in Set-Based Conceptual Design. *Computer Aided Design*, 41, pp. 217-227.
11. McKenney, T. A., & Singer, D. J. (2012, February 9-10). *Determining the Influence of Variables for Functional Design Groups in the Set-Based Design Process*. Paper presented at ASNE Day 2012, Arlington, VA.
12. McKenney, T. A., Gray, A. W., Madrid, C., &Singer, D.J. (2012, October-December). The Use of a Fuzzy Logic Set-Based Design Tool to Evaluate Varying Complexities of Late-Stage Design Changes. *Transactions of the Royal Institution of Naval Architects Part A: International Journal of Maritime Engineering*, 154(A4), pp. 179-189.
13. McKenney, T.A., Kemink, L.F., & Singer, D.J. (2011). Adapting to Changes in Design Requirements Using Set-Based Design. *Naval Engineers Journal*, 123(3), pp. 66–77.
14. Mebane, W. L., Carlson C. M., Dowd, C., Singer, D. J., & Buckley, M. E. (2011, February 9-10). *Set-Based Design and the Ship to Shore* Connector. Paper presented at ASNE Day 2011, Arlington, VA.
15. Nahm, Y.E., & Ishikawa, H. (2006, May). Novel space-based design methodology for preliminary engineering design. *International Journal of Advanced Manufacturing Technology*, 28(11-12), pp. 1056-1070.

16. Panchal, J., Fernandez, M., Allen, J., Paredis, J., & Mistree, F. (2005, September). *An Interval-Based Focalization Method for Decision-Making in Decentralized, Multi-Functional Design*. Paper presented at the ASME 2005 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, Long Beach, CA.
17. Singer, D. J. (2003). *A Hybrid Agent Approach for Set-Based Conceptual Ship Design Through the Use of a Fuzzy Logic Agent to Facilitate Communications and Negotiation*. (Doctoral dissertation). University of Michigan, Ann Arbor.
18. Singer, D. J., Doerry, N., & Buckley, M. E. (2009, October). What is Set-Based Design? *Naval Engineers Journal*, 121(4), pp. 31-43.
19. Smith, P. (2007). *Flexible Product Development*. 1st ed. San Francisco: Jossey-Bass.
20. Sobek, D. K. (1997). *Principles that Shape Product Development Systems: A Toyota-Chrysler Comparison*. (Doctoral dissertation). University of Michigan, Ann Arbor, MI.
21. Sullivan, P.E. (2008, February 4). *Ship Design And Analysis Tool Goals* (COMNAVSEA memo 9000 Ser 05D/047). Washington, D.C.
22. Ward, A. C., Liker, J. K., Christiano, J. J., & Sobek, D. K. (1995, Spring). The Second Toyota Paradox: How Delaying Decisions Can Make Better Cars Faster. *Sloan Management Review*, 36(2), pp. 43-61.
23. Ward, A., Sobek, D., Christiano, J. J., & Liker, J. K. (1995). Toyota, Concurrent Engineering, and Set-Based Design. In J. K. Liker, J. E. Ettlie, & J. C. Campbell (Eds.), *Engineered in Japan: Japanese Technology Management Practices* (pp. 192-216). New York: Oxford University Press.

Chapter 2: Early-Stage Design

Design is a broad and extensive topic that spans multiple fields from business and marketing, to engineering. The amount of effort put into product design is substantial, and decisions made early in the process significantly impact the end result. For decades, the importance of design and its impact on total life-cycle cost has been established through observations and quantifiable studies at various companies. Researchers have stated that 70-80% of a product's cost is committed during the design stage (Gatenby & Foo, 1990; Huthwaite, 1994; Ullman, 2003; Anderson, 2004; Belay, 2009), while others emphasize the impact of design on quality and manufacturing productivity (Dixon & Duffey, 1988; Suh, 1990). There are a few researchers who disagree with these statements and believe that further downstream activities, such as manufacturing, have more influence than most researchers acknowledge (Ulrich & Pearson, 1993; Barton, Love, & Taylor, 2001). It is, however, difficult to challenge the fact that design is an essential aspect of product development, and possibly the most critical.

While this chapter discusses all aspects of product development to some degree, the main focus is on early-stage design, which involves the transition between understanding requirements and incorporating them into the initial design of a system. The goal of this chapter is to describe effectively the current landscape of design, to identify why more traditional methods are no longer adequate, and to establish the need for a method such as SBD to handle the present-day design environment.

This chapter begins by defining what early-stage design is in more detail and the distinction between the components of a design effort. Characterizing a design effort is then discussed including a discussion of the act of design, design complexity, and design types. The traditional design approach is then discussed, and concurrent engineering, a much needed improvement to traditional design is covered. Focus is then placed on design processes, particularly systems engineering. Multiple methods and tools are discussed, including an introduction to SBD and why it is considered superior to other methods.

Before continuing, it is important to note that the topics discussed in this chapter are largely *domain independent*, meaning that principles, methods, and approaches mentioned do not depend on the domain or industry of interest. The naval ship design practice is used as a case study, but unique aspects of this type of design will be identified.

2.1 Defining Early-Stage Design

Early-stage design, while defined differently at various organizations, plays an important role in any product development or acquisition process. It is different from other stages, mainly due to its focus on understanding requirements as opposed to actual design work. Andrews (2004) describes the importance of understanding requirements by evaluating the true nature of early-stage design. This knowledge does not involve transforming a set of requirements to an engineering design, but rather identifying the true nature of the design problem. Andrews (2004) states, "… [T]he wicked problem demands to be tackled through a dialogue between the requirements generator (the naval staff or ship owner) and the preliminary ship designer. The purpose of the dialogue is to elucidate the best mix of conflicting requirements within what is affordable and achievable, which necessarily <u>has to be done by reference to materially feasible potential solutions</u>" (p. 42). In order to understand the design problem in terms of potential requirements, actual solutions must be explored. But the intention of evaluating these solutions is *not* to design a ship, but to define reasonable and obtainable requirements.

While all early-stage design efforts, as described above, deal with the definition of reasonable and obtainable requirements, there are different ways to achieve this goal. A clear definition, therefore, of the components of a design effort is required. For the work presented in this dissertation, the following definitions are used:

- Design Approach: The overarching guiding principles of a design effort
- Design Process: A series of structured steps to implement the design approach
- Design Method: The way in which design alternatives are understood, analyzed, and selected for a particular approach and process
- Design Tool: In support of design methods, tools are used to provide information that enables designer decision making

Design approaches and processes are the high-level attributes of a design effort. The approach describes the initial guidance required to initiate a design effort. For example, is the design effort sequential in nature, or are activities completed in parallel? A design process is a structure or framework within which the approach must be applied. Sometimes processes are developed around an approach and sometimes an approach must fit a given process. A design method describes the specific way in which the approach within the process is carried out, including how design alternatives are understood, analyzed, and selected. Finally, a design tool is used to support and enable the methods by providing design information.

It is important to note that a design tool is distinctly different from a design method. As mentioned in Chapter 1, certain tools can sometimes be confused as methods. This confusion can restrict design efforts through the overreliance on design tool results, which leads to a lack of understanding of the complete design problem. This reason is one of the reasons why clear definition of design components is so important. Throughout this chapter, comparisons between the different components are made, and proper usage is discussed. Finally, the implications of this confusion on the need for new methods are presented.

2.2 Characterizing a Design Effort

Before discussing specific design approaches, processes, methods, and tools, various aspects that characterize a design effort must be introduced. This section first focuses on the act of designing, as well as what it takes to complete a successful design, namely teams of human designers. Next, the increasing design complexity and present day challenges associated with tougher design environments are discussed. This analysis includes important consideration of incrementally improved and wholly innovative design components. These aspects of a design effort provide an initial understanding of design problems and leads into the discussion of two design approaches.

2.2.1 The Act of Designing

While tools and methods have changed over the course of history, design has remained a fundamental exercise that precedes the Egyptians' construction of the pyramids. There are a number of definitions for "designing" proposed over the years. Jones (1992, p. 3) has compiled a comprehensive list of requisite elements that includes:

- Decision making, in the face of uncertainty, with high penalties for error
- The performing of a complicated act of faith
- The imaginative jump from present facts to future possibilities
- A creative activity – it involves bringing into being something new and useful that has not existed previously

While the definition elements above describe the effort of design in different ways, the one common aspect is that they all refer "not to the outcome of designing, but to its ingredients" (Jones, 1992, p. 4). Design should be thought of as a *process*, not the final product.

A designer has two main objectives. The first is to act as an interpreter from a customer's desire (which can vary over time) to a functional working product, called "the interpretation objective." Interpretation incorporates transforming what a customer requests into requirements and then using these requirements to develop a design specification. This interpretation process is an art in itself and can have varying degrees of customer input. For example, Apple has an uncanny ability to predict what consumers want before they know they want it. In the case of other product developers, customers can have substantial input, and a successful product can still result. This phenomenon occurs in engineering when a customer says one thing, but really means something completely different. It is the engineer's duty to interpret properly customer statements and then to turn them into a functional system design. While some interpretations are relatively easy, others are much more difficult.

The second main objective is to predict the future behavior of the product and identify if it can be used for its intended purpose, the prediction objective. An interpretation may be complete, but not adequate now or in the future. There must be a feedback loop that determines if the functional description of the product addresses the set of requirements. This process can be equally, if not more, difficult than identifying and interpreting these requirements successfully. A visual representation of a designer's objectives and their relations can be seen in Figure 2.1.

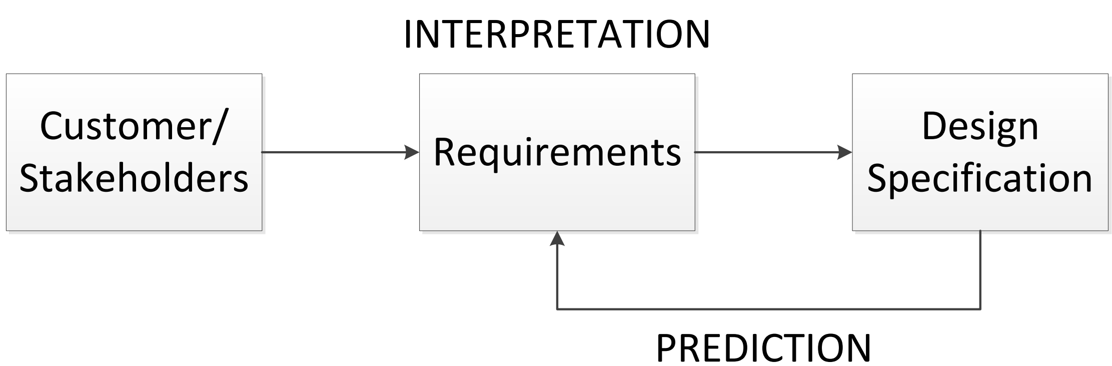


Figure 2.1: Designer Objectives

These two objectives lead perfectly into the difficulties of designing, which revolve mainly around the critical problem that "Designers are obliged to use current information to predict a future state that will not come about unless their predictions are correct" (Jones, 1992, pp. 10-11). Designing is, in one sense, moving backwards from an assumed outcome to the steps that must be taken to achieve that outcome. The designer's advantage is that they are *human* and therefore have the ability to solve problems that cannot be input into a computer or have an equation made to describe them. Even in an age where computers are part of almost every aspect of life, a designer's brain is the key ingredient that makes designing possible. Additionally, it is the teams of designers working together that enable large-scale complex design efforts to be accomplished.

2.2.2 Design Complexity

While the human designer remains the centerpiece of the design process, there are many contemporary challenges to address. Cost growth within many engineering fields has exhibited rates exceeding the rate of inflation over the past few decades, especially within the government sector. Cost growth is usually correlated with the complexity of a project: the more complex, the larger cost growth. Nicholas and Steyn (2012) provide a few historical examples of cost escalations: "The Concorde supersonic airliner exceeded the original estimate by a factor of five, nuclear power plants often exceed estimates by a factor of two or three, and NASA spacecraft often exceed estimates by a factor of four to five" (p. 282). Nicholas and Steyn (2012) also provide a list of reasons for cost escalations, some of which can be avoided and some of which may not. These reasons include:

- Uncertainty and Lack of Accurate Information
- Changes in Requirements or Design
- Economic and Social Factors
- Inefficiency, Poor Communication, and Lack of Control
- Ego Involvement of the Estimator
- Project Contract
- Bias and Ambition (pp. 283-286)

In addition to the above reasons that can cause cost overruns, design complexity continues to increase as customers/stakeholders continue to expect more and more. Under current budget and economic constraints, cost growth and associated complexity trends may not be sustainable.

U.S. Navy cost escalation rates for the fleet, including submarines and aircraft carriers, has been between 7 and 11 percent (Arena, Blickstein, Younossi, & Grammich, 2006). This number has been typical not just for U.S. Navy ships, but also for other defense sectors, including weapon systems and aircraft developments. A RAND study focusing on identifying why costs for U.S. Navy ships has risen identified two major sources of cost escalation: economy-driven and customer-driven. Of particular interest to designers are the customer-driven factors that include complexity, standards and requirements, and procurement rate (Arena, Blickstein, Younossi, & Grammich, 2006).

Complexity can be an ambiguous term, referring to anything from multiple component interactions and levels of subsystems to a measure used to describe the difficulty of understanding and predicting system operation and operational effectiveness. The RAND study observed that ships are becoming more and more difficult to build. This difficulty is indicated in the strong correlation between characteristic complexity measures, such as light ship weight or power density, evaluated over time. The RAND study defines characteristic complexity as "a measure of how changes to basic ship features (e.g., displacement, crew size, number of systems) make them more difficult to construct" (p. xv). Requirements changes, requirements creep and increased regulations also contribute to this increased difficulty. Figure 2.2 and Figure 2.3 provide examples of correlated measures that can provide some insight into these current trends.

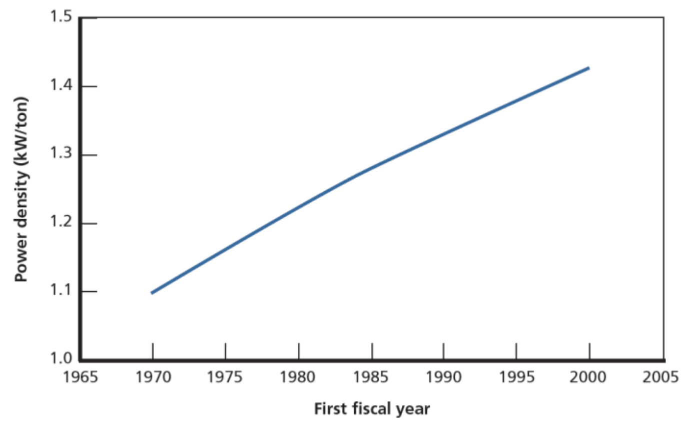


Figure 2.2: Power Density Trend for Surface Combatants (Arena, Blickstein, Younossi, & Grammich, 2006)

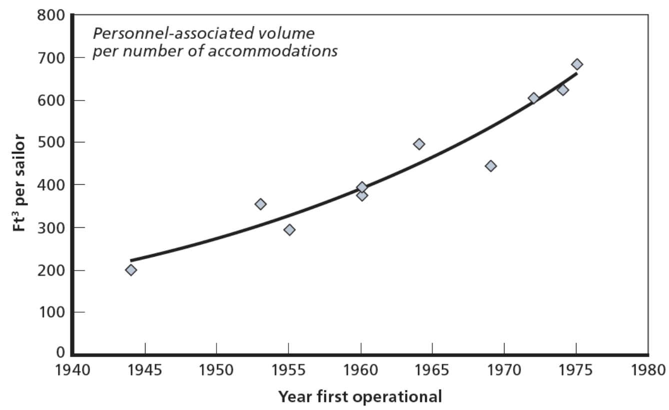


Figure 2.3: Average Living Space per Sailor on Surface Combatants (Arena, Blickstein, Younossi, & Grammich, 2006)

While the RAND study focuses more on a macro-level analysis, true design complexity embraces another aspect, which, while related, is not directly discussed. Complexity is often thought of as a description of the product itself, but what is often overlooked is the process taken to design that product, hence why complexity is often described as a function of process, not product (Doerry, 2009). Identifying how complexity affects a design process is important because a "project success is so sensitive to unknowns" (Colwell, 2005, p. 11). A definition of complexity that is suitable for this research is "a measure of the uncertainty in understanding what it is we want to know or in achieving a functional requirement" (Suh, 2005, p. 4). Along with the need to design and build more complex systems, deal with new regulations, and meet higher customer expectations, comes a *more complex design process.*

Although there are different types of complexity, combinatorial complexity is more important for analyzing a design process. Doerry (2009) states, "Combinatorial complexity results from having many dependencies between the design activities" (p. 8). For the purposes of this research, a general complexity metric can be identified using basic dependencies between design activities, or groups of designers working on various aspects of the design. Maier and Fadel (2004) describe an approach to measuring complexity "…based upon the coupling between design targets and design variables. The underlying assumption here is that the more coupled the design problem, the more complex it is" (p. 3).

Along with more complex (and almost always larger) systems comes a larger design team that must collaborate to develop a cohesive design. Complexity increases in the design process due to more dependencies between design activities. While the advent of computers has enabled automation of analyses and digitally produced drawings, the substantial increase in complexity has caused teams to remain large. The importance of design team communication and facilitation increases for complex designs. Without effective communication during a large-scale design effort, decisions could be made based on inaccurate or out-of-date information.

2.2.3 Design Types

A major complexity consideration when designing is related to the type of design. As mentioned earlier, there can be varying degrees of input or direction when designing a product. A design effort can have varying degrees of difficulty depending on a variety of factors. One of the most important factors is the uncertainty based on the limits of current understanding. Uncertainties rise when there is lacking information available to predict product behavior and outcomes; for example, by not being able to identify a functional design that meets predicted requirements.

Evolutionary design is often defined as a continuous or incremental improvement based on a previous design. This enhancement could include making a substantial change to only one subsystem. Revolutionary design is described as a significant change to the entire system, which in most cases means starting with a "clean sheet of paper." One design type is not necessarily superior to the other, and selecting evolutionary and revolutionary design components is based on the ability of the design specifications to meet the desired requirements.

Additionally, it is possible to select aspects of both design types since they exist on a continuous spectrum of possible design types that are related to other aspects of design, such as risk. Englhardt (1993) states that an evolutionary design has lower risk than a revolutionary design (Figure 2.4). Figure 2.5 illustrates how time and performance are affected by varying the type of design. Revolutionary designs typically require a substantial amount of research and development before increases in performance can be realized, while evolutionary designs take less time and increment smaller increases in performances.

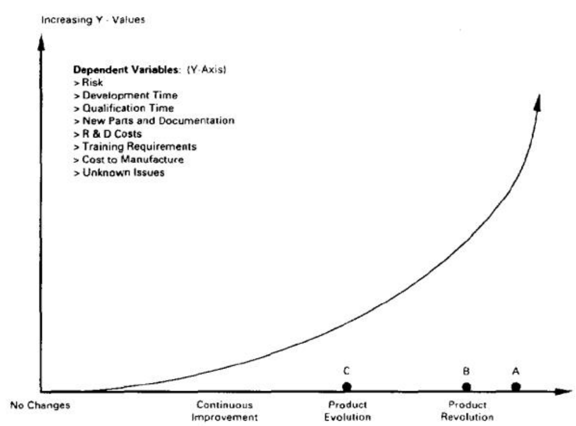


Figure 2.4: Development Strategy Spectrum (Englhardt, 1993)

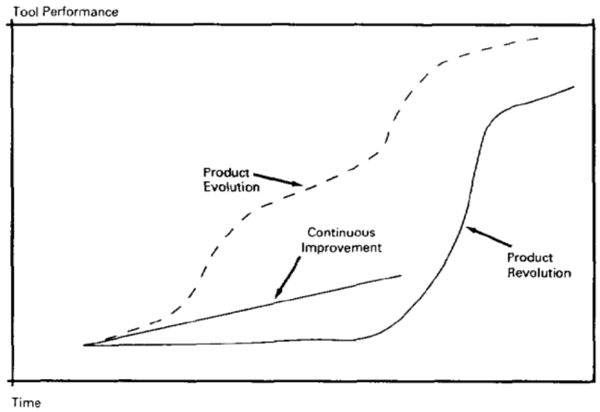


Figure 2.5: Development Strategy Performance Impact (Englhardt, 1993)

A good example of the difference between evolution and revolution may be found in comparing the most recent U.S. Navy Destroyer design known as the DDG 1000 (first ship scheduled to be delivered in 2014) and the DDG 51 Class Destroyer, which has been under construction since the early 1990s. The DDG 51 Class Destroyer design has gone through a series of evolutions from its initial design in the 1980s, including the most recent Flight IV design work currently being undertaken. A typical evolutionary change, for example from Flight I to Flight II, consisted of weapon technology and system control upgrade. The DDG 1000 is closer to a revolutionary design because of major desired changes to multiple systems including the hull, power plant, radar, and weapons that eventually led to a nearly "clean sheet" design. While the DDG 1000 design team carried multiple designs during the process until risk was deemed manageable, the two main alternatives were drastically different, and it was indicative of an all or nothing approach.

There are many factors that must be considered when identifying evolutionary and revolutionary components of a design, most of which are not under the direct control of designers. Acquisition strategies and politics within organizations, such as the U.S. Navy, can heavily influence design decisions, with little true technical merit. For example, the Congressional restriction of the deadweight of the DDG-51 Class Destroyer during early design efforts. The importance of discussing evolution versus revolution in design lies in how designers implement each type of design. The ability to successfully complete a more revolutionary design effort can depend on the specific design method used. For example, Sobek (1997) identifies the importance of open development with dynamic or revolutionary products, while most product domains for more evolutionary systems may remain unchanged.

2.3 Design Approaches

Along with identifying various characterizations of design, the approaches used to develop and select solutions lay the groundwork for defining the complete design effort. In a typical traditional approach (known as iteration), designers start by selecting a solution. This solution is then synthesized, analyzed, and evaluated (Sobek, 1997). After the evaluation stage, changes are made to the design based on whether the design is feasible and/or meets all requirements. As more iterations are completed, fidelity of analysis increases and becomes more detailed. Selecting which designs to iterate is another important component of design. Typically, a chief engineer (or small group) develops a series of alternatives that are then evaluated. A design (or a few alternatives) is selected and subsystems are identified before the whole design team is engaged. This strategy can be challenging when designs are revolutionary, because of the difficulty for one person (or a small group) to hold the necessary knowledge to understand the design in its entirety (Jones, 1992). In addition, an iterative approach compliments the extensive field of design optimization, which (most of the time) requires single inputs and completes multiple evaluations (Sobek, 1997). This traditional approach is the basis for point-based design, which will be discussed later in this chapter.

One alternative approach to iteration, which is the basis for SBD, is using convergent strategies. There are a number of issues associated with selecting a single solution. Sobek (1997) defines two characteristics of design that make selection a challenge:

- Most designers do not truly understand the design problem until they have tried several detailed solutions
- Designers cannot foresee all the interactions that will result as the details of the concept are worked out (p. 18)

These challenges can be partially resolved by using convergent strategies that analyze many alternatives. Convergent methods allow for greater understanding of alternatives and design relationships before making a decision. This section introduces the two major design approaches seen in design. It is important to note that some approaches are a combination of both iterative and convergent strategies.

2.3.1 Traditional Design

The traditional design approach, which still to some degree takes place within some organizations, represents design as a sequential process. Concept or preliminary design is first, contract and detailed design second, then manufacturing, and finally operation and disposal. This approach is often referred to as the "over-the-wall" approach, where the most notable "wall" is between design and manufacturing. The phrase refers to what occurs when a designer finishes a design in one phase and throws it over the wall to the next phase, such as manufacturing, where construction must be completed (Boothroyd, Dewhurst, & Knight, 2002).

While the practice of a sequential "over-the-wall" approach might seem unfavorable, there are a number of valid reasons for such a strategy. First, communication between different design groups can be challenging and expensive. Additionally, it is often easier to pass a design to a downstream group instead of dealing with integration (Wheelwright & Clark, 1992). Second, simultaneously addressing all aspects of the system's lifecycle during design can be daunting, and the complexity of integration can be a difficult task (Wheelwright & Clark, 1992). The "walls" help divide the work into manageable pieces that can be completed individually. Finally, contractual requirements for a division of labor allow for open bidding. For example, shipbuilding requires division of labor when the builder is not determined when design begins. This "wall" makes it difficult to incorporate manufacturing input earlier in design.

A negative consequence of the approach is splitting the design into a sequential and only downstream process (Sobek, Ward, & Liker, 1999). The "we design it, you build it" attitude leads to integration issues and a substantial amount of rework (Boothroyd, Dewhurst, & Knight, 2002). Delay of work is the main issue associated with the sequential process, since major changes must be made once information is transferred to downstream activities (Ward, Liker, Christiano, & Sobek, 1995). The issues associated with the traditional design approach have worsened as systems have become more complex, and the design landscape has changed with numerous technological advancements. The difficulties of the traditional and sequential design processes have been established, but a substantial amount of research has been conducted to improve integration. Research that focuses on lowering the "wall" between design and manufacturing include, but are not limited to, Design for Production (Storch, Sukapanpotharam, Hills, Bruce, & Bell, 2000), Design for Manufacturing Assembly (Molloy, Tilley, & Warman, 1998), Design for Six Sigma (Yang & El-Haik, 2009), and Lean Product Design (Liker & Lamb, 2002). Other research areas that aid in lowering the "wall" specifically focused on in this dissertation will be discussed throughout the remainder of this chapter, including concurrent engineering and SBD.

2.3.2 Concurrent Engineering

After identifying the issues associated with traditional design, including fragmented communication and rework, it was evident that a new method was required. Some argue that the answer to these issues could be found via concurrent engineering (CE). CE, also referred to as simultaneous engineering or integrated product/process development, is not a new concept. Even before extensive literature on the topic in the 1990s, CE practices were used during the World War II era (Ziemke & Spann, 1993). A generally accepted definition of CE in literature from the Institute for Defense Analysis (1988) states:

Concurrent engineering is a systematic approach to the integrated, concurrent design of products and their related processes, including manufacturing and support. This approach is intended to cause the developers, from the outset, to consider all elements of the product life cycle from conception through disposal, including quality, cost, schedule, and user requirements.

The value of being able to consider all aspects of a product's life cycle during design can easily be considered a major advantage, but accomplishing this task can be extremely challenging. Salomone (1995) states that "…it is hard, if not impossible, to define the process of making a product before a product design has been created" (p. 1). The push for the use of CE practices arises from the fact that existing traditional sequential design processes present serious limitations. Also, the traditional method is no longer suitable due to the rapid pace of technology development and increased competition, resulting in a need for shorter development times, higher quality, and lower costs (Salomone, 1995; Bennett & Lamb, 1996; Addo-Tenkorang, 2011). Furthermore, shifting environmental conditions for teams have made the traditional method less viable. These environmental conditions refer specifically to unique work environments, such as having team members in multiple locations, or understanding cultural differences among team members and the team leader's role (Parker, 2008).

CE directly conflicts with traditional design practices where the design is passed along with consideration of one set of factors at a time. CE introduces Integrated Product Teams (IPTs) and co-location to improve communication. An IPT is a group that is comprised of experts from many disciplines that work together and are collectively responsible for a particular product design effort. Co-location is the placement of all people involved on a project in the same physical location. Typically, downstream activities, such as manufacturing, are able to be initially considered during primary design stages using CE (Sobek, 1997). Figure 2.6 provides a visual depiction of the development process using CE. The main advantages of CE include lower cost, higher quality, shorter time to market, and less re-work (Bennett & Lamb, 1996; Addo-Tenkorang, 2011). The "wall" discussed in the previous section is lowered substantially using CE. CE does not change the design process, but addresses concurrent communication and coordination needs for any type of process. Nonetheless, some processes are more effective at implementing CE principles, which will be shown later in this chapter when discussing SBD.

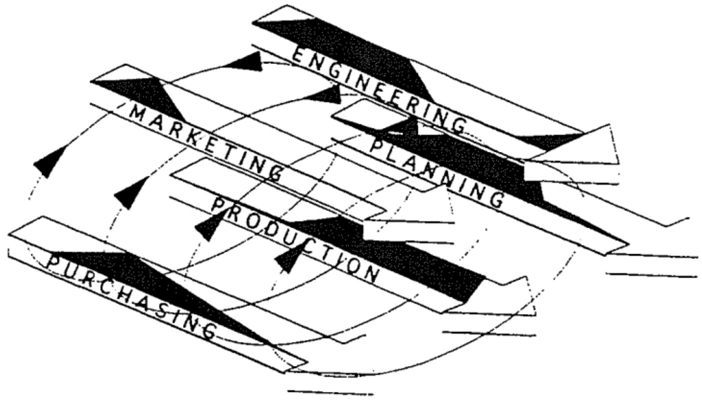


Figure 2.6: Concurrent (Parallel and Integrated) Product Development (Bennett & Lamb, 1996)

While the need for a new method was identified and extensive research was conducted, struggle with practical execution in recent years has caused CE to lose some popularity. Attempts at implementing CE practices within organizations have occurred over the last decade with varying degrees of success. Results from the successes indicate that, if done properly, CE can have a major positive impact, while results from the failures illustrate the difficulty of execution. The identified advantages, when implemented correctly, have led companies to continue practicing CE practices. Organizations such as NASA have continued to work towards a CE approach (McGuire, Oleson, & Sarver-Verhey, 2012), even in light of major system failures like the Columbia accident in 2003. These mixed results should not deter the pursuit of the proven advantages of CE, but should provide appreciation of the difficulties of execution and the value in seeking practical process solutions.

Significant challenges associated with CE execution include cultural hurdles intrinsic to the company implementing the approach. Shifts in thinking must occur at all levels, including becoming more customer-focused and working in teams (Bennett & Lamb, 1996). Interest must change from individual to team-focused, so that decisions can be made through consensus. Ogawa (2008) stresses the difficulty of implementing a CE approach, stating, “People have to accept use of a new method of working which may require the difficult decision to change their behavior and step away from their experienced working style" (p. 16). Beyond natural opposition to change, more difficult questions arise from using CE in practice for employees, such as in assigning credit for accomplishments and determining promotions.

An important aspect of design efforts, that is typically underestimated when using CE, is forming design teams and the team dynamics associated with designing a product. Parker (2008) emphasizes the definition of a team by stating, "A group of people is not a team. A team is a group of people with a high degree of interdependence geared toward the achievement of a goal or completion of a task" (p. 13). The main issue with forming a team rests in the fact that an optimal team organization is circumstantial (Smith, 2004). Selecting the size of the team and the members themselves is critical for success. Ogawa (2008) warns that a "design session will stop if there is any lack of information, resources, and capabilities in the team" (p. 18). The NASA COMPASS Team at the Glenn Research Center identified four factors essential to forming their CE team (McGuire, Oleson, & Sarver-Verhey, 2012):

1. The right people
2. The appropriate tools
3. A supportive meeting space
4. A design project of sufficient magnitude around which to coalesce the multi-discipline capabilities of the team

These factors emphasize selecting proper team members and tools (which will be further discussed in the next section), but also determine that location and project magnitude directly impact the effectiveness of a CE approach. One final note is the importance of communication among team members. Smith (2004) offers the suggestion that a "…small team (fewer than ten) strengthens commitment and eases communication" (p. 441). Other effective communication principles are strongly associated with CE, such as co-location and two-way communication (Sobek, 1997). Design is a team-based activity, and team dynamics cannot be ignored when designing complex systems.

There are many advantages to using CE during the product development process, especially during the early-stage design phase. However, proper and effective application of CE principles has proven challenging, which can be seen by the steady decrease in industry interest since the late 2000s. While numerous organizations have succeeded, many others have failed. For some organizations, the issues associated with substantial organizational change caused by applying CE principles can sometimes be too much of a hindrance on operations. There can be varying degrees of application of CE and most design organizations adopt some form of CE. However, few apply it completely and successfully. Advancements in present-day design methods and tools, including SBD and work presented in this dissertation, can facilitate the spread and success of CE practices. The remaining two sections focus on the various types of methods and tools used during design and their ability to apply CE practices.

2.4 Design Processes

Design processes are a series of structured steps to implement the design approach. In some situations, the process is developed to fit certain approaches, while in other situations the process is dictated by an organization and therefore must be fit to the structure. This section presents one of each scenario, starting with a description of systems engineering. The second subsection briefly describes the U.S. Navy acquisition process for the early-stages of design.

2.4.1 Systems Engineering

Kossiakoff, Sweet, Seymour and Biemer (2011) provide the following definition of systems engineering (SE): "The function of systems engineering is to *guide* the *engineering* of *complex systems*" (p. 3). SE focuses on the system as a whole and places emphasis on aspects outside of pure engineering design, including its interaction with the environment and meeting various customers' needs. Systems engineers are actively involved in the design of the system through the guidance of concept development. Guidance is provided in the form of making key design decisions that are not only based on quantitative information provided by other disciplines, but qualitative assessments of the design and its component interactions. Finally, SE is able to bring together multiple engineering disciplines to understand better the system as a whole during the development process (Kossiakoff, Sweet, Seymour & Biemer, 2011).

The foundations of SE are rooted in the fact that when dealing with new and innovative concepts, there is a requirement for many diverse people working together, in some cases, for years at a time. While the origins of SE can be traced back to before formal engineering design disciplines existed, its official formulation grew during the same time CE did, and was concentrated during and after World War II. This fact is not believed to be a coincidence, mainly because there is evidence that SE was, and continues to be, a structured approach to utilizing CE principles (Loureiro, 1999; Adams & Douthit, 2000; Lightfoot, 2002; Loureiro & Leaney, 2003). During the development of SE, engineers that worked on complex system designs were required to communicate regularly with all disciplines, which increased demand for integration of CE principles (Loureiro, 1999). The requirement for integration made SE a good fit for utilizing CE principles.

The SE structure is broken down into stages and further phases within each stage (Kossiakoff, Sweet, Seymour & Biemer, 2011). The first stage is concept development, which consists of needs analysis, concept exploration, and concept definition. Engineering development is the second stage, and it consists of advanced development, engineering design, integration, and evaluation. The third stage, post development, consists of production, operation, and support. The basic elements can be seen in Figure 2.7.

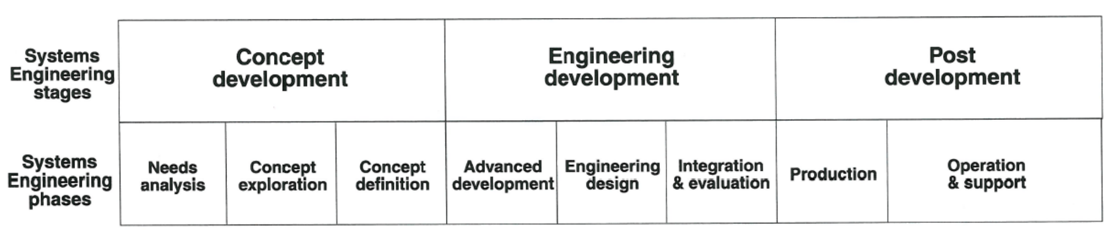


Figure 2.7: Systems Engineering Stages and Phases (Kossiakoff & Sweet, 2003)

Concept development includes identifying the need for a system, exploring for potentially feasible design solutions, and translating system requirements to a functional description.

The functional description outlines basic subsystems and the system architecture, or rather how the subsystems will fit together to form the overall system.

The engineering development stage focuses on engineering a system to make sure it can operate effectively to meet the desired requirements set in concept development. The early phase of engineering development entails identifying gaps in current technology and developing the necessary technology to meet the desired needs. The bulk of design work is during the engineering design phase, where the system is developed and its performance is evaluated. The final phase, integration and evaluation, verifies that the system meets requirements and that it can be economically produced.

Post Development is an area that designers are not usually involved in and consists of production, operation, and support. Production is a major and significant part of product development and includes the manufacturing process associated with the production of the system. After the system is delivered and/or sold, operation and support allows for the system to continue operating as required for its lifetime.

While SE provides a good structure to frame the product development process for a complex system, the actual method or approach used varies. Andrews, Papanikolaou, Erichsen, & Vasudevan (2009) state that SE can be considered synonymous with project management, while Kossiakoff, Sweet, Seymour and Biemer (2011) believe SE is just one aspect of project management, not including aspects such as project fiscal, contractual, and customer relations. Either way, it is generally agreed that SE is not, in and of itself, a complete design approach or method (Andrews, 2011). Kossiakoff, Sweet, Seymour and Biemer (2011) propose the "spiral life cycle model" that they claim captures the iterative nature of design through multiple applications of the SE method (the design spiral or point-based design will be discussed in the next section).

Since SE's origins, there have been a number of changes, similar to the changes that led to the development of CE. Kossiakoff, Sweet, Seymour and Biemer (2011) summarize three basic developments that led to the development of SE:

1. *Advancing Technology*, which provide opportunities for increasing system capabilities, but introduces development risks that require systems engineering management
2. *Competition*, whose various forms require seeking superior (and more advanced) system solutions through the use of system-level trade-offs among alternative approaches
3. *Specialization*, which requires the partitioning of the system into building blocks corresponding to specific product types that can be designed and built by specialists, and strict management of their interfaces and interactions (p. 6)

With these three developments, the SE discipline has matured, producing new ways to look at the problem, which, in turn, has engendered new design methods.

2.4.2 U.S. Navy Acquisition

For the U.S. Navy, the "Requirements Elucidation" process as defined by Andrews (2004) occurs pre-Milestone A, during Analysis of Alternatives (AoA) and Pre-Preliminary Design. Figure 2.8 outlines the U.S. Navy 2 Pass-6 Gate process that was introduced in 2008 and "ensures that the appropriate stakeholders are involved in acquisition decisions from the development of the Initial Capabilities Document through detail design and construction" (Singer, Doerry, & Buckley, p. 32). The traditional ship design stages can be seen at the bottom of the figure, and emphasize requirement definition, not design, during the early stages leading up to Preliminary Design. While other navies have different terms for these stages, the same issues related to understanding requirements must be addressed.

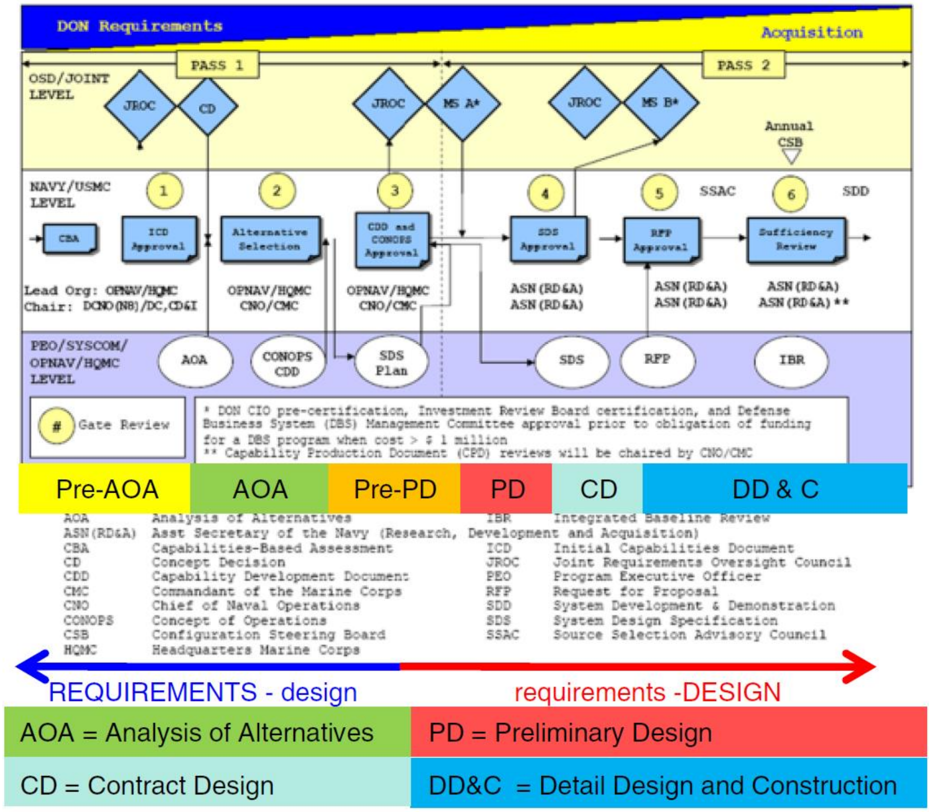


Figure 2.8: U.S. Navy 2 Pass-6 Gate Acquisition Process (Singer, Doerry, & Buckley, 2009)

The U.S. Navy acquisition process is a good example where the design process is set and the design approaches and methods must be developed to fit the given structure. The traditional design approach has typically been applied for such a process, however, this dissertation presents research that can aid in proper execution of more CE practices within the given design process.

2.5 Design Methods

Until now, the discussion has not ventured into the design method realm. There are many aspects of design that can be independent of the method used, including the characterization of a design effort and the given design process. Some methods have proven to be better than others, and some methods are outdated due to advancements in today's environment. This section begins by describing iterative methods, also known as point-based design (PBD) methods. Next, convergent methods are discussed, including an introduction to SBD, which is a method that shows promise in meeting present day design challenges and is compatible with CE practices.

2.5.1 Iterative Methods

PBD, also known as the design spiral, has traditionally been the method of choice when describing engineering design, and is still taught today, especially for initial ship design efforts. PBD provides a structure to complete an iterative design process. This model, first described for ship design by Evans (1959), focuses on the sequential nature of analysis in increasing detail as the spiral continues inward. This eventually produces a single design that meets all requirements and constraints, while balancing all considerations (Singer, Doerry, & Buckley, 2009). The spiral approach is also called PBD because the process is iterative in nature and attempts to develop a single solution that meets the desired requirements and constraints. A visual depiction of the ship design spiral is presented in Figure 2.9.

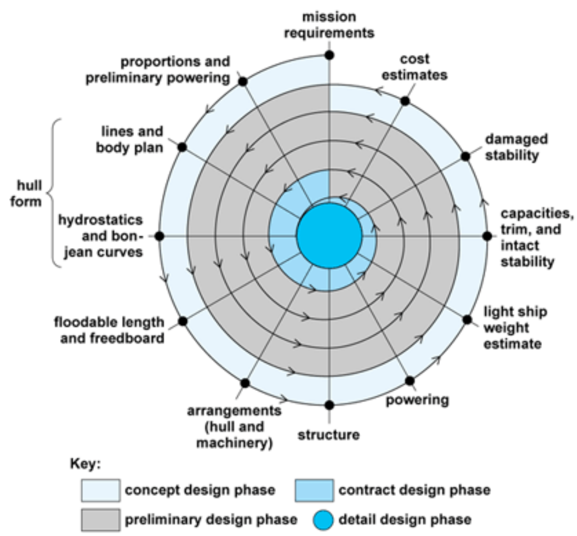


Figure 2.9: Ship Design Spiral (pkboatplans.blogspot.com/2011/11/design-spiral.html)

Liker, Sobek, Ward, & Cristiano (1996) provide a general description of PBD:

> "The typical approach to design problems, as taught in the United States, begins by defining the problem, then generating many alternative solutions. After preliminary analysis, engineers select the alternative with the most promise, then

> analyze, evaluate, and modify it until a satisfactory solution emerges. If the alternative proves infeasible, then designers select another alternative and/or revise the problem definition, and begin the process again. The key point is that a *single* solution is synthesized first, then analyzed and changed accordingly…" (p. 167).

PBD is proven to produce sound and feasible designs, but there are a number of disadvantages, including the inability to achieve a globally optimal design, a bias towards old designs, limitation on the number of iterations available due to time and/or budget, and susceptibility to premature, costly design decisions (Mistree, Smith, Bras, Allen, & Muster, 1990; Liker, Sobek, Ward, & Cristiano, 1996; Singer, Doerry, & Buckley, 2009; Gray, 2011; McKenney, Buckley, & Singer, 2012).

CE practices have been applied to the PBD method, but have not negated the disadvantages mentioned above. A PBD approach to CE often attempts to improve communication through co-location (Singer, Doerry, & Buckley, 2009) and move a design closer to "optimal" (Liker, Sobek, Ward, & Cristiano, 1996). In most areas, however, PBD contradicts the simultaneous design emphasized in CE practices by allowing downstream analyses to invalidate previous work (Liker, Sobek, Ward, & Cristiano, 1996). Nowacky (2010) states that PBD correctly describes the iterative nature of design, but can be deceiving by dictating a set order of steps.

With the design spiral as a baseline and the recognition of the shortcomings of traditional design, numerous modified PBDs and improved iterative methods have been proposed. Andrews, Papanikolaou, Erichsen, and Vasudevan (2009) provide an overview of ship design methodologies throughout the years in their paper entitled, "IMDC 2009 State of the Art Report on Design Methodology." These methodologies include the introduction of the design spiral by Evans (1959), an exploration phase flow diagram by Mandel and Chryssostomides (1972), a building block design methodology by Andrews and Dicks (1997), and an integrated ship design and optimization procedure by Papanikolau (2010). The paper by Andrews, Papanikolaou, Erichsen, and Vasudevan (2009) provides a comprehensive overview of more traditional methods that revolve around the iterative nature of design; however, it does not discuss CE practices or more convergent design approaches that play an important role in design.

The limitations of traditional or iterative design methods have identified a need for new methods. However, a clear description of the issues that should be addressed must first be developed. Ulrich and Eppinger (2008) provide a list of common dysfunctions in design teams during concept generation:

- Consideration of only one or two alternatives, often proposed by the most assertive members of the team.
- Failure to carefully consider the usefulness of concepts employed by other firms in related and unrelated products.
- Involvement of only one or two people in the process, resulting in lack of confidence and commitment by the rest of the team.
- Ineffective integration of promising partial solutions.
- Failure to consider entire categories of solutions (p. 99).

The downfall of many iterative or PBD methods is that there is inherent bias in the selection of a design. In an effort to avoid these situations, consideration of many alternatives should be considered. The integration of these solutions using input from the entire design team is an important element that new methods should include.

2.5.2 Convergent Methods

Convergent methods emphasize the importance of analyzing many alternatives and carry multiple alternatives as the design progresses, eliminating solutions only when the decision is justified. Considering a wide range of solutions and eliminating solutions as the design progresses can reduce the incidence of common design team failures in the early stages of design, and their potentially devastating impacts on design schedules. Keeping multiple options open longer during a design effort allows the design team to have a better understanding of the design and the requirements that it is supposed to meet.

Convergent methods consider multiple alternatives and have various procedures for eliminating or including these alternatives. This section introduces three different convergent methods, including SBD, the method focused on in this dissertation. Design-build-test and total design were selected due to them being other major convergent methods that have been proposed.

2.5.2.1 Design-Build-Test

The design-build-test (DBT) cycle is an approach that consists of three phases: the design phase, the build phase, and the test phase. The design phase focuses on framing the problem and establishing goals followed by generating multiple alternatives. The build phase includes building a working model of the design alternatives. This phase includes the work necessary for the alternatives to be tested. Lastly, the test phase focuses on evaluating certain aspects of the design of importance (Wheelwright & Clark, pp. 223-225). Figure 2.10 shows the DBT cycle.

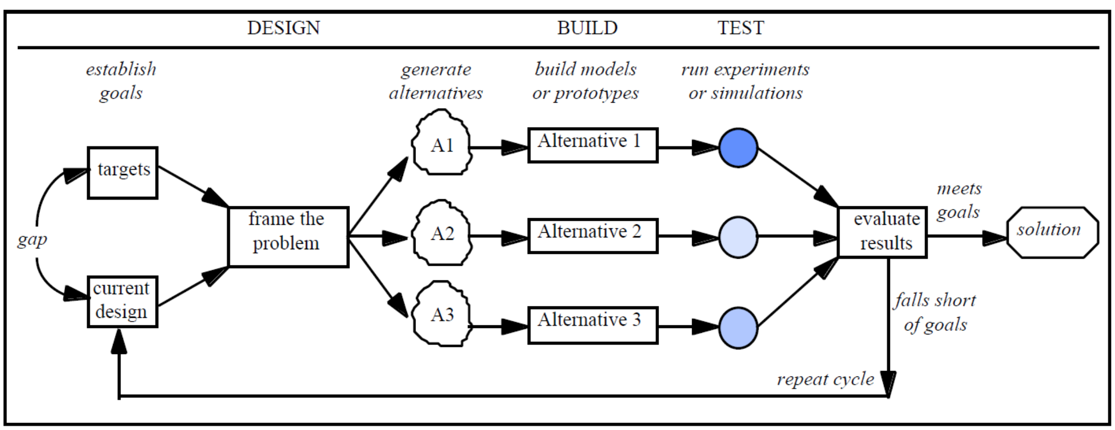


Figure 2.10: Design-Build-Test Cycle (Bernstein, 1998)

This cycle is repeated based on the results of each test phase. The key to this method is the ability to evaluate multiple alternatives at once, as the cycle is repeated and the fidelity of analysis is increased. The effectiveness of this method rests in the effectiveness of each cycle, as well as the combination of the individual cycle results to form a cohesive understanding of the solutions (Bernstein, 1998).

2.5.2.2 Total Design (Method of Controlled Convergence)

Another convergent method is called Total Design, also known as the Method of Controlled Convergence. This method, introduced by Pugh (1991), focuses on all aspects of a design activity, but with special emphasis on external factors, such as the working environment. Pugh (1991) defines total design as: "…the systematic activity necessary, from the identification of the market/user need, to the selling of the successful product to satisfy that need – an activity that encompasses product, process people and organization" (p. 5). Within Pugh's total design approach, the concept design method proposed is of particular interest. The method of controlled convergence (MCC) is a repetitive two-step process. Figure 2.11shows the method.

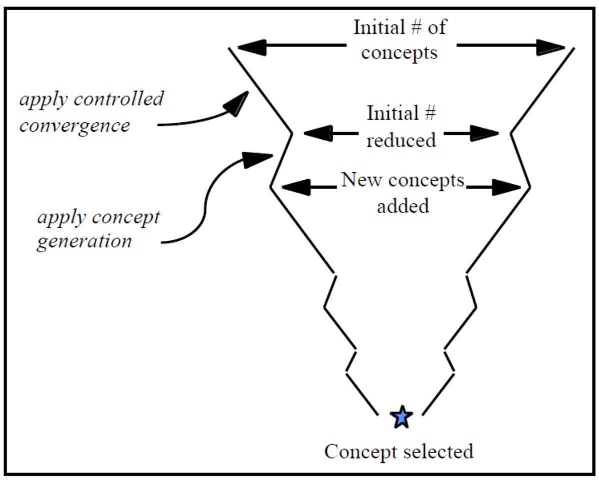


Figure 2.11: Method of Controlled Convergence (Bernstein, 1998)

The first step focuses on generating a large number of alternatives. The second step focuses on evaluating and selecting alternatives. Evaluation consists of determining whether alternatives meet requirements, or if they are dominated by other alternatives. Alternatives that do not meet requirements are either discarded or modified (Singer, Doerry, & Buckley, 2009). This method is a combination of divergent and convergent steps that continue as fidelity of analysis increases and fewer alternatives are being considered. This reduction continues until only one alternative remains. Each alternative is analyzed using a PBD method, which forces the process at each stage in order to be sequential in nature.

2.5.2.3 Set-Based Design

The final convergent method, also the main focus of this dissertation, is SBD. In its most basic form, SBD is design discovery by way of elimination. The process is characterized by: (1) communicating broad sets of design values, (2) developing sets of design solutions, and (3) delaying design decisions until adequate information is known. Throughout this process, separate groups of experts involved in the design continuously provide preferences for design values within the design space. By identifying intersections between these groups' feasible and preferred regions, the design space can be reduced, and a higher-level fidelity of analysis ensues. As the sets are reduced and fidelity of analysis increases, more information is learned about the design, which reduces uncertainty and allows designers to make more informed decisions. The final reduced region may not be contiguous, in fact, it will likely have candidates from various and disparate elements of the design space. It can be considered to be more globally feasible, because it spans so many factors; but it is achieved through elimination of infeasible or dominated alternatives, not a search for the optimal.

The Toyota Motor Corporation was the first to develop what is now referred to as SBD (Ward, Sobek, Christiano, & Liker, 1995), which, along with the Toyota Production System (Monden, 1983), has contributed to the company's success within the automotive industry. There has been considerable research on certain aspects of the SBD approach since 1995, when Allen Ward, an American researcher, coined the term. Ward, along with colleagues Jeffrey Liker and Durward Sobek, at the University of Michigan, detailed Toyota's use of set-based practices in a series of publications predominantly in the late 1990s and early 2000s. Since these initial publications, SBD practices have been applied in other areas, including the aerospace (Bernstein, 1998) and Naval ship design (Singer, Doerry, & Buckley, 2009) industries.

Gray and Singer (2011) have stated:

> "To some degree, researchers have succeeded at facilitating individual components of the SBD process using methods such as response surfaces and

optimization methods (Venter & Haftka, 1999), computer aided design systems (Nahm & Ishikawa, 2006b), analytical hierarchical processes (AHP), expert systems, and multi-criteria decision making (Ray, Gokarn, & Sha, 1995)."

While there are advantages to these methods, Singer (2003) and Gray (2011) identified the need to integrate all aspects of the SBD approach within a large-scale, team-based approach.

2.5.2.3(a) Concept and Principles

As mentioned earlier, the SBD concept can be described as design by elimination of dominated or infeasible solutions. This method is, in a sense, the opposite of typical design methods that emphasize focusing on the "optimal" or preferred solutions. To illustrate this important distinction, a commonly used Pareto front graph can be used (Figure 2.12). A Pareto front is used extensively in MCDC or MDO frameworks, and describes the optimal non-dominated solutions with respect to multiple objectives. While many points in the objective spaces are evaluated, typically the only points that are shown are along the actual Pareto front, or solid blue line in Figure 2.12. Design decisions are typically made based on this line by selecting the "best" solution. SBD does not consider the Pareto front or "best" solutions directly. Instead, designers make decisions to eliminate the highly infeasible solutions (found in the red solid oval in the bottom left of the graph) and the highly dominated solutions (found in the red solid oval in the top right of the graph).

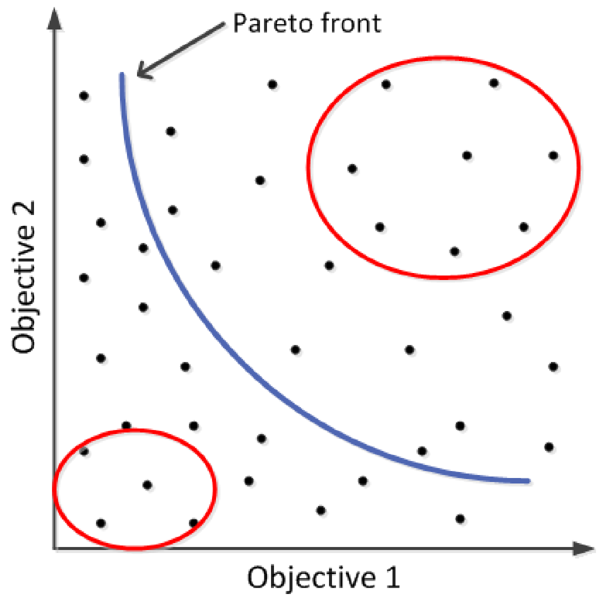


Figure 2.12: SBD Concept

An important distinction that makes the SBD concept of eliminating dominated or infeasible solutions is that selecting the "best" solution is *not* the same as what you have left when you eliminate the worst. "Best" solutions can change radically as design progresses and fidelity of analysis increases. SBD reduction decisions are different (and less risky) based on the fact that different areas of the design space are being considered and eliminated rather than relying on inherently uncertain, yet optimal solutions associated with the "best" solutions.

Another important distinction is the use of elimination versus selection when reducing set-ranges. Some argue that selecting the best region is the same as eliminating the worst; however, the methods cannot be directly compared. By selecting the "best" region, an assumption of where the boundary of that region is required. That assumption would most likely be based on infeasibility and/or dominance. Therefore, understanding the infeasible and dominant regions is still required. By solely focusing on these regions using elimination, there is no need for the identification of the best solutions.

An analogy that can be used to understand better the SBD concept is the selection of the questions asked in the 20 Questions game. The game requires at least two people: one is the answerer who chooses an object or thing; the other players are the questioners. Each questioner takes turns asking a question that must be answered using “yes” or “no”. The questioner that can correctly guess the object or thing within 20 questions wins. What children learn quickly when playing the game is that they cannot randomly guess irrelevant questions, but must instead use questions that eliminate possible answers until they are guided to deduce the correct person/place/object. Questions such as “Is it an animal?” can greatly reduce possible options, as opposed to “Is it a lion?” which only eliminates one (if it is not a lion, of course). Ingenuity in eliminating solutions or options can be an effective strategy for both childhood games and complex design processes.

Beyond the SBD concept, there are a number of SBD principles that describe the elements of a SBD process. Again, these principles can be understood better by using a simple analogy, planning a meeting. The goal is to find a time that allows everyone to attend. One method is for the meeting organizer to select a time that is convenient for them and then ask the others if that time is suitable. In most cases, this strategy does not work for everyone. A series of emails back and forth between participants and the organizer ensues, with individuals proposing new times, hopefully resulting in a time that works for all. This approach would be comparable to a PBD approach, where the organizer iterates a single solution (or time) until it is feasible. A potentially easier, but more time-consuming approach would be to have an ad hoc meeting to schedule the meeting. This way, everyone is present to discuss proposed times and they could reach a more optimal option quicker. However, there is still the problem of finding a time to meet to schedule the meeting. This problem illustrates how CE principles, such as co-location, can help improve any type of method, including PBD. Finally, a much superior option is for the meeting organizer to request that each participant send their availability for a set period of time they wish to meet. Using all the availabilities, times that do not work can be eliminated immediately, and overlaps between availabilities can be identified. In this situation, not only can a feasible meeting time be determined, but an optimal one as well, based on information provided by the participants about a degree of availability. This would be considered a set-based approach that can be seen as the best approach to the scheduling problem.

The scheduling problem can be used as a good example of the overarching SBD principles that guide a design effort. SBD's main differentiating feature is eliminating infeasible or dominated solutions instead of searching for an optimal. The SBD approach can be described as a concurrent engineering approach with the following characteristics (Bernstein 1998; Singer, Doerry, & Buckley, 2009):

1. A large number of design alternatives are considered through an extensive exploration of the design space
2. Separate groups of specialists are able to evaluate the design and provide preferences for solutions based on their own perspectives
3. Intersections between sets are used to establish feasibility before commitment and guide the design towards a more optimal solution
4. Fidelity of analysis is increased as the design progresses

Figure 2.13 provides a visual depiction of the SBD approach. The circles represent the feasible regions of the design space for different functional design groups. By exploring the design space, intersections between groups can be identified. The highlighted portions show these intersections. As the design progresses downwards in the figure, the sets continue to be narrowed through the elimination of infeasible or dominated solutions.

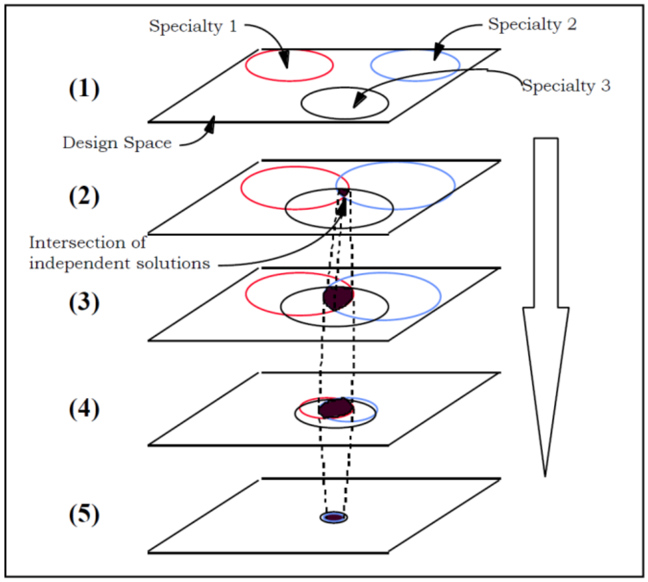


Figure 2.13: Set-Based Communication and Convergence (Bernstein, 1998)

SBD allows engineers to evaluate tradeoffs of a design with conflicting goals by gaining more information before making decisions. Decisions are made to eliminate parts of the design space when trade-off information is better known or other solutions dominate. At a point when all sets are feasible, and all tradeoffs are explored, the best possible design can be selected.

2.5.2.3(b) Advantages

At first glance, SBD can seem inefficient and wasteful. Many alternatives are evaluated in parallel, and decisions are delayed. However, SBD has shown to produce high efficiency and performance. Ward, Liker, Christiano, and Sobek (1995) described this phenomenon as "The Second Toyota Paradox." The advantages of SBD come from the use of sets and the ability to delay decisions until dominance or infeasibility is established. Communicating with sets allows for the delaying of decisions, which can reduce the amount of rework, allow for more informed decisions, and provide the ability to handle uncertainties. Also, the approach can facilitate the ability to obtain more globally optimal designs. Finally, a sometimes overlooked advantage, SBD promotes institutional learning.

The importance of the implications associated with using SBD is based on the nature of early-stage design, where decisions are made that commit costs and affect performance in the final product. These decisions are made when the least amount of information is known about the design, sometimes leading to later design changes and rework. Figure 2.14 shows the substantial cost increase of making changes later in the design process for the Naval ship design process.

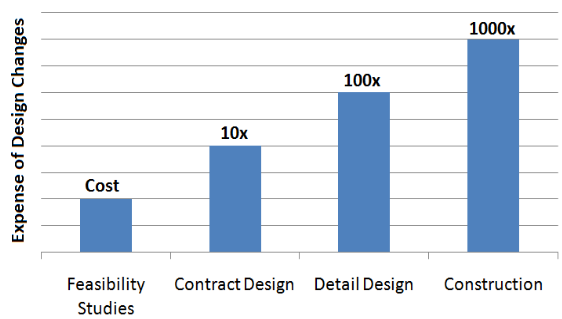


Figure 2.14: Cost of Design Changes during Different Naval Ship Design Phases (Adapted from Keane and Tibbits, 1996)

Typically in PBD, costs are committed earlier and management has greater influence over decisions when less design knowledge is known (Bernstein, 1998). Since SBD delays decision making until more knowledge is known, costs are committed later. This can be seen in Figure 2.15. While knowledge is not changeable within the product development process, delaying decisions causes more management influence later, hence committing costs later as well. The SBD approach of delaying decisions helps foster the attitude of making the right decision the first time around.

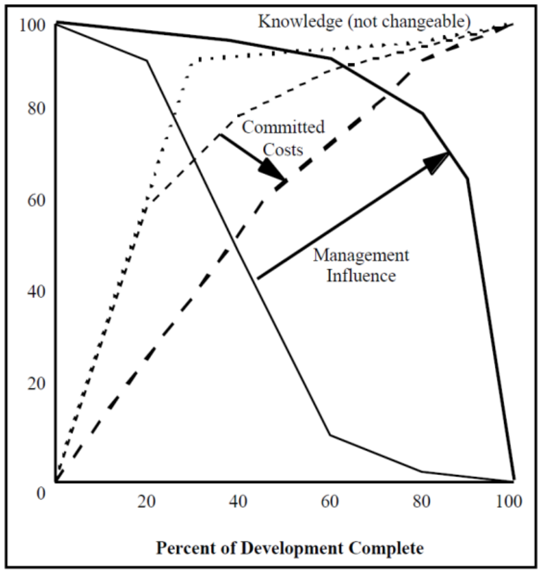


Figure 2.15: Advancing Product Development Practices using Set-Based Design (Bernstein, 1998)

SBD facilitates delaying decisions by using set-ranges to define design variables, so design can continue until a better-informed decision can be made (Singer, Doerry, & Buckley, 2009). This method prevents decisions from being made too early based on insufficient information. Only when sufficient knowledge of the design is known are options eliminated. By keeping the variables open longer, the amount of rework required is mitigated if a change occurs. Using set-ranges instead of single points also allows handling of uncertainties throughout the design process.

Maintaining flexibility in decision making ability during early-stage design allows designs to adapt to changing conditions (Nahm & Ishikawa, 2006a). Common design methods, such as point-based approaches require decisions to be made early when design alternatives are not fully developed. Ford and Sobek (2005) state that “often the performance, costs, and impacts on project duration of undeveloped alternatives cannot be predicted accurately enough in early stages to identify the best alternative.” By selecting an alternative too early, future iterative steps in the process could lead to incompatibility between design components and cascading changes. SBD avoids this incompatibility by allowing functional design groups to complete useful work early by defining constraints and managing the design space (Smith, 2007).

Another advantage based on the use of sets is the ability to obtain more globally optimal designs than comparable approaches, such as PBD. Instead of basing the current design effort on previous designs, SBD forces the exploration of many different concepts, some of which can be a significant improvement. Also, Ward, Liker, Christiano, and Sobek (1995) state, "It also allows a company to pursue radical improvements with a fair degree of safety: if one idea does not work out, another is likely to" (p. 59). Singer (2003) and Gray (2011) identified this advantage through a series of design experiments and concluded that for the same design project, SBD achieved a more globally optimal design than a PBD approach.

The last, but certainly not least, main advantage is SBD's ability to facilitate institutional learning. As the various functional design groups communicate, designers can gain insight on the design problem from different perspectives (Gray, 2011). Also, the practice of documenting the solution space and design decisions provides a reference for future design efforts. Designers have a much better understanding of the design space and can use these lessons learned on other designs (Ward, Liker, Christiano, & Sobek, 1995). In the next chapter, an explanation of the decision to use SBD for the preliminary design of the U.S. Navy's Ship-to-Shore Connector will be provided. The main reason for its use was not the major advantages researchers commonly cite, but SBD's ability to document the design space and decision making process.

Along with its advantages, there are currently a number of challenges associated with executing SBD practices. Due to its importance in this research, the entirety of Chapter 3 is dedicated to these issues as well as potential solutions.

2.5.3 Design Method Comparison

Iterative methods are more traditional and have been used extensively in multiple fields. However, there are serious limitations to iterative methods, as systems have become larger and more complex. Convergent methods are able to improve certain aspects of iterative methods by considering many design alternatives and having a thorough understanding of the design space. SBD shares some of the same properties as the other convergent methods, but adds additional value through the consideration of separate groups of specialists and the use of dominance and infeasibility to guide set reduction. This section first compares iterative methods to SBD, then highlights the differences between SBD and the other convergent methods.

A direct comparison between PBD and SBD highlights the key differences. During any design process, there are a series of tasks that each method completes in different ways. Table 2.1 provides a direct comparison between PBD and SBD for a series of design tasks.

Table 2.1: Comparison of Point-Based and Set-Based Design (Singer, Doerry, & Buckley, 2009)

Task	Point-Based Design	Set-Based Design
Search: How to find solution ideas?	Iterate an existing design by modifying it to achieve objectives and improve performance. Brainstorm new ideas	Define a feasible design space, then constrict it by removing regions where solutions are proven to be inferior
Communication: Which ideas are communicated?	Communicate the best idea	Communicate sets of possibilities that are not Pareto dominated
Integration: How to integrate the system?	Provide teams design budgets and constraints. If a team cannot meet budget or constraints, reallocate to other teams	Look for intersections that meet total system requirements
Selection: How to identify best idea?	Formal schemes for selecting the best alternative. Simulate or make prototypes to confirm that the solution works	Design alternatives in parallel. Eliminate those proven inferior to others. Use low-cost tests to prove infeasibility or identify Pareto dominance
Optimization: How to optimize the design?	Analyze and test the design. Modify the design to achieve objectives and improve performance	Design alternatives in parallel. Eliminate those proven inferior to others
Specification: How to constrain others with respect to your subsystem design?	Maximize constraints in specifications to assure functionality and interface fit	Use minimum control specifications to allow optimization and mutual adjustment
Decision Risk Control: How to minimize risk of "going down the wrong path?"	Establish feedback channels. Communicate often. Respond quickly to changes	Establish feasibility before commitment. Pursue options in parallel. Seek solutions robust to physical, market, and design variations
Risk control: How to minimize damage from unreliable communications; how to control communications?	Establish feedback channels. Communicate often. Respond quickly to changes. Review designs and manage information at transition points	Stay within sets once committed. Manage uncertainty at process gates

A more real-world comparison can be completed by evaluating the approaches from a design review perspective. During a design review, experts from different fields review a design effort and its findings. When using a PBD approach with extensive use of optimization techniques, the designers must defend the alternative they selected as "optimal." Questions might be asked in regard to other alternatives that the designers did not evaluate. Designers might then be forced to go back and evaluate additional options, which costs more and consumes more time. This method does not provide a designer with the appropriate information. SBD focuses on eliminating what is not considered to be the solution. It is often much easier to agree on what the solution *is not* as opposed to convincing someone that a solution *is* correct. SBD provides the designer with adequate information to answer questions and explain their reasoning for eliminating options, which better agrees with the design review process.

While the underlying structures of both PDS and SBD methods can be contrasted using Table 2.1, in practice it is more difficult to show that one method is better than another. A set of experiments conducted by Singer (2003) showed the advantages of SBD over traditional PBD approaches. Singer (2003) states, "The set-based design paradigm can replace point based design construction with design discovery; it allows more of design to proceed concurrently and defers detailed specifications until tradeoffs are more fully understood." The advantages of SBD over point-based approaches have been detailed in other references as well, including Liker (1996), Bernstein (1998), and Sobek (2008).

The SBD method can also be compared to the other two convergent methods presented. While convergent methods as a whole have similar properties, SBD is more robust in two important ways. In common, convergent methods consider many design alternatives and aid in developing a thorough understanding of the design space. Additionally, fidelity of analysis is increased, knowledge is gained, and uncertainty is reduced as the design process progresses. SBD is more robust by (1) allowing for separate groups of specialists to explore and conduct analysis concurrently and independently (Singer, Doerry, & Buckley, 2009) and (2) using dominance and infeasibility to guide design convergence. This distinction is key and will be discussed in the following sub-sections. The other convergent methods discussed do not place specific emphasis on using design alternatives in this way (Bernstein, 1998).

While arguments can be made regarding what is the best design method, it is important to note that this dissertation does not focus on proving SBD is the better design method. The focus of this dissertation is on SBD execution, which will be discussed in detail in the next chapter.

2.6 Design Decision Making Tools

Design tools can generally be used within any design method. Each design method, however, can use these tools in different ways. The focus of this section is to discuss tools used in the higher-level design decision making process. The first three tools, quality function deployment, axiomatic design, and failure mode and effect analysis, focus on understanding requirements, relationships, and potential failure modes early in the design. The last two focus on the visualization and understanding of design alternatives or solutions and their associated value. It is important to note that these are *not* design approaches or methods, but rather tools that can support a design method.

2.6.1 Quality Function Deployment

One technique that is used to improve understanding of requirements is quality function deployment (QFD). QFD originated in Japan, but was first popularized in the United States in a Harvard Business Review article by Hauser and Clausing (1988). The goal of QFD is to understand and meet customer requirements throughout all product development activities. Advantages of QFD include increased customer satisfaction, better design process planning, and a reduced product development cycle (Cristiano, Liker, & White, 2001). One important aspect of most QFD implementations is the house of quality. Hauser & Clausing (1988) describe the house of quality as "…a conceptual map that provides the means for interfunctional planning and communication" (p. 3). This includes relationships between customer attributes (requirements) and engineering characteristics. Functions that conflict can easily be identified and relative importance ratings can be used to prioritize aspects of the design. Finally, it allows for a direct comparison to competitor's products. Figure 2.16 shows an example of a house of quality analysis.

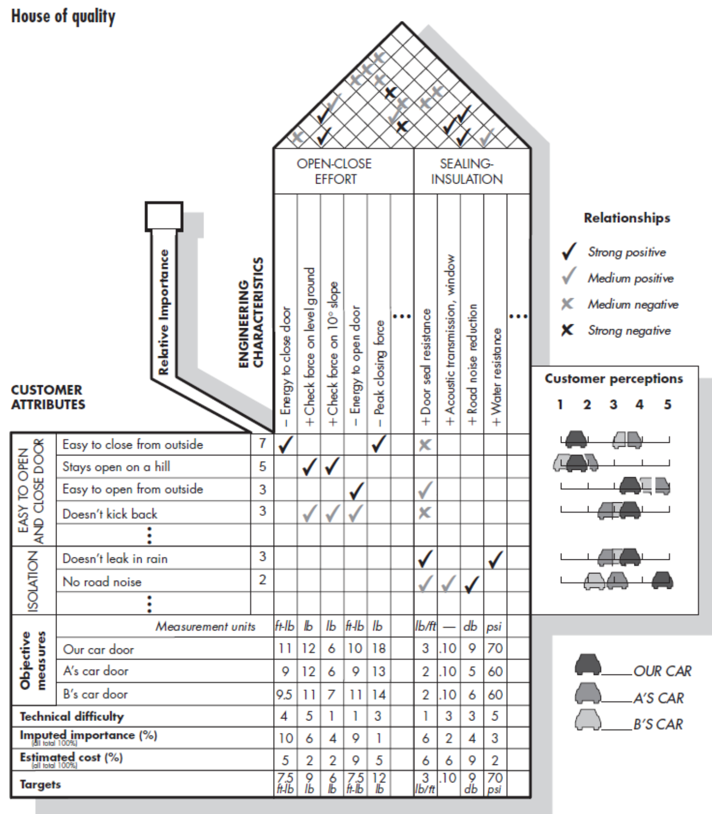


Figure 2.16: House of Quality (Hauser & Clausing, 1988)

There have been a number of difficulties associated with QFD execution, such as interpreting the customer voice, working in teams, and a lack of knowledge about using the method (Carnevalli & Miguel, 2008), which is why the technique is not widely used today. Most current work in the QFD field focuses on improving the house of quality formulation. Emphasis is currently being placed on the use of fuzzy logic and the analytical hierarchy process (AHP) to assist in developing the house of quality matrix (Carnevalli & Miguel, 2008).

2.6.2 Axiomatic Design

Axiomatic design is another technique used under the CE umbrella, and focuses on mapping the relationships in a design. Introduced by Suh (1995), axiomatic design "…is about how to think and use *fundamental principles* during synthesis or mapping between the domains of the design world" (p. 2). The domains that Suh refers to are the customer, functional, physical, and process domains. Interrelations between these domains are represented by a design matrix, and are determined using a form of transfer function or a qualitative description, also known as mapping (Lee, 2003). The domain structure and mapping relations are shown in Figure 2.17. Moving from left to right, the mapping represents the transition from what is desired to how it can be achieved.

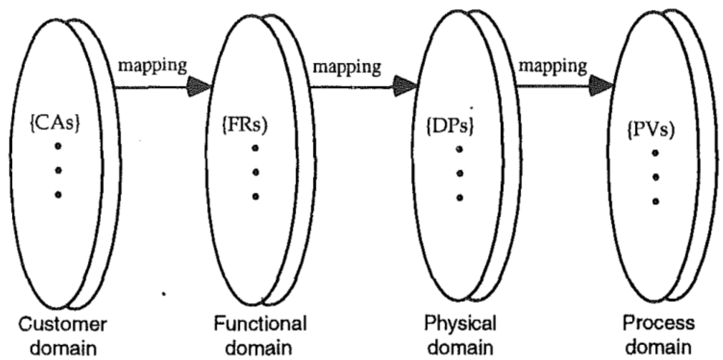


Figure 2.17: Four Axiomatic Design Domains (Suh, 1995)

Suh states that there are two fundamental axioms to govern the design process:

- Axiom 1: The Independence Axiom – Maintain the independence of the functional requirements (1995, p. 3).
- Axiom 2: The Information Axiom – Minimize the information content (1995, p. 4).

Axiom 1 states that during the mapping process, functional requirements that the design must meet are independent, which translates into a design matrix that is either diagonal or triangular. Axiom 2 defines information content as the probability of satisfying a given functional requirement. Higher probabilities of success are preferred designs. Within each domain, there are hierarchies that represent the design decomposition. Mappings can occur between any hierarchy levels across domains. The stated advantage of this formulation is that all aspects of product development can be described using the axiomatic design domains, which can facilitate CE practices.

Axiomatic design has been proposed in many fields and applications, but has recently lost support due to the difficulty of describing a practical design in its axiom and domain formulation (Hintersteiner & Zimmerman, 2000). Axiomatic design still has close ties to similar CE techniques and execution structures, including its use to improve the QFD process (Carnevalli, J. A., Miguel, P. A. C., & Calarge, F. A., 2010), and its use in the systems engineering process (Hintersteiner & Zimmerman, 2000). Similar to QFD, the intentions are valid and the structure shows promise, but execution requires substantial effort.

2.6.3 Failure Mode and Effect Analysis

Failure mode and effect analysis (FMEA) is used mainly as a risk management tool is. FMEA was first applied by the U.S. military and became widely adopted within multiple industries in the 1970s. Currently, FMEA is used in industries ranging from semiconductor processing to healthcare (Fadlovich, 2007). FMEA is a technique that is used to "…define, identify, and eliminate known and/or potential failures, problems, errors, and so on from the system, design, process, and/or service before they reach the customer" (Stamatis, 2003, p. 21). FMEA also characterizes the type of failure based on factors, such as frequency, severity, detection, and a total risk rating.

By anticipating potential failures, a design team can focus on designing them out of the product (Loureiro, 1999). This foresight can be a valuable tool when using CE practices since FMEA is able to consider all predictable failure modes from every aspect of the product development process. The same problems that can inhibit CE practices can also lead to difficulties with completing FMEA. These difficulties include working as a team, consensus decision making, and dedicating too much time on one particular issue. Nonetheless, when used properly, FMEA can be a valuable tool that can be used throughout the product development process.

2.6.4 Multi-Criteria Decision Making

The design decision making process typically dictates whether a design effort is successful or not. There are many alternatives associated with decisions and each person must go through an evaluation and selection process every time a decision is made. This process consists of evaluating and comparing the alternatives based on determined criteria, and then selecting the alternative that best achieves those criteria. Decisions are sometimes obvious, or intuitive, because there are so few factors involved; however, intuitive decision makers often continue to make decisions based on few factors even in the face of more complex situations and be confident in the outcome. Multi-criteria decision making (MCDM) can be used in these situations to incorporate greater complexity. In early-stage design of complex systems with many alternatives, making design decisions can be challenging. Additionally, the decision making process is usually completed by a team, rather than one individual, which may make reaching a decision more time-consuming. The number one challenge when making decisions is usually handling the various elements of uncertainty associated with the decision making process. Most of the time, decision-makers use their subjective viewpoints to make a final decision because capturing all aspects is believed not possible or perceived to be too difficult to accommodate in a quantitative manner.

While decision making is an extensive research area separate from design, the two are closely related and the importance of understanding design decision making cannot be ignored. The recent changes that have limited the applicability of traditional design practices and led to the development of concurrent engineering are applicable to decision making as well. Pedrycz, Ekel, and Parreiras (2011) explain that:

> "[N]ew, more complicated, and unusual problems have emerged. For many centuries, people made decisions by considering one or two main factors, while ignoring others that were perceived to be marginal to the essence of the problem. They lived in a world where changes in the surroundings were few and new phenomena arose "in turn" but not simultaneously" (p. 3).

Today there are many other factors that must be incorporated into the decision making process, and attempting to understand the complexities of a system while comparing and contrasting alternatives can also be challenging.

MCDM is a discipline that focuses on providing a structure and methods for making multi-criteria decisions. The elements that make up a MCDM problem consist of a set of known alternatives and multiple criteria to evaluate the alternatives. There are many approaches that are used to solve these problems, including fuzzy set theory, multi-attribute utility theory, and the analytic hierarchy process.

2.6.5 Synthesis Models and Optimization

Synthesis models and optimization techniques are used to compare and select alternatives that a DSE has evaluated to make the decision making process easier. Synthesis models analyze multiple aspects of a design using mathematical models to determine a feasible solution. Optimization is the use of mathematical models to analyze and compare alternatives to identify an "optimal" or best alternative using various methods. Multi-objective design optimization (MDO), also known as multidisciplinary design optimization, combines optimization techniques with synthesis models to trade-off aspects of a design to achieve an "optimal" solution, not just a feasible one. The MDO field is extensive and spans many disciplines. Martins and Lambe (2012) and Wit and van Keulen (2011) provide useful overviews of MDO architectures and strategies. Kerns (2011), Fox (2011), and Hefazi, Mizine, Schmitz, Klomparens, and Wiley (2010) provide examples of ship design synthesis models used within a MDO framework.

While a valuable tool within any design process, synthesis or optimization should not be confused with the design process itself. Where possible, designers desire a synthesis model that can fully describe the complete design situation. Similar to concurrent engineering practices, a completely encompassing synthesis model is ideal. In reference to ship design synthesis models, Fox (2011) states, "The author has found that the 'perfect' computer-aided design (CAD) program or 'ship design synthesis model' for the use in ship design is something of a 'Holy Grail' for the naval architecture community" (p. 35). For complex design efforts, it is clear that a synthesis model that fully describes the complete design situation is not possible, especially when considering how the design situation changes as the design progresses.

While useful, it is important to understand the limitations of synthesis models and optimization techniques within a design process. The most important consideration when using such methods is determining the various biases introduced. The creation of a model is based on the subjective judgment of the modeler, and different methods can produce different results (Papalambros & Wilde, 2000). Additionally, the lack of information, especially at early design stages, can make the model difficult to develop or too time-consuming to evaluate. Finally, the context in which a solution can be declared "optimal" should be clear. Papalambros and Wilde (2000) state:

> "A criterion for evaluating alternatives and choosing the 'best' one cannot be unique. Its choice will be influenced by many factors such as the design application, timing, point of view, and judgment of the designer, as well as the individual's position in the hierarchy of the organization."

If synthesis models and optimization techniques could be used to describe the design situation, then it is fair to say that human designers would not be required for complex design. Synthesis and optimization are valuable tools that aid designers in the decision making process and should not be ignored. However, results incorporating these tools should be tempered with an understanding of how the models were developed and by whom.

2.7 Chapter Summary

Even within product development, engineering design is an extensive and broad research area. This chapter was not intended to provide details of all aspects of early-stage design, but serve as an introduction to the concepts and aspects of design relevant to the research presented in this dissertation. The first, and most important, consideration is that *design matters*. Design is an integral aspect of product development and the methods used can greatly impact the success or failure of the final product. What makes design possible, however, are not high speed computers or optimization algorithms, but rather the human designers managing the process and making key decisions at the right time in that process. Additionally, it is usually not a single designer, but teams of designers that must deal with the ever increasing complexity and size of design efforts. An often downplayed aspect of design research is the influence of teamwork on the design effort, and how teams of designers can work together to develop a system that meets requirements. This factor cannot be ignored and a framework to allow for teams of designers to work together on a large-scale and complex systems design is essential. The size of design efforts is not only related to the physical complexity or size of the system itself, but the complexity of the design process.

While traditional design practices focused on more iterative or point-based methods that have produced feasible and sound designs for decades, the need for concurrent engineering in today's fast-paced, technologically advanced, and competitive world is clear. There are, however, a number of challenges to practical execution of CE principles. It is important to understand these challenges and learn from organizations that have succeeded and failed at implementing various degrees of CE.

There are a number of design approaches that attempt to achieve or improve upon various aspects of traditional design. Systems engineering is one approach that provides a structure for interacting with teams in a CE setting. SE is not a complete design method, however. There have been, and continue to be, numerous proposed methods based on PBD or the design spiral. While it does represent the iterative nature of design, there are several disadvantages that cannot be overlooked. Convergent methods carry multiple alternatives throughout the design process and provide a solid structure for CE execution. Specifically, SBD has shown to be a promising research area. Its advantages over more traditional point-based and other convergent methods have been identified and proven by numerous researchers. The area within SBD that still has major unanswered research questions is the proper execution of SBD principles within an organization. It is impossible to replicate Toyota's culture. Therefore, a framework that can facilitate SBD execution in other organizations is needed.

Chapter Citations

1. Adams, G., & Douthit, D. (2000, September 19-21). *Managing Concurrent Development – A Systems Engineering Approach*. Paper presented at the IEEE Systems Readiness Technology Conference, Anaheim, CA.
2. Addo-Tenkorang, R. (2011, October 19-21). Concurrent Engineering (CE): A Review Literature Report. In S. I. Ao, C. Douglas, W. S. Grundfest, & J. Burgstone (Eds.) *Proceedings of the World Congress on Engineering and Computer Science* (pp. 1074-1080). Hong Kong: Newswood Limited.
3. Anderson, D. M. (2004). *Design for Manufacturability & Concurrent Engineering*. Cambria: CIMA.
4. Andrews, D. J. (2004). Marine Design – Requirement Elucidation rather than Requirement Engineering. *Journal of Naval Engineering*, 41(Book 1, Paper 3).
5. Andrews, D. J. (2011). Marine Requirements Elucidation and the Nature or Preliminary Ship Design. *International Journal of Maritime Engineering*, 153(Part A1).
6. Andrews, D. J., & Dicks, C. A. (1997, June). *The Building Block Design Methodology Applied to Advanced Naval Ship Design*. Paper presented at the International Marine Design Conference, Newcastle, UK.
7. Andrews, D., Papanikolaou, A., Erichsen, S., & Vasudevan, S. (2009). *State of the Art Report on Design Methodology*. Paper presented at the International Marine Design Conference, Trondheim, Norway.
8. Arena, M. V., Blickstein, I., Younossi, O., & Grammich, C. A. (2006). *Why Has the Cost of Navy Ships Risen? A Macroscopic Examination of the Trends in U.S. Naval Ship Costs Over the Past Several Decades* (MG-484-NAVY). Santa Monica, CA: RAND Corporation.
9. Barton, J. A., Love, D. M., & Taylor, G. D. (2001). Design determines 70% of cost? A review of implications for design evaluation. *Journal of Engineering Design*, 12(1), pp. 47-58.
10. Belay, A. M. (2009). Design for Manufacturability and Concurrent Engineering for Product Development. *International Journal of Social and Human Sciences*, 3, pp. 1-7.
11. Bennet, J. G., & Lamb, T. (1996). Concurrent Engineering: Application and Implementation for U.S. Shipbuilding. *Journal of Ship Production*, 12(2), pp. 107-125.
12. Bernstein, J. I. (1998). *Design methods in the aerospace industry: looking for evidence of set-based practices*. (Master's thesis). Massachusetts Institute of Technology, Cambridge, MA.
13. Boothroyd, G., Dewhurst, P., & Knight, W. (2002). *Product Design for Manufacture and Assembly*. 2nd ed. New York: Marcel Dekker.
14. Carnevalli, J. A., Miguel, P. A. C., & Calarge, F. A. (2010). Axiomatic design application for minimising the difficulties of QFD usage. *Int. J. Production Economics*, 125, pp. 1-12.
15. Carnevallie, J. A., & Miguel, P. C. (2008). Review, analysis and classification of the literature on QFD – Types of research, difficulties and benefits. *Int. J. Production Economics*, 114, pp. 737-754.
16. Colwell, B. (2005, October). Complexity in Design. *Computer*, 38(10), pp. 10-12.

17. Cristiano, J. J., Liker, J. K., & White, C. C. (2001, February). Key Factors in the Successful Application of Quality Function Deployment (QFD). *IEEE Transactions on Engineering Management*, 48(1), pp. 81-95.
18. de Wit, A. J., & van Keulen, F. (2011, July). *Overview of Multi-Level and/ or Multi-Disciplinary Optimization strategies for preliminary aircraft design optimization: Overview of Methods for Multi-Level and/ or Multi-Disciplinary Optimization* (NLR-TP-2010-359). Amsterdam, The Netherlands: National Areospace Laboratory NLR.
19. Dixon, J. R., & Duffey, M. R. (1988, June 26). Quality is not accidental – it's designed. *The New York Times*.
20. Doerry, N. (2009, May 20-21). *Using the Design Structure Matrix to Plan Complex Design Projects*. Paper presented at the ASNE Intelligent Ships Symposium.
21. Englhardt, Eric A. (1993). *Product Evolution vs. Product Revolution: Maximizing Continuous Improvement While Minimizing Risk*. Paper presented at the IEEE/SEMI Int'l Semiconductor Manufacturing Science Symposium.
22. Evans, J. H. (1959, November). Basic Design Concepts. *Naval Engineers Journal*, 71(4), pp. 671-678.
23. Evans, S. (1993). Implementation: common failure modes and success factors. In H. R. Parsaei, & W. G. Sullivan (Eds.), *Concurrent Engineering: Contemporary Issues and Modern Design Tools* (pp. 24-41). London: Chapman & Hall.
24. Fadlovich, E. (2007, December 31). Performing Failure Mode and Effect Analysis. *Embedded Technology*.
25. Ford, D., & Sobek, D. (2005). Adapting Real Options to New Product Development by Modeling the Second Toyota Paradox. *IEEE Transactions on Engineering Management*, 52(2), pp. 175-185.
26. Fox, J. (2011). *A Capability-Based, Meta-Model Approach to Combatant Ship Design*. (Master's thesis). Naval Postgraduate School, Monterey, CA.
27. Gatenby, D. A., & Foo, G. (1990). Design for X (DFX): Key to competitive, profitable products. *AT&T Technical Journal*, 69(3), pp. 61-76.
28. Gray, A. W. (2011). *Enhancement of Set-Based Design Practices Via Introduction of Uncertainty Through the Use of Interval Type-2 Modeling and General Type-2 Fuzzy Logic Agent Based Methods*. (Doctoral dissertation). University of Michigan, Ann Arbor, MI.
29. Gray, A.W., & Singer, D. J. (2011, October). *Applied Set-Based Communications and Negotiation System*. Paper presented at ASNE Human Systems Integration Symposium, Vienna, VA.
30. Hauser, J. R., & Clausing, D. (1988, May-June). The House of Quality. *Harvard Business Review*.
31. Hefazi, H., Mizine, I., Schmitz, A., Klomparens, S., & Wiley, S. (2010, September). Multidisciplinary Synthesis Optimization Process in Multihull Ship Design. *Naval Engineers Journal*, 122(3), pp. 29-47.
32. Hintersteiner, J. D., & Zimmerman, R. C. (2000, June 21-23). *Implementing Axiomatic Design in the Systems Engineering Process: An Axiomatic Design Capability Maturity Model*. Paper presented at the First International Conference on Axiomatic Design, Cambridge, MA.

33. Huthwaite, B. (1994). *Strategic Design: A Guide to Managing Concurrent Engineering*, Institute for Competitive Design.
34. Jones, C. J. (1992). *Design Methods* (2nd ed.). New York: Van Nostrand Reinhold.
35. Kerns, C. (2011). *Naval Ship Design and Synthesis Model Architecture Using a Model-Based Systems Engineering Approach*. (Master's thesis). Virginia Polytechnic Institute and State University, Blacksburg, VA.
36. Kossiakoff, A., & Sweet, W. N. (2003). *Systems Engineering: Principles and Practice*. Hoboken, NJ: John Wiley & Sons.
37. Kossiakoff, A., Sweet, W. N., Seymour, S. J., & Biemer, S. M. (2011). *Systems Engineering: Principles and Practice*. Hoboken, NJ: John Wiley & Sons.
38. Lee, T. (2003, May). *Complexity Theory in Axiomatic Design*. (Doctoral dissertation). Massachusetts Institute of Technology, Cambridge, MA.
39. Lightfoot, R. S. (2002, August 18-20). *Enhanced Concurrent Engineering: An Approach for Accelerating the Systems Engineering Process While Minimizing the Risk*. Presented at the IEEE International Engineering Management Conference, Cambridge, UK.
40. Liker, J. K., & Lamb, T. (2002, August). What is Lean Ship Construction and Repair? *Journal of Ship Production*, 18(3), pp. 121-142.
41. Liker, J. K., Sobek, D. K., Ward, A. C., & Cristiano, J. J. (1996, May). Involving Suppliers in Product Development in the United States and Japan: Evidence for Set-Based Concurrent Engineering. *IEEE Transactions on Engineering Management*, 43(2), pp. 165-178.
42. Liker, J. K., & Ogden, T. N. (2011). *Toyota Under Fire: How Toyota Faced the Challenges of the Recall and the Recession to Come Out Stronger*. New York: McGraw-Hill.
43. Loureiro, G. (1999). *A Systems Engineering and Concurrent Engineering Framework for the Integrated Development of Complex Products*. (Doctoral dissertation). Loughborough University, Loughborough, UK.
44. Loureiro, G., & Leaney, P.G. (2003). A systems and concurrent engineering framework for the integrated development of space products. *Acta Astronautica*, 53, pp. 945-961.
45. Maier, J. R. A., & Fadel, G. M. (2004, May 16-21). *Understanding the Complexity of Design*. Paper presented at The New England Complex Systems Institute Fifth International Conference on Complex Systems, Boston, MA.
46. Mandel, P., & Chryssostomidis, C. (1972, September 5). A Design Methodology for Ships and other Complex Systems. *Phil. Trans. R. Soc. London*, 273(1231), pp. 85-98.
47. Martins, J. R. R. A., & Lambe, A. B. (2012). Multidisciplinary Design Optimization: A Survey of Architectures. *American Institute of Aeronautics and Astronautics Journal* (Submitted).
48. McGuire, M. L., Oleson, S. R., & Sarver-Verhey, T. R. (2011, September 27-29). *Concurrent Mission and Systems Design at NASA Glenn Research Center: The Origins of the COMPASS Team*. Paper presented at the AIAA Space 2011 Conference and Exposition, Long Beach, CA.

49. McKenney, T. A., Buckley, M. E., & Singer, D. J. (2012, June 11-14). *The Practical Case for Set-Based Design in Naval Architecture*. Paper presented at the International Marine Design Conference, Glasgow, UK.
50. Mistree, F., Smith, W. F., Bras, B. A., Allen, J. K., & Muster, D. (1990, October 31 – November 3). *Decision-Based Design: A Contemporary Paradigm for Ship Design*. Paper presented at the Society of Naval Architects and Marine Engineers Conference, San Francisco, CA.
51. Molloy, O., Tilley, S., & Warman, E. (1998). *Design for Manufacturing and Assembly: Concepts, Architectures, and Implementation*. New York: Springer.
52. Monden, Y. (1983). *Toyota Production System: Practical Approach to Production Management*. Norcross, GA: Industrial Engineering and Management Press.
53. Nahm, Y. E., & Ishikawa, H. (2006a, May). A New 3D-CAD System for Set-Based Parametric Design. *The International Journal of Advanced Manufacturing Technology*, 29(1-2), pp. 137-150.
54. Nahm, Y. E., & Ishikawa, H. (2006b, May). Novel space-based design methodology for preliminary engineering design. *International Journal of Advanced Manufacturing Technology*, 28(11-12), pp. 1056-1070.
55. Nicholas, J. M., & Steyn, H. (2012). *Project Management for Engineering, Business, and Technology*. 4th ed. New York: Routledge.
56. Nowacki, H. (2009, May 26-29). *Development in Marine Design Methodology: Roots, Results and Future Trends*. Paper presented at the International Marine Design Conference, Trondheim, Norway.
57. Papalambros, P. Y., & Wilde, D. J. (2000). *Principles of Optimal Design: Modeling and Computation*. 2nd ed. New York: Cambridge University Press.
58. Papanikolaou, A. (2010). Holistic ship design optimization. *Computer-Aided Design*, 42, pp. 1028-1044.
59. Pedrycz, W., Ekel, P., & Parreiras, R. (2011). *Models and Algorithms of Fuzzy Multicriteria Decision-Making and Their Applications*. Chichester, West Sussex, UK: John Wiley & Sons.
60. Pugh, S. (1991). *Total Design: Integrated Methods for Successful Product Development*. Wokingham, UK: Addison-Wesley.
61. Ray, T., Gokarn, R.P., & Sha, O.P. (1995, May). A Global Optimization Model for Ship Design. *Computers In Industry*, 26(2), pp. 175-192.
62. Salomone, T. A. (1995). *What Every Engineer Should Know about Concurrent Engineering*. New York: Marcel Dekker.
63. Singer, D. J. (2003). *A Hybrid Agent Approach for Set-Based Conceptual Ship Design Through the Use of a Fuzzy Logic Agent to Facilitate Communications and Negotiation*. (Doctoral dissertation). University of Michigan, Ann Arbor.
64. Singer, D. J., Doerry, N., & Buckley, M. E. (2009, October). What is Set-Based Design? *Naval Engineers Journal*, 121(4), pp. 31-43.
65. Smith, P. (2007). *Flexible Product Development*. 1st ed. San Francisco: Jossey-Bass.
66. Smith, P. G. (2004). Concurrent Product Development Teams. In D. I. Cleland (Ed.), *Field Guide to Project Management* (pp. 594-608). Hoboken, NJ: John Wiley & Sons.

67. Sobek, D. K. (1997). *Principles that Shape Product Development Systems: A Toyota-Chrysler Comparison*. (Doctoral dissertation). University of Michigan, Ann Arbor, MI.
68. Sobek, D. K., Ward, A. C., & Liker, J. K. (1999, Winter). Toyota's Principles of Set-Based Concurrent Engineering. *Sloan Management Review*, 40(2), pp. 67-83.
69. Stamatis, D. H. (2003). *Failure Mode and Effect Analysis: FMEA from Theory to Execution* (2nd ed.). Milwaukee, WI: Quality Press.
70. Storch, R. L., Sukapanpotharam, S., Hills, B., & Bell, M. (2000). Design for Production: Principles and Implementation. *Journal of Ship Production*, 16(1), pp. 27-39.
71. Suh, N. P. (1990). *The Principles of Design*. New York: Oxford UP.
72. Suh, N. P. (1995, June). Axiomatic Design of Mechanical Systems. *Journal of Mechanical Design*, 117, pp. 2-10.
73. Ullman, D. G. (2003). *The Mechanical Design Process*. Boston: McGraw-Hill.
74. Ulrich, K. T., & Eppinger, S. D. (2008). *Product Design and Development*. 4th ed. Boston: McGraw-Hill.
75. Ulrich, K. T., & Pearson, S. A. (1993, August). *Does Product Design Really Determine 80% of Manufacturing Cost?* (Working Paper No. 3601-93). Cambridge, MA: Alfred P. Sloan School of Management, Massachusetts Institute of Technology.
76. Venter, G., & Haftka, R. (1999). Using Response Surface Approximations in Fuzzy Set-Based Design Optimization. *Structural Optimization*, 18(4), pp. 218-227.
77. Ward, A. C., Liker, J. K., Christiano, J. J., & Sobek, D. K. (1995, Spring). The Second Toyota Paradox: How Delaying Decisions Can Make Better Cars Faster. *Sloan Management Review*, 36(2), pp. 43-61.
78. Ward, A., Sobek, D., Christiano, J. J., & Liker, J. K. (1995). Toyota, Concurrent Engineering, and Set-Based Design. In J. K. Liker, J. E. Ettlie, & J. C. Campbell (Eds.), *Engineered in Japan: Japanese Technology Management Practices* (pp. 192-216). New York: Oxford University Press.
79. Wheelwright, S. C., & Clark, K. B. (1992). *Revolutionizing Product Development: Quantum Leaps in Speed, Efficiency, and Quality*. New York: The Free Press.
80. Winner, R.J., Pennell J.P., Bertend H.E., & Slusarczuk, M.M.G. (1988). *The Role of Concurrent Engineering in Weapon System Acquisition* (R-338). Alexandra, VA: Institute for Defense Systems Analysis.
81. Yang, K., & El-Haik, B. (2009). *Design for Six Sigma: A Roadmap for Product Development*. 2nd ed. New York: McGraw Hill.
82. Ziemke, M. C., & Spann, M. S. (1993). Concurrent engineering's roots in the World War II era. In H. R. Parsaei, & W. G. Sullivan (Eds.), *Concurrent Engineering: Contemporary Issues and Modern Design Tools* (pp. 24-41). London: Chapman & Hall.

Chapter 3: Set-Based Design Execution

While theoretical advantages of SBD have been proven, practical execution of SBD principles remains a challenging task. The previous chapter highlights the need for a framework that can aid organizations in executing SBD. Although organizations like the U.S. Navy are different from Toyota, SBD principles can and should be adapted to other organizations. Before SBD can be adopted, however, methods to aid in the facilitation and guidance of SBD principles are required. This chapter identifies the necessary considerations for a successful SBD execution and highlights the limitations of current research in addressing them.

An overview of the recent SBD execution for the U.S. Navy Ship to Shore Connector Program and its results are described as an introduction to SBD application with regard to ship design. Based on the successful execution of SBD for the SSC Program, important lessons are identified. Major SBD criticisms and execution challenges are then discussed to form a better understanding of current misconceptions and execution gaps. In an effort to distinguish SBD from other methods and ensure all necessary elements are considered, a novel SBD rigor standard is proposed. Next, an overview of related work associated with the execution of certain SBD principles is provided as well as the limitations or applicability of this work to the problems discussed in this dissertation. Finally, a description of the areas necessary for proper SBD execution that currently lack research focus is presented.

3.1 U.S. Navy's Ship to Shore Connector SBD Efforts

SBD has been demonstrated in mainly commercial sectors, including aerospace and automotive industries, but was recently used for the first time in a ship design and acquisition program for the U.S. Navy (Singer, Doerry, & Buckley, 2009; Mebane et al., 2011). Beginning in 2007, the Ship to Shore Connector (SSC) Program executed SBD, based on a decision by its Naval Sea Systems Command (NAVSEA) program office, in part to test SBD advantages. One of these advantages is the ability to improve design flexibility as the design progresses (CDI Marine, 2009). The main reason for the use of SBD, however, which was voiced by the SSC Program Office, was the ability to document design decisions and the accumulation of important corporate knowledge (McKenney, Buckley, & Singer, 2012). The reasoning behind this notion is that the ship design process often takes years to complete, with substantial personnel turnover, and can lead to a dilution of design knowledge and rationale. This section provides an overview of the SSC design efforts and the results of the SBD execution.

3.1.1 Execution

Without any formal SBD execution process, an effort to design a formal process was conducted using the Decision Oriented Systems Engineering (DOSE) method. DOSE is a patented systems engineering method that facilitates process design and uses knowledge mapping techniques to facilitate operations of the decision making team (Buckley & Stammnitz, 2004; Buckley & Womersley, 2007; CDI Marine, 2009). The goal was the creation of a detailed execution process based on the decisions made throughout the set reduction process.

Once the process was defined, the actual design effort began. The SSC requirements were derived from the need to replace the current fleet of Navy Landing Craft Air Cushions (LCACs) and other high-level requirements. Figure 3.1 shows an image of the SSC design. The provided requirements were used to define the initial design space (DS). The DS was then partitioned into six element responsibilities: Performance (Skirt), Hull, Machinery, Auxiliaries, Command, Control, Communications, Computers, and

Navigation (C4N), and Human Systems Integration (HSI). These responsibilities were determined based on aspects of the design that required particular expertise.

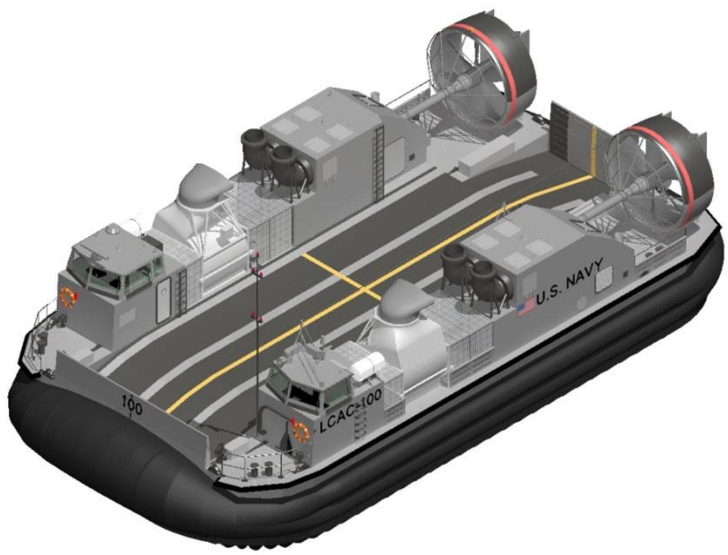


Figure 3.1: SSC Artist Rendition (www.ship2shoreconnector.com)

Analysis within each responsibility was completed concurrently and the trade spaces were reduced based on these analyses and expert recommendations. Set reduction decisions required rationale, which was conducted by each System Engineering Manager (SEM) through trade studies and comparative assessments at the element level. Infeasible and dominated solutions were eliminated, leaving only feasible non-dominated solutions. An integration team facilitated the reduction efforts by overseeing the reduction process and evaluating craft-level concepts. A balancing filter was used to evaluate combinations of non-dominated solutions that determined platform viability. Finally, a multi-attribute utility model used craft-level metrics to compare the remaining solutions to reach the final and most viable candidates (CDI Marine, 2009). The set reduction process is provided in Figure 3.2.

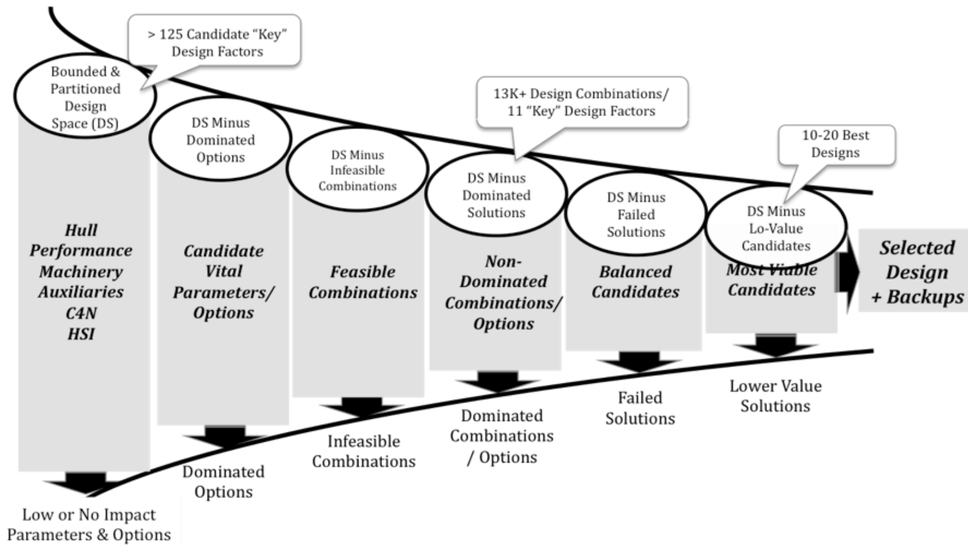


Figure 3.2: SSC Set Reduction Process (McKenney, Buckley, & Singer, 2012)

3.1.2 Results

After completion of the SBD effort in September 2008, advantages of SBD were proven and most SSC members saw value in the method (Doerry, 2010; Singer, Doerry, & Buckley, 2009; Mebane et al., 2011). The SSC preliminary design also was completed on schedule, less than 10% over the original budget, and used no design margin (Doerry, 2011). However, with any execution of a new method, come lessons learned and areas for improvement. Results from the study revealed ways in which SBD execution could be improved and how SBD could be applied to other types of ship designs. To help determine the degree of success of the SSC SBD effort, four questions were posed at the beginning of the program. These included:

1. Did it produce a thorough canvass of the design space, with a sound body of analysis substantiating the tradeoffs available?
2. Did it identify those design parameters of greatest impact to a good design and which options or ranges of these parameters are of greatest value to a good craft?
3. Did it produce a truly unique and unexpected solution?
4. Did it produce a staged progression towards a globally optimal design, with each stage resolving design details with successively greater fidelity? (CDI Marine, 2009, p. 8).

It was concluded that the SSC effort succeeded in the first two points. While the thoroughness of the canvassing effort can be argued to some degree, the SBD effort did force the exploration of a wide variety of options that could have potentially remained unexplored. More importantly, the SBD process itself was successful and a final solution was achieved using the set reduction process identified at the beginning of the effort. Also, the SBD effort did identify key design parameters (11 in total) and the degree of importance relative to each other. The extensive amount of data and analysis results used to make design decisions throughout the process continue to be available if any requirements change later in the design or for future design efforts.

The SSC SBD effort did not succeed in the last two points. Not achieving a truly unique and unexpected solution was not surprising, mainly because of the tight constraints placed on the design at the onset. These include the readiness of usable technologies, schedules, and well deck dimensional restrictions. Being a first attempt at executing SBD for ship design, it is not surprising that a complete staged progression with higher fidelity was not achieved. Additional restrictions, such as schedule constraints limited the execution strategy to a more simple form. However, with a more robust execution of the SBD method, the fourth point could have been tested to a fuller degree. Overall, the SBD method has shown promise through its execution during the SSC Program. It has also identified a number of execution challenges that need to be improved upon before SBD can be used for a larger-scale design effort.

3.2 Major SBD Criticisms

Although the SSC SBD efforts were deemed successful, there were also substantial criticisms. While these criticisms can be rebuked quite easily, it is important to first address these issues and then attempt to understand why these types of misconceptions occur. The three major criticisms of SBD include:

1. An effort using a more traditional spiral model could have produced a candidate design in less time and with less effort.

2. SBD is not different from other global optimization search efforts (linked software codes), and people have been doing SBD all along.
3. SBD is undoable because it takes too much time.

The first major criticism is that an effort using a more traditional spiral model could have produced a candidate design in less time and with less effort. This criticism confuses the reasoning behind the use of SBD and under what design scenarios SBD is most effective. SBD was chosen for the SSC program mainly to produce a more defensible design with greater resilience to requirement changes. The design spiral or PBD methods have difficulty providing these added values. A more traditional spiral model could have been used to design the SSC and potentially produce a sound and feasible design similar to the final design produced by the SBD efforts, but it would be more difficult to defend and potentially susceptible to changes. The ability to handle changes is a major advantage and can reduce the amount of rework later in the design process.

There is an additional consideration that is worth noting when discussing the best design method for a particular design type. As mentioned earlier, when discussing the difference between evolutionary and revolutionary designs, the design type (in most cases) lends itself to a particular design method. For example, with the highly constrained design space and few major changes compared to the LCAC, the SSC did not necessarily require the use of the SBD method. This consideration does not mean that the added benefits of a SBD process should be ignored. As described at the conclusion of the SSC SBD effort, a truly unique design was not obtained. However, while the SSC looks similar to the LCAC on the surface, many of its internal components are different. This difference is a product of the higher fidelity analysis that was conducted using the SBD method.

The second major criticism is that SBD is not different from other global optimization search efforts (linked software codes), and people have been doing SBD all along. An important distinction exists between global optimal search and design discovery by elimination of infeasible or dominated solutions, which the SBD method uses. There are also many other aspects of SBD that global search methods do not incorporate, most importantly team dynamics and communication between team members. SBD is not closed-loop optimization. Also, what synthesis loops and global search methods produce is not a complete design. If a software code could completely design a ship, then human designers would not be needed. SBD incorporates multiple aspects of designing, focusing on how human designers can reach the best possible design.

The third criticism is that SBD is untenable because it takes too much time. The first important distinction is that the fidelity of analysis and information increases as the design progresses. This increase in fidelity means that design quality is also increasing. This must be balanced with time and cost, major considerations in any design. The time and cost associated with a prescribed level of detail or quality should be determined at the outset. Additionally, it has been proven at Toyota that putting additional design effort upfront can help develop better systems faster. As mentioned in the previous chapter, this effect is known as the Second Toyota Paradox and is defined by Ward, Liker, Cristiano, and Sobek (1995) as "delaying decisions, communicating 'ambiguously,' and pursuing excessive numbers of prototypes…to design better cars faster and cheaper" (p. 44). The basic premise behind this fact is that the design is better understood when critical decisions are made, which reduces substantial rework that typically takes place during a product development process. While the actual SBD effort might take longer than a traditional design process, in relation to the total development process, total time can be reduced greatly.

3.3 Execution Challenges

While it was identified in the previous section that the major SBD criticisms are off-base, it should be further identified why such misconceptions occur. Similar to CE practices, practical execution of SBD can be challenging based on a lack of specific process or execution strategies. This section discusses what the challenges of execution are and, more importantly, why they exist. Four distinct challenges are discussed: textbook SBD execution, the unique nature of design spaces, moving from individuals to teams, and adopting a new paradigm. Only after identifying why such challenges exist, can a method be developed to aid in the execution process.

3.3.1 Textbook SBD Execution

While Toyota has been successful in their product development practices, execution of SBD principles can be more difficult for certain types of organizations, especially government-related organizations, such as the U.S. Navy. The important question to ask is: how has Toyota been successful? Jeffrey Liker outlines Toyota's management practices, ways of thinking, and culture in his book *The Toyota Way,* which is a compilation of over 20 years of experience studying the Toyota process. Liker outlines 14 principles of what he calls the "Toyota Way," which include:

Section I: Long-Term Philosophy

1. Base your management decisions on a long-term philosophy, even at the expense of short-term financial goals.

Section II: The Right Process Will Produce the Right Results

2. Create continuous process flow to bring problems to the surface.
3. Use "pull" systems to avoid overproduction.
4. Level out the workload (*heijunka*). (Work like the tortoise, not the hare.)
5. Build a culture of stopping to fix problems, to get quality right the first time.
6. Standardized tasks are the foundation for continuous improvement and employee empowerment.
7. Use visual control so no problems are hidden.
8. Use only reliable, thoroughly tested technology that serves your people and processes.

Section III: Add Value to the Organization by Developing Your People and Partners

9. Grow leaders who thoroughly understand the work, live the philosophy, and teach it to others.
10. Develop exceptional people and teams who follow your company's philosophy.
11. Respect your extended network of partners and suppliers by challenging them and helping them improve.

Section IV: Continuously Solving Root Problems Drives Organizational Learning

12. Go and see for yourself to thoroughly understand the situation (*genchi genbutsu*).
13. Make decisions slowly by consensus, thoroughly considering all options; execute decisions rapidly.
14. Become a learning organization through relentless reflection (*hansei*) and continuous improvement (*kaizen*). (Liker, 2004, pp. 37-41).

After reviewing the 14 principles, it is evident that Toyota's success comes from much more than simply the type of product development process they use. Set-based concurrent engineering is only mentioned a few times in the whole book, with most attention focusing on only one principle, Principle 13.

Toyota has spent decades developing the way they do business, and continues to evolve today (their response to recent recalls being a good example). Therefore, it is impractical to assume that an organization, especially one such as the U.S. Navy, can completely change their structure, values, culture, and personnel in a short period of time.

One additional advantage that Toyota has by practicing over decades is extensive documentation from multiple development projects. There are numerous documents outlining design relationships and linkages between aspects of designs. Also, the design decisions and the reasoning behind them are documented to aid in future projects. These are extremely valuable pieces of information because they can be used to understand the design space and relationships earlier in future design efforts. Organizations attempting to execute SBD principles must overcome the difficult hump and learning curve to gain the advantages seen through studying Toyota. While Toyota's product development process is impressive, designing automobiles is different from designing other complex engineering systems.

3.3.2 Unique Design Spaces

Every design problem is unique, and how a problem is formulated impacts the solutions, but also generalizations can be made for certain types of problems. A way to characterize a design space is related to the interdependencies of its variables and performance metrics. There has been an extensive amount of research on design space exploration and response surface methodologies that deal with characterizing a design space, also called a solution space. However, only a few methods focus on creating these spaces for CE approaches such as SBD. The research presented in this dissertation adds additional insight by characterizing the design space for set-based thinking. A detailed description of this work is presented in the next chapter. Irrespective of the exploration method, the key distinction of ship design spaces is that they are relatively flat. A flat design space is defined as one "in which ranges of control variables will produce similar behavior" (Bailey, Bras, & Allen, 1998, p. 7). This characteristic makes the design process exceptional because there are many options that produce similar results when low fidelity analysis is used. As design progresses to detailed design, however, the solution space becomes more constrained. SBD can handle the increase in fidelity while managing the solution space, but initial effort is needed to be able to differentiate and eliminate options. This needs to be taken into consideration when attempting to execute SBD principles.

3.3.3 Moving from Individuals to Teams

SBD concepts can inherently make sense to individuals when attempting to design a system. Great designers mentally use a method similar to SBD. Experts evaluate many alternatives in their heads, determine their preference, and make decisions based on what they believe is the best design. The difficulty is extending the set-based thinking of one designer to a team of designers that must make similar decisions. This process is much more difficult, and without some aid in the process, it could break down quickly. This is why the extension from one designer to a team of designers is a major implication of effectively executing SBD principles.

3.3.4 Adopting a New Paradigm

There are two important points that must be considered when adopting a new paradigm. First, the identification of whether the paradigm is actually new or if aspects are rooted in other work must be completed. A "new" theory or method is rarely a genuine invention. Typically, it is a new application of a previous theory or method, or it is a combination of multiple theories or methods in a unique and beneficial manner. By understanding its roots and similarities to other theories or methods people are familiar with, adopting a new paradigm can become much easier. The second point is the need to identify where the challenges of adopting a new paradigm come from and how can they be overcome. While this is a broad and challenging subject, understanding the challenges of adopting a new paradigm can help designers have a better handle on the task ahead of them. Attempting to overcome these challenges and potential aids in this process are also essential.

The first point mentioned above leads to an evaluation of the roots of SBD. A common misconception about SBD is that its underlying theory is in new and untested territory. Upon examination, however, McKenney, Buckley, and Singer (2012) determined that one of its major components is not completely unique. The concept of eliminating design alternatives based on feasibility has been utilized in many design methods and design space evaluations. The additional use of dominance to reduce sets is also not new and is rooted in utility theory, originally presented as a part of game theory (Van Neumann & Morgenstem, 1944). An alternative dominates another if it is considered superior in all attributes relative to the other alternative. Set reduction based on dominance, as practiced in SBD, is the same as dominance relationships using utility theory. Related research using utility theory for SBD reduction is described in more detail in Section 3.5.

Even though the use of feasibility and dominance is not new, SBD remains somewhat speculative in the eyes of some within the ship design community. The majority of the resistance is believed to be associated with the introduction of a new paradigm (McKenney, Buckley, & Singer, 2012). As described by Kuhn (1962), new paradigms are seen as difficult to adopt, as most people attempt to hold on to known and comfortable ideas or methods. In U.S. Naval ship design, the conventional use of the design spiral and PBD methods are understandable, tried and true methods to ship design. Additionally, most ship design tools have been developed around the spiral method (a good example being the Advanced Ship and Submarine Evaluation Tool (ASSET)), which further enhances preference towards the conventional methods. Using the conventional method has led to extensive use of synthesis models being used to select designs, instead of used as a design tool (McKenney, Buckley, & Singer, 2012). While synthesis models can be useful tools, the same issues associated with PBD methods apply, such as the introduction of design bias. The difficulty of adopting a new paradigm goes hand-in-hand with the first execution challenge related to textbook execution of Toyota's process. It is impossible to transplant a different culture into an organization overnight.

While the difficulty of making a transformation from one paradigm to another can intuitively make sense, how to effectively make the transformation is less clear. If there is ambiguity in relation to comparing two different paradigms, there should be a method to define the differences.

3.4 SBD Rigor Standard

As indicated in the previous sections, there are substantial challenges associated with SBD execution. Not only are there misguided criticisms and serious cultural hurdles, there is no formal method to describe a SBD execution. Similar to CE, there are degrees of SBD execution; therefore, there should be a method to determine how "set-based" a design activity actually may be. A formal and generic rigor standard can both differentiate SBD from other methods, and increase understanding of SBD by defining key decisions and their resultant products. In conjunction with Buckley and Singer, this author developed a SBD rigor standard that was presented at the 2012 International Marine Design Conference (McKenney, Buckley, & Singer, 2012). This section presents this work in the context of improving the understanding of SBD executions and providing a framework to evaluate current and future SBD execution efforts.

3.4.1 Proposed Standard

It is usually stated that the most cost effective designs are the ones where more costly decisions are made later in the process. The difficulty is that a designer is unable to identify these decisions at the beginning of the design process because design knowledge is minimal. Patience is an essential quality in this respect, which is counterintuitive for most engineers. SBD requires a substantial amount of effort upfront, which is not usually common for more traditional design methods. Just because a design effort is labeled SBD, does not mean it necessarily supports its principles. Also, the execution of SBD will have to be tailored to meet specific design scenarios. A rigor standard should instead focus on a process exemplifying key SBD principles rather than a specific rigid set of rules.

The most rigorous application of SBD is one where set reductions occur based on dominance and feasibility until one solution remains. This is not practical from a time and effort perspective. While the most rigorous application is not practical, a degree of rigor can still be determined based on the key elements of SBD. Thorough characterization of the design space, maintaining flexibility throughout set reductions, tracking convergence, documenting reduction decisions, continuous communication, and proactive leadership during execution are all important elements of a productive SBD process. The proposed approach evaluates a design process before it starts to assess how much it coincides with SBD principles. There are five major SBD elements that should be focused on during an evaluation. The goals that should be achieved by a design process to support key SBD principles are provided in Table 3.1.

Table 3.1: Key Elements of SBD (McKenney, Buckley, & Singer, 2012)

SBD Element	**GOAL:** ***To what extent does the planned SBD process***
Characterization	Ensure that the design space is defined, bounded, described and documented
Flexibility	Facilitate, review, track and document reduction decisions, while maintaining the flexibility to accommodate errors and changes in requirements
Convergence	Support set convergence and staying within previously defined sets
Facilitation	Support communication across functional design groups

Table 3.2 provides recommended levels of support for a SBD process. Level 1 equates to a minimum level of SBD process support. Level 3 equates to a sophisticated level of process support. These levels are intentionally broad to ensure applicability while being specific enough to identify a degree of support for the identified key SBD elements.

Table 3.2: SBD Rigor Standards (McKenney, Buckley, & Singer, 2012)

SBD Element	Levels of Success
Characterization	1. Process characterizes design space based on heuristics with little formal data 2. Process supports formal declaration and documentation of parameters, bounds, and partitioning into functional design groups 3. Process supports protocol for 3rd party review and approval
Flexibility	1. Process supports concurrent evaluation of alternatives across functional design groups 2. Process supports tracking, documentation, and review of set reductions decisions and rationale 3. Process supports 3rd party review and approval reduction decisions and a protocol for reopening design space with good reason.
Convergence	1. Process provides a design space sizing strategy to estimate the relative size of the design space and track set reduction progress. 2. Process defines measures for tracking convergence, documents progress and projects completion time 3. Process supports tracking and documentation and 3rd party review of deviations outside previous set ranges
Communication	1. Process defines a grouping strategy to facilitate communication 2. Process establishes a formal communication protocol 3. Process provides facilities for tracking, documenting and 3rd party review of negotiations
Facilitation	1. Process provides simple integration protocol where the integration lead resolves conflicts 2. Process provides integration protocol that supports convergence strategy and uses preferences to eliminate infeasible or inferior regions 3. Process provides for facilitation, tracking, documentation and 3rd party review of negotiations involving competing and conflicting preferences across functional design groups

While some of these aspects have been presented in some form in the previous chapter, it is important to understand key distinctions between the elements and the reasoning behind identifying them as key elements. The following sub-sections discuss each aspect of the standard and the important components associated with a successful SBD execution.

3.4.1.1 Characterization

Characterization attempts to define, bound, partition, and document the design trade space. This is the typical first step for most design methods, and relies mainly on experienced designers and their understanding of the design space. History has shown that there is often a failure to record the reasons for design decisions, which necessitates frequent relearning of the same lessons (Brown, 1992). Also, with the time-consuming nature of design processes, young designers are not gaining the proper experience to become design managers (Brown, 1993). While experienced designers provide valuable insight and can have a general idea of where a design is headed, it is important to not eliminate any designs too early if the decision is based only one designer’s opinion. Crucial components of the design can be overlooked if there is an overreliance on heuristic methods.

SBD utilizes experienced designer’s knowledge and known information to explore large areas and conduct high level analysis to evaluate the design space for infeasible or inferior candidate solutions. Alternatives should not be eliminated prematurely, especially when the level of detail remains low. SBD then bounds the design space and partitions it for functional design groups to initiate the search regions. Documentation of the design space, preferences of the functional design groups, and infeasibility criteria are also an important element of characterization. The steps associated with SBD characterization forces designers to explore alternatives and areas of the design space more thoroughly than they may have otherwise.

3.4.1.2 Flexibility

Maintaining flexibility in decision-making during design permits adaptation to changing conditions (Nahm & Ishikawa, 2006). This point is particularly important when making set reduction design decisions. Common design methods, such as point-based or spiral methods, invite decisions when design alternatives are not fully developed. In a typical Analysis of Alternatives, a single design (or a few designs) are selected and characterized in greater detail, which could lead to incompatibility and costly changes (such as premature elimination or filtering). According to Ford and Sobek (2005), “[o]ften the performance, costs, and impacts on project duration of undeveloped alternatives cannot be predicted accurately enough in early stages to identify the best alternative." By eliminating or selecting an alternative too soon, future iterative steps could lead to incompatibility between design components and substantial rework. In SBD, multiple alternatives can continue to be evaluated and carried forward until more information is known, and a more informed decision can be made. Functional design groups are able to complete useful work early by defining constraints and managing the design space (Smith, 2007).

Another component of maintaining flexibility is the way in which a solution is obtained. Focus is placed on the elimination of infeasible or dominated solutions as opposed to searching for favorable solutions. It is important to distinguish between SBD and global optimization within the overall ship design process. Optimization methods search for favorable solutions, ignoring or being unaware of the other solutions deemed less favorable.

Design decisions are considered robust if "the decisions remain valid regardless of the choices made by other engineers working on the product" (Bernstein, 1998). The most robust design decision is one that impacts no other decision within the design space, which means it is independent of any other decisions. As sets narrow and negotiations between functional design groups continue, decisions should be made that accommodate as many groups' preferences as possible. In an ideal case, where all decisions are completely robust, convergence would not be needed and the optimal design would be found. This solution would indicate that there were no tradeoffs or interdependences between any component of the design and overall satisfaction with the result. Obtaining a completely robust design decision early in the process is not a practical pursuit; therefore, convergence is required to move towards a more robust and optimal solution.

3.4.1.3 Convergence

Convergence consists of set reduction (and expansion) progress metrics and protocols that are defined and executed. One of the major SBD principles initially developed by

Toyota is a strong desire to stay within the initially defined sets, hence avoiding divergence. Sobek (1997) stated that this was mainly due to the fact that "downstream sets are subsets of upstream ones, thus any work or communication based on upstream sets is also valid for all downstream sets, including the final solution." Additional work must be completed in order to fully understand the design space if set-ranges are reopened. Expansion of sets should only occur when there are special exceptions, such as a good improvement idea or a problem that occurs (Sobek, 1997). While expanding a set for legitimate reasons is allowed, convergence and set reduction is a SBD principle that should be followed.

3.4.1.4 Communication

Another principle that is an essential part of all concurrent engineering efforts, including SBD, is communication. A formal negotiation protocol for managing complex interactions throughout the process should be established and executed. Negotiating the preferences of functional design groups in a way that captures tradeoffs is an important component of SBD. Preference-based reasoning methods are used to handle uncertainties, to provide and communicate preferences from functional design groups, and to integrate preferences to guide convergence (McKenney & Singer, 2012). Communication facilitation tools allow for easier transfer and combination of information between functional design groups and the chief engineer. Specific development of communication/facilitation methods by Singer (2003) and Gray (2011) is provided in the next chapter.

It is important that functional design groups communicate preferences for negotiation, as well as other important information regarding designs, such as the importance or influence of variables and design components. At the integration stage, this information would help determine what design decisions are the most important (McKenney & Singer, 2012). For example, Toyota waits until later in the design process to make decisions on low-impact components, like exhaust systems (Smith, 2007).

3.4.1.5 Facilitation

A final and critical aspect of SBD is the role of the design manager or integration leader in managing the SBD effort and facilitating the process. This referee (or team) is responsible for the review of rationale for elimination of solutions and documenting progress. Guiding set reduction is the most important role of the facilitation lead, and is usually under the responsibility of the engineering manager or chief engineer in charge of managing the design process. It is generally agreed upon that the SBD method requires a large amount of experience to manage correctly and efficiently (Sobek, 1997; Panchal, Fernandez, Allen, Paredis, & Mistree, 2005; Smith, 2007). A solid engineering base is required for the integration leader to be able to understand interactions and tradeoffs that must be made. SBD facilitates this process, but the role of the manager is essential. Toyota provides another good example of the importance of this role. Smith (2007) states, "Toyota's managers are all excellent engineers first, so they are prepared for this role. In a company with weaker engineering managers, convergence might be choppy or delayed, thus jeopardizing the set-based process."

The role of facilitation includes combining preferences and information, communicating with functional design groups, and confirming or approving important design decisions. The key activities of the SBD method that the facilitation leader controls and oversees include: the characterization and set reduction review, convergence rate, integration, and the documentation of the process. As mentioned earlier, the most rigorous application of SBD is when convergence continues until there is only one solution remaining. In order to be efficient, the facilitation leader must take schedule and cost into account when setting set reduction strategies and reduction rate goals. Documentation should also occur extensively so the reasons for making design decisions can be tracked in case changes occur. Also, design decisions, if documented, can be recorded and used to teach younger designers the ship design process.

3.4.2 Evaluation of U.S. Navy Design Efforts

The five aspects of the rigor standard discussed in the previous section can be used to evaluate a SBD effort, using the scale provided in Table 3.2. While the use of the SBD rigor standard should be used at the start of a design effort to validate an intended method, it can also be retrospective and review past design efforts. In addition to developing the rigor standard, McKenney, Buckley, and Singer (2012) also tested the standard using the authors' experience with the SSC SBD execution. Based on this initial assessment, a total score of 9 out of a possible 15 was achieved. Table 3.3 provides a summary of the ratings. Characterization was the most successful element with a maximum score of three, while flexibility and convergence both had scores of two. Communication and facilitation both had scores of one, indicating that these two elements were weakly executed. This score results because communication during the SSC effort was tied to the team structure and no formal protocol was set in place. Also, there was no formal negotiation related to integration. One team leader dealt with most of the tradeoff decisions. This rigor rating aligns closely with the conclusions of the SSC program where it was identified that a substantial amount of work was completed up front, but much less was done on the back end due to schedule constraints.

Table 3.3: SSC Execution Rigor Rating

SBD Element	Maximum	Assessed SSC's SBD Level
Characterization	3	3
Flexibility	3	2
Convergence	3	2
Communication	3	1
Facilitation	3	1
Total Score	**15**	**9**

The SSC was the first officially labeled SBD execution for the Navy, but the five elements of the rigor standard have been applied in some form to various past U.S. Navy design efforts. While a detailed evaluation of all past design efforts has not been completed, some insight into a specific design effort can be gained by reading the literature on the U.S. Navy Joint Maritime Command and Control Capability (JCC(X)) concept exploration. As the four Navy command ships were reaching the end of their service life (almost 40 years), a functional replacement of their capabilities was required.

The beginning of the Analysis of Alternatives (AoA) phases began in 2000. There were no set requirements at the beginning of the concept exploration; in fact, it had not even determined if replacement ships were required. This fact did not allow the designers to use a typical point-based method by using a baseline design. A different type of method, similar in many aspects to SBD, was instead pursued.

The most noticeable aspect of SBD used in the studies was an emphasis on eliminating alternatives. It was first concluded that a completely shore-based capability would not be possible, but that did not initially mean that a dedicated ship was required. Distributing the capability across multiple current and future platforms (ships) was still an option. It was later identified that this distributed alternative was not affordable. Next, analysis identified that extending the service life of the current ships or converting other ships was not cost effective. Finally, a modified repeat design was rejected since it would not cost significantly less than a new build, which led to the decision to develop a new ship design concept (Doerry & Sims, 2002). Throughout the AoA, a JCC(X) Oversight Group reviewed the available data and recommended the elimination of alternatives or suggested other areas of study (Doerry, Austin, & Strasel, 2002). This process identified the desire to eliminate infeasible or dominated alternatives through an increasing detail of analysis. Other SBD principles could be identified as well, including concurrent evaluation of multiple aspects of the design, and effectively exploring the design space using contour charts (Doerry, Austin, & Strasel, 2002).

Overall, and as further examined in this section, defining a SBD rigor standard allows design efforts to be evaluated based on SBD principles. Also, designers can use the proposed rigor standard to identify when their previous efforts have resembled aspects of SBD.

3.5 SBD Execution Tools

Looking back at the SSC as the main example, the rigor standard was able to identify specific areas of SBD execution that require improved structures and/or tools. This section covers current research in the specific area of SBD execution efforts. It is important to keep in mind the five elements of the SBD rigor standard as the methods used in the tools are discussed. It will be shown that, while these methods provide insight into certain aspects of SBD, most are unable to be applied to or capture all aspects.

3.5.1 Space Mapping and Preference Facilitation

Space mapping and preference facilitation methods can handle the temporal aspects of SBD by combining preferences throughout the design process. These methods are used to handle uncertainties, provide and communicate preferences, and link the various design spaces, such as the variable, performance, and constraint spaces. Current space mapping and preference facilitation research efforts were made with application to SBD include fuzzy set-based, interval set-based and probabilistic-based methods (Nahm & Ishikawa, 2006).

The Method of Imprecision (MoI), a fuzzy set-based design mapping method, considers the fuzziness of both constraints and design variables (Antonsson, 2001; Law, 1996). MoI gives preference to design variable set-ranges that are mapped to an objective space, which is a function of the variables, to generate a preference function over the objective space. This function is then aggregated with a preference for the objective set-range to form an overall preference function in the objective space. Then, it is mapped back to the design variable space to determine what variables have more influence on the objective and what regions of the design variable space are the most preferred (Scott, 1999; Wang, 2003). MoI is able to provide a designer with the link between design alternatives and performance, but results in a wider solution based on the use of standard interval arithmetic (Nahm & Ishikawa, 2006).

Finch and Ward (1997) developed an interval-based automated method that extends constraint satisfaction problems to set-constraints using predicate logic and constraint satisfaction techniques. This method has been applied to simple catalog-based designs. Malak, Aughenbaugh, and Paredis (2009), as well as Rekuc (2005) have proposed similar interval-based methods that introduce the ability to evaluate alternatives under uncertainty and eliminate dominated solutions. The methods use utility theory combined with a branch and bound algorithm that cannot explicitly express the degree of desirability or preference of the designers, but generates bounds on the membership of feasible sets of design variations.

Chen, Allen, Mavris, and Mistree (1996) present a probabilistic robustness method by integrating response surface methods, robust design techniques, and the compromise Decision Support Problem. This method identifies a set of solutions based on a desirable set of preferences, but requires a substantial amount of information, involves detailed synthesis, and cannot explicitly determine preferences for design solutions (Nahm & Ishikawa, 2006a).

Singer (2003) initially developed a fuzzy logic SBD communication facilitation tool that was later modified by Gray (2011) to incorporate uncertainty modeling. These two topics will be discussed further in the next chapter, as they are the foundation of the research presented in this dissertation. However, limitations of these methods also factored into the identification of key SBD execution components that required additional research. These limitations are also discussed in the next chapter.

3.5.2 Design Optimization

There is extensive SBD research in the optimization field that uses the intent of SBD, such as the use of set-ranges for variable values, but is not pertinent to the problem presented in this research. The results presented in SBD optimization research are valuable for their specific applications, but do not directly solve the problem of large-scale, team-based design. Recognizing one of the major drawbacks of using optimization, which is that only a single point design can be pursued, researchers have focused on incorporating sets of design variables and developing various algorithms that facilitate design space reduction (Hannapel, 2012).

The most recent example of set-based multi-objective optimization (MDO) is presented by Hannapel (2012), who developed a new MDO algorithm that incorporates SBD principles, including managing sets of design variables, gradual reduction of the design space, and seeking a reduced design space, rather than a single point. Avigad and Moshaiov (2010) have proposed a MDO problem involving the delay of decisions and handling changes in performance requirements. The method focuses on variability under uncertainty, versus optimality for potential design solutions, when selecting the aspect of the design that is delayed. This sequential method finds multiple Pareto fronts that have different locations due to design concept uncertainty.

Madhaven, Shahan, Seepersad, Hlavinka, and Benson (2008) developed a set-based method where designers collaborate by exchanging targets for shared parameters using a Decision Support Problem mathematical model for multi-objective decisions. Subsystem design teams use simulation models to identify Pareto sets of solutions based on the defined targets, who then communicate their results to the system level team. The set of solutions is evaluated and a final design is selected. Another process developed by Nahm and Ishikawa (2006) divides the design variable set-ranges into smaller regions. A design of experiments (DOE) evaluates combinations of sets instead of points to determine a "possibilitic" distribution in the objective space. This distribution is compared to an objective preference to determine feasible points. Infeasible sets are eliminated, but if two or more feasible combinations exist, a metric is used to pick the optimal design (Nahm & Ishikawa, 2006; Nahm, Ishikawa, & Yang, 2007).

3.5.3 Design Reduction Methods

Focus on reducing the design space within a set-based framework has been limited, but researchers have identified some methods related to guiding design reduction. A method using Bayesian networks for representing interesting regions of the design space and identifying interactions between local design spaces has been proposed (Shahan & Seepersad, 2009). The method uses joint probability distributions for design variables and local Bayesian networks are shared to improve communication. This method emphasizes the changing of preferences over time and does not restrict its applicability to only the use of meta-models.

There are also several decentralized decision making methods based on game theory (Panchal, Gero Fernandez, Paredis, Allen, & Mistree, 2007; Canbaz, Yannou, & Yvars, 2011; Wang & Terpenny, 2003; Liang, Yan, & Shang, 2009). These methods are much more decision-focused, guiding set reduction by eliminating infeasible portions of the design space and describing interactions between collaborators (Panchal, Fernandez, Allen, Paredis, & Mistree, 2005).

Ford and Sobek (2005) use a basic real options framework to identify the interactions between design decisions and their effects on project performance. Real options can be used to value product development strategies, including “an option to postpone the elimination of design alternatives” (Ford and Sobek, 2005). Through the ability to model and evaluate various decision strategies, real options can potentially identify the value of certain design decisions.

3.6 Limitations of Current Research

Current research on the SBD method is broad and ranges from detailed MDO algorithms and design selection automation to new, decision-oriented methods. By identifying current research motives, there is a limited amount of work attempting to solve the specific problem addressed in the proposed research, which is the understanding of design reduction in large-scale, team-based design. Most of the current methods that guide SBD reduction focus on an algorithm or automated process that either attempts to find a single solution or does not allow for human input along the way. The decisions to go in one design direction or eliminate certain solutions are unknown within most optimization frameworks. Some methods have identified the importance of design decisions, but restrict human designer input throughout the process as sets of solutions change along with design component interactions. Certain components of the methods evaluated provide insight into the problem defined in this dissertation, specifically regarding mapping and preference facilitation methods.

In team-based design, the ability to facilitate preference negotiation and to understand requirements is essential. The methods researched provide a first step towards having an integrated approach, but need to be extended to allow guidance of set reduction with the SBD method in a team environment. The extension should focus on modeling design relationships over time, as designer preferences change and fidelity of analysis increases. In addition, tracking or modeling design decisions, including the elimination of solutions, should be identified.

3.7 Chapter Summary

While the theoretical advantages of the SBD method have been proven, practical execution of SBD principles, similar to CE efforts, can be difficult. The U.S. Navy's use of SBD for preliminary design of the SSC outlined a successful SBD effort, but also identified challenges associated with its use. SBD criticisms voiced before and during the SSC SBD execution were mainly off base, but identified the common misconceptions surrounding the use of a SBD method. Beyond the criticisms, there are real and difficult execution challenges, including the inability to conduct a textbook execution like Toyota, the difficulty of dealing with flat design spaces, moving from a person to teams, and the unwillingness to adopt a new paradigm.

McKenney, Buckley, and Singer (2012) introduced a SBD rigor standard to be able to evaluate a design activity and determine how "set-based" it truly was. Using the standard to evaluate the SSC SBD execution, specific areas that needed improvement were identified. The rigor standard can also be helpful when evaluating current research on SBD execution methods and aids. Research areas of interest include design space mapping and preference facilitation, design optimization, and reduction methods. By identifying current research motives, it can be seen that there is a limited amount of work attempting to solve the specific problems addressed in this dissertation, which is the guidance of set reduction decisions and the development a facilitation framework to understand design spaces and relationships for CE and large-scale, team-based design.

Chapter Citations

1. Antonsson, E. K., ed. (2001). *Imprecision in Engineering Design*. Engineering Design Research Laboratory, Division of Engineering and Applied Science, California Institute of Technology, Pasadena, CA.
2. Avigad, G., & Moshaiov, A. (2010). Set-based concept selection in multi-objective problems involving delayed decisions. *Journal of Engineering Design*, *21*(6), pp. 619-646.
3. Bailey, R., Bras, B., & Allen, J. K. (1998, September 13-16). *A Decision-Based Approach to Improving Behavior over Time of Complex Systems*. Paper presented at the ASME Design Technical Conference, Atlanta, GA.
4. Bernstein, J. I. (1998). *Design methods in the aerospace industry: looking for evidence of set-based practices*. (Master's thesis). Massachusetts Institute of Technology, Cambridge, MA.
5. Brown, D. K. (1992). History as a Design Tool. *Journal of Naval Engineering*, 34(1).
6. Brown, D. K. (1993, January). Naval Architecture. *Naval Engineers Journal*, 105(1), pp. 42-50.
7. Buckley, M. E. & Stammnitz, V. (2004). *Decision Oriented Systems Engineering (DOSE) – A Structured, Systematic Approach to Function Allocation*. Paper presented at the 14th Annual International Symposium for INCOSE.
8. Buckley, M. E. & Womersley, M. (2007). *Mapping the Decision Landscape of Port Security Governance Issues*. Paper presented at the Maritime Technology (MTEC) Conference.
9. Canbaz, B., Yannou, B., & Yvars, P. A. (2011, August). *A New Framework for Collaborative Set-Based Design: Application to the Design Problem of a Hollow Cylindrical Cantilever Beam*. Paper presented at the ASME 2011 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, Washington, DC.
10. CDI Marine, Band Lavis Division. (2009, February). *Ship to Shore Connector Execution of Set-Based Design*. Working Paper No. 765.002.023-1.
11. Chen, W., Allen, J.K., Mavris, D.N., & Mistree, F. (1996). A concept exploration method for determining robust top-level specifications. *Engineering Optimization*, 26(2), pp. 137-158.
12. Doerry, N. (2011). *Transitioning Technology to Naval Ships* (Special Report 306). Paper presented for the Committee on Naval Engineering in the 21st Century Transportation Research Board.
13. Doerry, N. (2010). *Transitioning Technology to Naval Ships* (NAVSEA Report 05T/17). Washington, D.C.
14. Doerry, N., & Sims, P. (2002, February 29-30). *Concept Exploration Lessons Learned*. Paper presented at ASNE Day 2002, Arlington, VA.
15. Doerry, N., Austin, W. H., & Strasel, E. (2002, February 26-27). *JCC(X) Concept Exploration*. Paper presented at the ASNE Engineering the Total Ship Symposium.
16. Finch, W. W., & Ward, A. C. (1997, September 14-17). *A Set-Based System for Eliminating Infeasible Designs in Engineering Problems Dominated by Uncertainty*. Paper presented at the ASME Design Engineering Technical Conferences, Sacramento, CA.

17. Ford, D., & Sobek, D. (2005). Adapting Real Options to New Product Development by Modeling the Second Toyota Paradox. *IEEE Transactions on Engineering Management*, 52(2), pp. 175-185.
18. Hannapel, S. E. (2012). *Development of Multidisciplinary Design Optimization Algorithms for Ship Design Under Uncertainty*. (Doctoral dissertation). University of Michigan, Ann Arbor, MI.
19. Jones, C. (1992). *Design Methods*. 2nd ed. New York: Van Nostrand Reinhold.
20. Kuhn, T. S. (1962). *The Structure of Scientific Revolution*. Chicago, IL: The University of Chicago Press.
21. Law, W. S. (1996). *Evaluating Imprecision in Engineering Design*. (Doctoral dissertation). California Institute of Technology, Pasadena, CA.
22. Liang, Z. X., Yan, L., & Shang, J. Z. (2009, March). Collaborative multidisciplinary decision making based on game theory in ship preliminary design. *Journal of Marine Science and Technology*, 14(3), pp. 334-344.
23. Liker, J. K. (2004). *The Toyota Way: 14 Management Principles from the World's Greatest Manufacturer*. New York: McGraw-Hill.
24. Liker, J. K., Sobek, D. K., Ward, A. C., & Cristiano, J. J. (1996, May). Involving Suppliers in Product Development in the United States and Japan: Evidence for Set-Based Concurrent Engineering. *IEEE Transactions on Engineering Management*, 43(2), pp. 165-178.
25. Madhavan, K., Shahan, D., Seepersad, C., Hlavinka, D. A., & Benson, W. (2008, August 3-5). *An industrial trial of a set-based approach to collaborative design*. Paper presented at the ASME 2008 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, New York, NY.
26. Malak, R., Aughenbaugh, J., & Paredis, C. (2009). Multi-Attribute Utility Analysis in Set-Based Conceptual Design. *Computer Aided Design*, 41, pp. 217-227.
27. McKenney, T. A., & Singer, D. J. (2012, February 9-10). *Determining the Influence of Variables for Functional Design Groups in the Set-Based Design Process*. Paper presented at ASNE Day 2012, Arlington, VA.
28. McKenney, T. A., Buckley, M. E., & Singer, D. J. (2012, June 11-14). *The Practical Case for Set-Based Design in Naval Architecture*. Paper presented at the International Marine Design Conference, Glasgow, UK.
29. Mebane, W. L., Carlson C. M., Dowd, C., Singer, D. J., & Buckley, M. E. (2011, February 9-10). *Set-Based Design and the Ship to Shore* Connector. Paper presented at ASNE Day 2011, Arlington, VA.
30. Nahm, Y. E., Ishikawa, H., and Yang, Y. S. (2007, March). A Flexible and Robust Approach for Preliminary Engineering Design Based on Designer's Preference. *Concurrent Engineering*, 15(1), pp. 53-62.
31. Nahm, Y.E., & Ishikawa, H. (2006, May). Novel space-based design methodology for preliminary engineering design. *International Journal of Advanced Manufacturing Technology*, 28(11-12), pp. 1056-1070.
32. Panchal, J. H., Fernandez, M., Paredis, C. J. J., Allen, J. K., & Mistree, F. (2007, September). An Interval-based Constraint Satisfaction (IBCS) Method for Decentralized, Collaborative Multifunctional Design. *Concurrent Engineering*, 15(3), pp. 309-323.

33. Panchal, J., Fernandez, M., Allen, J., Paredis, J., & Mistree, F. (2005, September). *An Interval-Based Focalization Method for Decision-Making in Decentralized, Multi-Functional Design*. Paper presented at the ASME 2005 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, Long Beach, CA.
34. Rekuc, S.J. (2005). *Eliminating design alternatives under interval-based uncertainty*. (Master's thesis). Georgia Institute of Technology, Atlanta, GA.
35. Scott, M. J. (1999). *Formalizing Negotiation in Engineering Design*. (Doctoral dissertation). California Institute of Technology, Pasadena, CA.
36. Shahan, D., & Seepersad, C. C. (2009, August 30-September 2). *Bayesian networks for set-based collaborative design*. Paper presented at the ASME 2009 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, San Diego, CA.
37. Singer, D. J., Doerry, N., & Buckley, M. E. (2009, October). What is Set-Based Design? *Naval Engineers Journal*, 121(4), pp. 31-43.
38. Smith, P. (2007). *Flexible Product Development*. 1st ed. San Francisco: Jossey-Bass.
39. Sobek, D. K. (1997). *Principles that Shape Product Development Systems: A Toyota-Chrysler Comparison*. (Doctoral dissertation). University of Michigan, Ann Arbor, MI.
40. Van Neumann, J. & Morgenstern, O. (1944). *Theory of Games and Economic Behavior*. Princeton, NJ: Princeton University Press.
41. Wang, J., & Terpenny, J. (2003). Interactive evolutionary solution synthesis in fuzzy set-based preliminary engineering design. *Journal of Intelligent Manufacturing*, 14(2), pp. 153-167.
42. Wang, X. (2003). *Set Mapping in the Method of Imprecision*. (Doctoral dissertation). California Institute of Technology, Pasadena, CA.
43. Ward, A. C., Liker, J. K., Christiano, J. J., & Sobek, D. K. (1995, Spring). The Second Toyota Paradox: How Delaying Decisions Can Make Better Cars Faster. *Sloan Management Review*, 36(2), pp. 43-61.

Chapter 4: Initial Set-Based Design Research

The two major areas of SBD execution identified in the previous chapter that require additional research, and are the focus of this dissertation, include the guidance of set reduction decisions and understanding design relationships within the SBD environment. Before a method can be developed to support SBD execution in these areas, however, a better understanding of SBD reduction and the types of design relationships is required. While there are several theoretical advantages and execution challenges associated with the use of SBD, most have not been sufficiently explored to identify their actual impact on a design effort.

This chapter begins by presenting work completed by previous researchers that is used extensively as the basis for the research in this dissertation. Next, an initial case study is introduced to provide a basic description and understanding of the SBD method, including its advantages and challenges. The goal of the case study is to show that the SBD method is robust to changing conditions. For the U.S. Navy, the ability to utilize a design method robust to changes would be extremely beneficial, as requirements and desired technologies are constantly changing. Using the conclusions of this case study, a novel design facilitation tool is developed to aid in the preference generation process and to understand design relationships at the functional design level. The chapter concludes by summarizing major issues identified throughout the author's initial research stages that merit further research.

4.1 Basis of Current Work

The work presented in this chapter is primarily based on research completed by Dr. David Singer and Dr. Alexander Gray, both from the University of Michigan. Singer (2003) initially developed a fuzzy logic (FL) communication facilitation tool and conducted experiments that confirmed advantages of SBD over point-based methods. Gray (2011) later modified the facilitation tool to incorporate type-2 FL uncertainty modeling and validated its advantages for more constrained design problems. This section discusses each body of work individually and then defines which aspects are used in current research, as well as the potential areas of further development.

4.1.1 SBD Communication Facilitation

Singer (2003) predicated his research on the fact that the increasing of system complexity in the past has caused traditional design automation tools that exclude the human designer to become more likely to fail. More specifically, a lack of data and models for preliminary design efforts has led to unsuccessful implementation of optimization techniques and expert systems. The value of these tools is minimal during early design stages, mainly because the mathematical models that are used must be simplified to the point where major considerations are lost. Singer proposed set-based concurrent engineering as a potential solution to this preliminary design problem over the more traditional point-based method. Hybrid agents, defined as combinations of humans and elements of computer code, which perform specific actions, are introduced and used to structure and facilitate required communication and negotiation. Communication and negotiation is performed using a FL software agent. In an effort to investigate the use of different design methods during preliminary design, Singer planned and conducted a series of experiments using the FL software agent.

4.1.1.1 Fuzzy Logic Design Agent

Fuzzy logic allows for two types of knowledge to be combined: crisp (mathematical models) and linguistic (expert opinion). The combination of objective and subjective knowledge allows for managing of more complex problems that require the addition of subjective knowledge; a typical scenario during preliminary design. The key distinction between fuzzy set theory and crisp set theory is the assumption that an element can be a member of multiple sets at one time with varying degrees of membership. Figure 4.1 presents the conventional way of thinking about sets where a value is either completely in a set or not in one at all. The truth value describes the degree of membership in a set. For example, in the crisp theory example of Figure 4.1, a man is either tall or not tall. Therefore, a man who is 5' 11" has a truth value of 100% for not tall and 0% for tall. Figure 4.2 presents the fuzzy set and membership function representation for height. A membership function can be constructed to describe membership in the two sets describing height. Now a man who is 5' 11" is considered 50% tall and 50% not tall based on the membership function provided in Figure 4.2. The use of membership functions allows subjective knowledge to be inserted into an analysis.

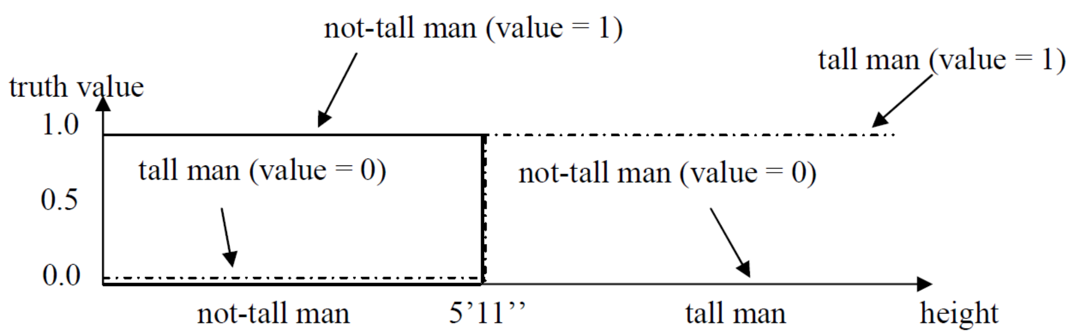


Figure 4.1: Conventional Set Membership Functions (Singer, 2003)

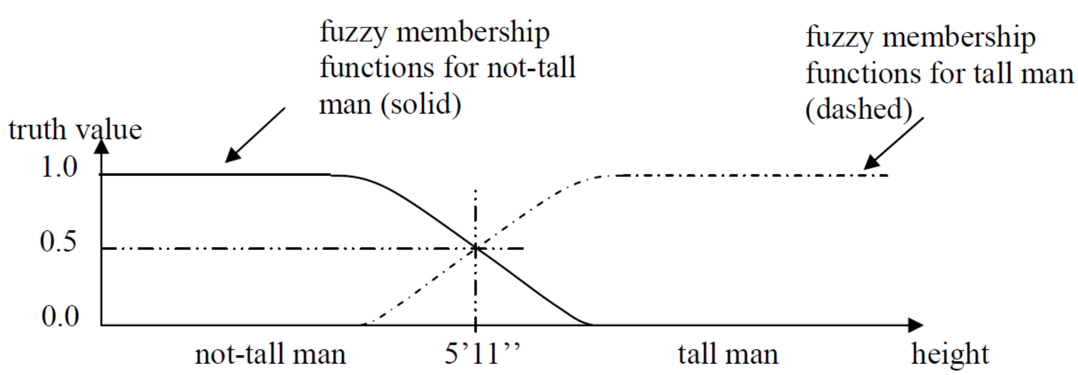


Figure 4.2: Fuzzy Sets and Membership Functions (Singer, 2003)

Fuzzy systems are used to complete a nonlinear mapping between crisp input variables and crisp output variables. They also allow linguistic expressions to be used as rules that define the relationship between inputs and outputs. The rules are defined based on all combinations of the input fuzzy sets that are activated. There are four main steps in a traditional fuzzy system: fuzzification, activation of fuzzy rules, fuzzy inference, and defuzzification. A diagram of the steps in the fuzzy system developed by Singer is provided in Figure 4.3. The bolded components in the figure represent to modified elements of a typical fuzzy system. Initially, the human agents determine limits of the sets and design preferences for a design variable. Fuzzification deals with taking crisp input variables (membership functions of agent preferences) and converting them into membership in one or multiple fuzzy sets. Next, a fuzzy rule bank is used to determine which rules are activated by the inputs. Fuzzy inference is the logic used to determine the resulting output fuzzy set. There are multiple inference formulas that can be used. The final step, defuzzification, is the process that converts a fuzzy membership function into a crisp valued output, or a joint output preference (JOP) curve.

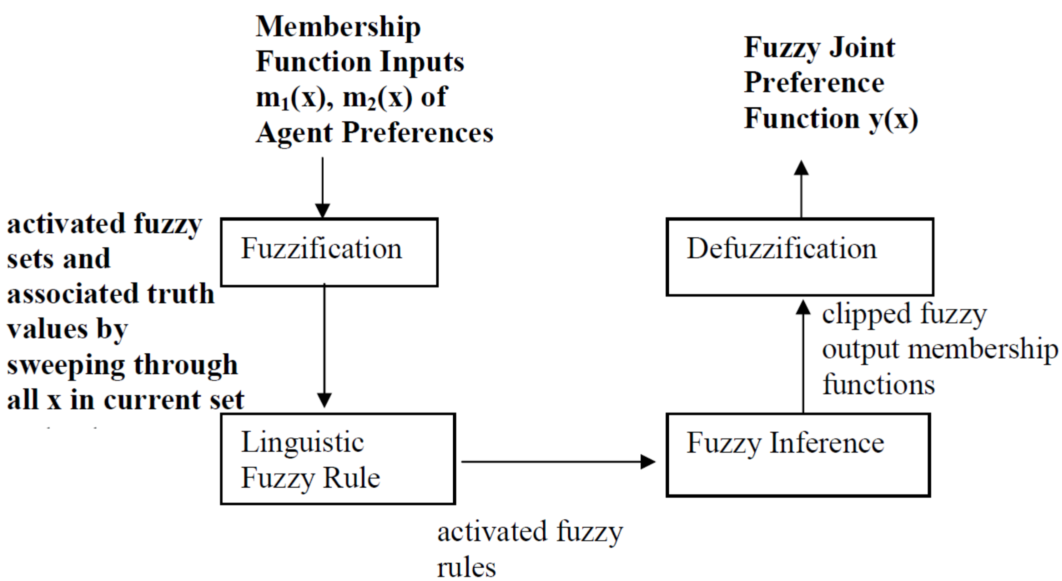


Figure 4.3: Negotiation Agent Fuzzy System (Singer, 2003)

The fuzzy software agent developed by Singer is a variation of a traditional fuzzy system due to its specific mechanics. First, the inputs to the FLS are membership functions rather than crisp values. Second, the FL rule bank spans the solution space and calculates the output by sweeping through the range of input variables to produce a JOP curve. Figure 4.4 shows these important differences and how they function. In the system developed by Singer, human design agents input preferences for design variables that are described via a set of design values ranging from [x_{min},x_{max}] utilizing any of three linguistic terms: Preferred (*P*), Marginal (*M*), and/or Unpreferred (*U*). The FL system sweeps across the set-range from minimum to maximum, activating rules from a fuzzy logic rule bank based on different combinations of the preference inputs. The activated rules are then defuzzified to a crisp preference value. As the process is repeated for every value x_i within the set-range, a continuous JOP curve is produced, representing the negotiated preference for all design values.

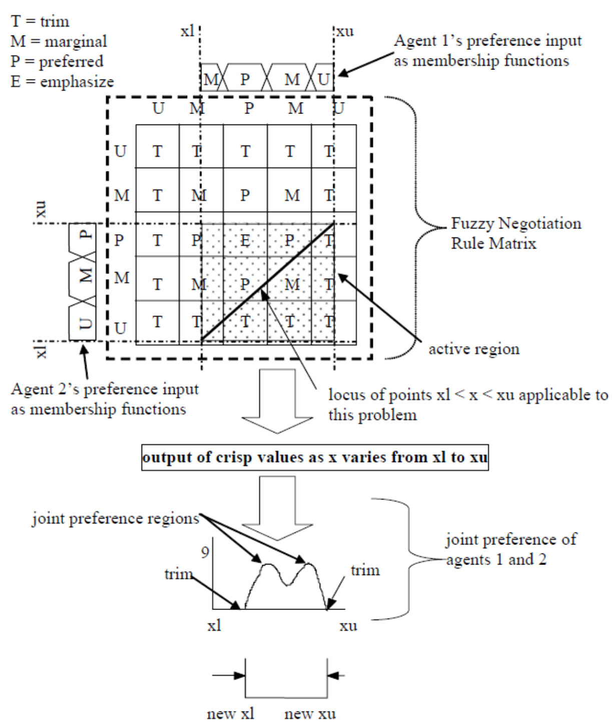


Figure 4.4: Design Assistant Software Two-Agent Example (Singer, 2003)

4.1.1.2 Experiment and Results

Singer's FL design software breaks the SBD method into a hierarchical structure, with a chief engineer agent at the top of the structure and functional design agents beneath. The chief engineer agent has the responsibility of controlling the analysis and preference generation time for the SBD method. This is done by sending requests for the negotiation of ship design variables to the design agents, and later narrowing the set-ranges of design variables based on JOP curve information, provided by the FL design tool. In Singer's study, six agents were used, including a chief engineer. The agent structure can be seen in Figure 4.5. All agents communicate with the fuzzy software agent, while the chief engineer sends information to other agents in a unidirectional manner.

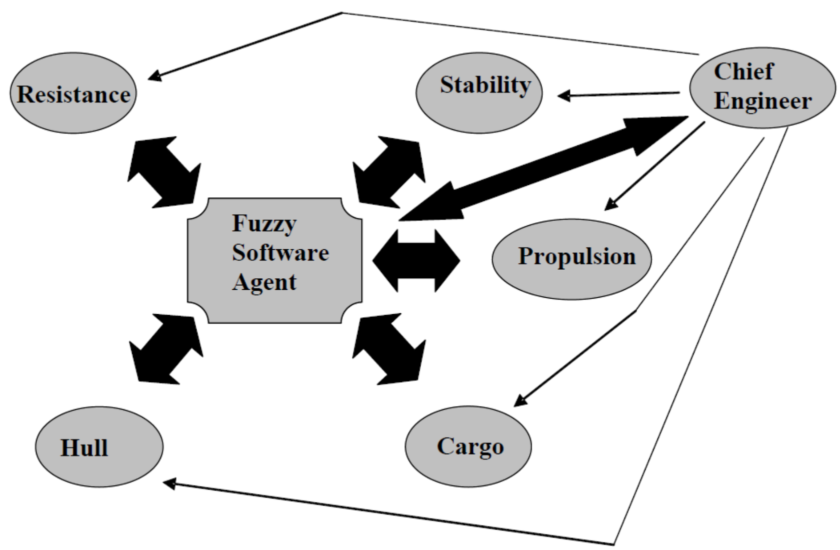


Figure 4.5: Agent Structure (Singer, 2003)

A series of experiments were used to identify the value of the FL software agent for facilitating set-based communications. The experiments utilized four groups of students that each completed two design experiments. One experiment was conducted using the FL software for negotiation and communication. The other experiment used an Internet chat window to communicate (participating members were not co-located). The main conclusion was that the FL agent-based software provides a more systematic approach for accomplishing SBD, which in turn increases the chance of obtaining a more global optimal. A separate conclusion was that SBD can replace a more point-based method, as was simulated using the chat window form of communication for design discovery. The main advantage of the FL agent-based software is the ability to keep design variable sets open longer; a design philosophy of SBD. Other advantages include the ability for concurrent development, and delaying design decisions until tradeoffs are better resolved through a gain of knowledge. The agent software's ability to control set reduction can also facilitate adaptation to changing conditions and helps balance input from multiple perspectives. Finally, the FLS agent-based structure enables the evaluation of a large number of alternatives, which means a larger portion of the design space is evaluated. This extensive evaluation of the design space can lead to a higher probability of finding a global optimal. Additionally, the results from the experiments were compared to an MDO and determined to be the same.

4.1.2 Uncertainty Modeling

Gray (2011) built on Singer's work to develop a FL design tool that further formalized the type-1 FL SBD negotiation process and introduced type-2 fuzzy logic that represents design uncertainty to improve SBD facilitation. Type-1 FL systems, such as the one developed by Singer (2003), do not involve any uncertainty modeling, which can lead to more constrained designs being led into infeasible areas of the design space. Gray introduces two additional methods that model uncertainty, a general type-2 FL method, and a more novel type-2 modeling FL system that utilizes randomization techniques. A series of experiments using both unconstrained and constrained ship designs were conducted to compare the three different FL systems. The results show that the introduction of uncertainty modeling to the SBD method can improve the overall set-based reduction process. More specifically, the experiments showed that when using uncertainty modeling within the SBD method, highly constrained designs were better managed. For highly constrained designs, the use of the type-1 FL system led to a longer set reduction process with multiple design failures. The type-2 FL systems resulted in completely feasible set reduction without any failures. All three systems were able to handle a more loosely constrained design. Also, SBD principles, such as delaying decisions and gradual set reductions, were identified.

4.1.3 Further Development Areas

Both Singer (2003) and Gray (2011) provide a solid foundation for current SBD research with many potential avenues of further improvement. There are a few common themes that can be identified from both Singer and Gray's work. These are provided below:

- Set reduction takes a heuristic approach
- The reduction path or set reduction process greatly impacts the feasibility of a design
- Success is based on feasibility achieved at the end of the design experiments
- SBD practices were able to manage changing design conditions
- Preference generation and set reduction is based only on variable level information

While Singer and Gray have provided a valuable method to structure set-based communication and negotiation of design variables, the set reduction process was completed in a heuristic manner. The chief engineer agent uses the JOP curves outputted from the FL system to determine how to reduce the variable set-ranges. No additional information other than the experience and knowledge of the chief engineer is used. The main reason why a purely heuristic approach should be improved upon is the fact that the reduction path taken greatly impacts the feasibility or outcome of the design. Whether it is the point-based method that led to failures in Singer's experiments, or the highly constrained designs that failed when not considering uncertainty in Gray's experiments, both identify the importance of the reduction path taken. Success was also based on feasibility, which is an important consideration during design. Nonetheless, additional metrics or methods of identifying the success and failure of particular reduction paths should be pursued. By accurately understanding the reduction process, early warning signs or more robust decision paths can be identified before it is too late in the design process.

Other considerations include understanding how SBD can handle changing conditions, especially changes to design requirements or constraints. A better understanding of how the SBD method manages changes and where the value of the flexibility specifically comes from would help future design efforts. Lastly, preferences are provided in the design variable domain, which makes the most sense from a design perspective. However, in managing the reduction process one should consider the objective or requirement domains as well, which are functions of the design variables. The relationships between these two domains have a major influence on the success of the design effort.

4.2 Initial Case Study

Using the advantages and further development areas of previous research, initial work began towards a basic understanding of the SBD method and its various components. Additionally, a better understanding of the decisions associated with making set reductions was desired. An initial case study using human designers focused on the ability of the SBD method to manage a design change. The objective of the initial case study was to confirm the theoretical advantages of the SBD method and identify major execution challenges. The initial case study, described in McKenney, Kemink, and Singer (2011), is presented in this section. The initial study was completed as a trial application of SBD for U.S. naval vessels in order to generate anecdotal data on the method, as well as to determine how SBD manages changes in design requirements. The case study simulated rounds of the SBD method using a mine countermeasure (MCM) vessel design that deploys and recovers autonomous vehicles.

4.2.1 Preparation

Preparation for a SBD effort is essential and includes a number of important steps including the determination of what functional design groups and negotiated variables are to be considered for the specific design of interest. Eight functional design groups were selected: general arrangements, weights, resistance, propulsion, stability, cost, payload, and seakeeping. To facilitate the SBD method, a tool and methodology is required for each functional design group to complete a proper evaluation. For example, the resistance group would require a resistance prediction program and basic hull characteristics or parent hull. These tools are either selected from an existing library or developed as needed, resulting in the creation of a methodology.

Variables and parameters were selected based on their influence on the design, and whether the functional design groups required them. Using the design groups identified earlier, variables were selected based on the possibility of conflicting preferences between two or more groups. For example, the resistance group would prefer a smaller beam, while the stability group would prefer a larger beam. The number of variables was limited in order to simplify the trial. A total of nine variables were chosen to represent the values having the most significant impact on the design.

Parameters are information that functional design groups have no specific preference for but still need to know. Most parameters are exchanged between design groups and are based on the required inputs and outputs of the tools used. These parameters were chosen based on the type of tool the design groups used and the specific values required by the tool to run.

In addition to variables and parameters, there are also specific requirements for the vessel that must be defined. These include: transit speed, transit range, and operational sea state. These requirements are used as inputs for some of the functional design groups. The trial organizers defined the set-ranges for these requirement values. An initial study was completed to determine reasonable starting values for all variables and parameters used in the case study. The selected negotiated variables, parameters, and requirements can be seen in Table 4.1.

Table 4.1: List of Negotiated Variables, Parameters, Requirement Ranges and Interactions

	Unit	Resistance	Propulsion	Stability	Arrangement	Weight	Seakeeping	Cost	Payload Evaluation
Negotiated Variable									
Length	m	N		N	N	N	N	N	
Beam	m	N		N	N	N	N	N	
Depth	m			N	N	In		N	
Draft	m	N	N	N		N	N	N	
USV/UUV Area	m^2				N				N
UAV Area	m^2				N				N
Engine room length	m		N		N				
Block coefficient (C_B)		N		In			N	In	
VCG	m			N	In		N		
Length of USV/UUV cargo	m				N				O
Length of UAV cargo	m				N				O
Requirement Ranges									
Transit Speed	kts	In				In			
Transit Range	nm					In			
Complement					In				
Parameter Ranges									
Required Thrust	N	O	In						
Propeller Diameter	m		In						
# Superstructure Decks		In			O				
Transit Power	kW		O			In		In	
Structural Weight	kg					O		In	
Outfit Weight	kg					O		In	
Propeller RPMs			O					In	
Displacement	mt					O		In	
Sea State							O		
Engine SFC	kg/kw-hr					In			
Prismatic Coefficient		In							
Midship Coefficient		In							
Waterplane Coefficient		In							
Wake Fraction		O	In						
UAV Weight	kg								O
USV/UUV Weight	kg								O
		In = Input			O = Output			N = Negotiated	

4.2.2 Design Process

As was identified in Chapter 2, SBD is more robust to changes. However, this was never shown explicitly in a design context. The goal of the case study was to prove this is in fact the case. Therefore, the design process for the case study differed in certain aspects from a more intensive SBD execution. It is important to note that the scope of this study was limited, and that the main focus was to complete a trial application of SBD and evaluate how SBD manages changes in requirements. To simplify the problem, assumptions were made in regards to design group interactions and the integration process.

An integration team, consisting of the case study organizers, was formed to facilitate and manage all aspects of the design process. The role of the integration team is similar to a chief engineer, and includes combining design group preferences, making design decisions, and guiding set reduction. Figure 4.6 shows how the process works. Initially, a range of variable and parameter values were defined by the integration team based on the initial design space exploration. These ranges were then distributed to the functional design groups. The functional design groups then took these values and used the designated tool to evaluate the design space. They took the results of their evaluation and provided preferences for the negotiated variable set-ranges to the integration team.

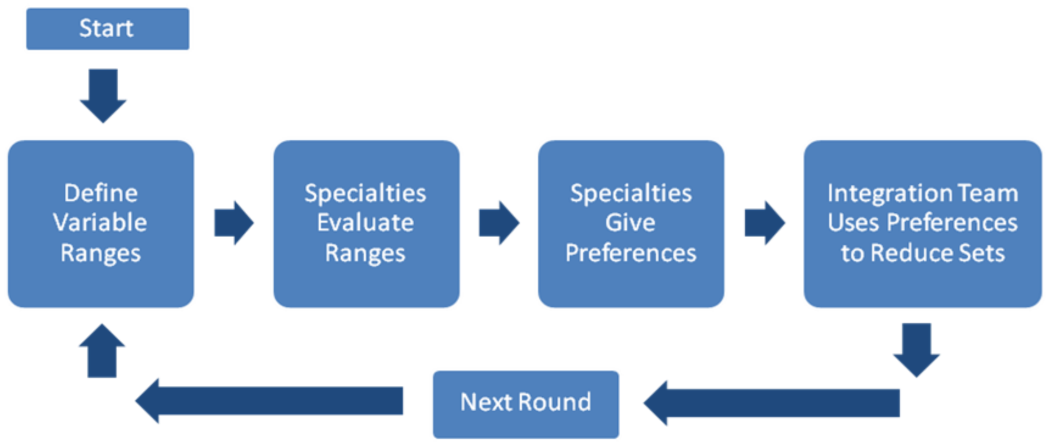


Figure 4.6: Case Study SBD Process

Preferences are provided to the integration team using two different methods. The first is a preference curve, which is a graph that provides preferences for specific values in a variable range by giving a rating between zero and one (basic utility function). A rating of zero would mean that value is infeasible. A rating of one would mean that it is the best, or one of the best, values from the design group's viewpoint at that point in the design. The second is information that cannot be captured in a preference curve: any type of recommendations or qualitative information that the design group wants to be known is also transferred to the integration team.

The individual design groups' preference curves are combined to form a single combined preference curve and all other information can then be gathered. The integration team uses the given preferences to reduce the variable set-ranges through the elimination of infeasible values. Variable set-ranges can be further reduced based on dominance. For the case study, performance metrics were also identified to further reduce set-ranges. The next round of the process begins when the integration team distributes reduced variable set-ranges. The integration team is integral to the process because all major decisions are made at this level. Furthermore, the integration team is required to record and document all factors involved in the design and decision making process.

4.2.3 Results

Three rounds of the SBD method were simulated, and different types of changing requirements occurred between rounds two and three, including an addition of storage and flight deck space, and the addition of a deck gun and ammunition stores in the bow. These changes affected the designer's preferences for certain dimensions, including the hangar length. Figure 4.7 shows how the preferences for hangar length changed between rounds two and three. In round two, the preference level remained the same at 1.0 for lengths greater than 16 meters. Following the requirement changes for round three, the preference level changed to favor the higher hangar length values, and never reached the preference level of 1.0 at any point. While it seems logical that the higher hangar length values would be preferred after the requirement changes occurred, a major value of the SBD method can be identified as the ability to determine the impact of a change on design variable preference values.

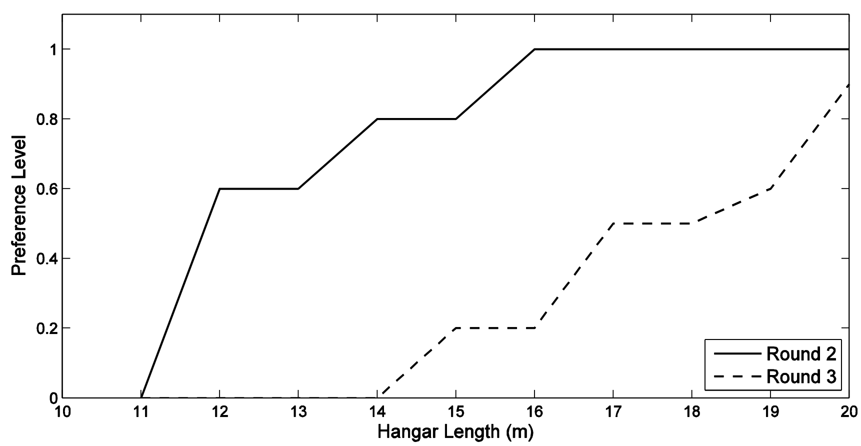


Figure 4.7: Hangar Length Preference Curves (Rounds 2 and 3)

The final results of the SBD case study were reduced sets for all of the negotiated variables. A negotiated variable exists when two or more functional design groups have a preference value for the variable. The study did not produce a specific design, but dramatically reduced each variable set to a reasonable and manageable range. The major conclusions that can be drawn from the SBD case study are:

- Changes in requirements can be managed by the SBD method, due to the robustness of the process
    - Specific values, such as speed and range, do not have to be chosen at the beginning
    - Variable and parameter ranges were flexible enough to allow for changes
- The SBD method demonstrates how changes impact the design

While the scope of the case study was narrow and did not cover all aspects of SBD, the goal of the study was achieved. The evaluation of delaying decisions using SBD and how requirement changes can be managed are shown in the results. Additionally, the case study revealed a number of challenges associated with implementing a SBD method.

4.2.4 Identified Challenges

There were two major challenges identified in this initial case study. The first deals with the difficulty of providing preferences within a SBD framework. The functional design groups must explore the design space and generate a preference that best represents this information based on their analyses and experience. Regardless of the preference-based reasoning method used, designers are forced to use personal judgment to describe their preference for set-range values. Additionally, the integration of these preferences can be a challenging effort when identifying what aspect of the design is more important at a specific time in the process.

A transition in thinking may be required to properly evaluate a design space and provide preferences for a set of values. A designer must transition from the traditional way of thinking in terms of discrete design variables to viewing design variables as sets of values. It is human nature to reduce complex sets of data to discrete values, which are much simpler to process (Gray & Singer, 2011). A good example is the use of a mean to describe a large data set that spans a range of values. Also, as mentioned earlier, most design tools are structured around the spiral model and discrete outcomes, which describes a static representation of the solution space. Information communication between functional design groups and the chief engineer should be aided as well. In an attempt to avoid the infamous “garbage-in, garbage-out” scenario, the quality of preference generation is essential. A more formalized method, in the form of a design tool, which explores the design space and generates and relays preferences, would be beneficial within a SBD execution.

The second challenge identified by the initial case study is the decision making process associated with variable set-range reductions. The integration team in the case study consisted of the two organizers using a combination of preference functions and additional information to make reduction decisions. The method was heuristic and used no standardized decision making framework. The case study results identified the challenge of guiding set reduction and how different reduction paths can result in different outcomes. A better understanding of how and when decisions are made, as well as determining the reproducibility of heuristic set reduction techniques would be the first step towards a more structured framework for set reduction decision making.

4.3 Design Facilitation Tool

In an effort to improve upon the challenges identified in the previous section, a design facilitation tool specifically tailored to the SBD method was developed by the author. The development of the tool is outlined by McKenney and Singer (2012) and was presented at the American Society of Naval Engineers Day 2012. The tool focuses on the specific SBD problem of providing functional designers with valuable and relevant exploration and analysis tools to facilitate preference generation and guide communication within the SBD environment. It also provides a basic understanding of design relationships. The purpose of the tool is to link the design relationships to set reductions.

As mentioned earlier, a functional designer or design group focuses on a component or aspect of the design, for example: structures, propulsion, or weights. While gathering data on the design space is the first step towards preference generation, the analysis and interpretation of the data is much more difficult to accomplish. Finally, helping the human designer transition to set-based thinking can aid in preference generation and information communication. Figure 4.8 provides an overview of the method with its three distinct components.

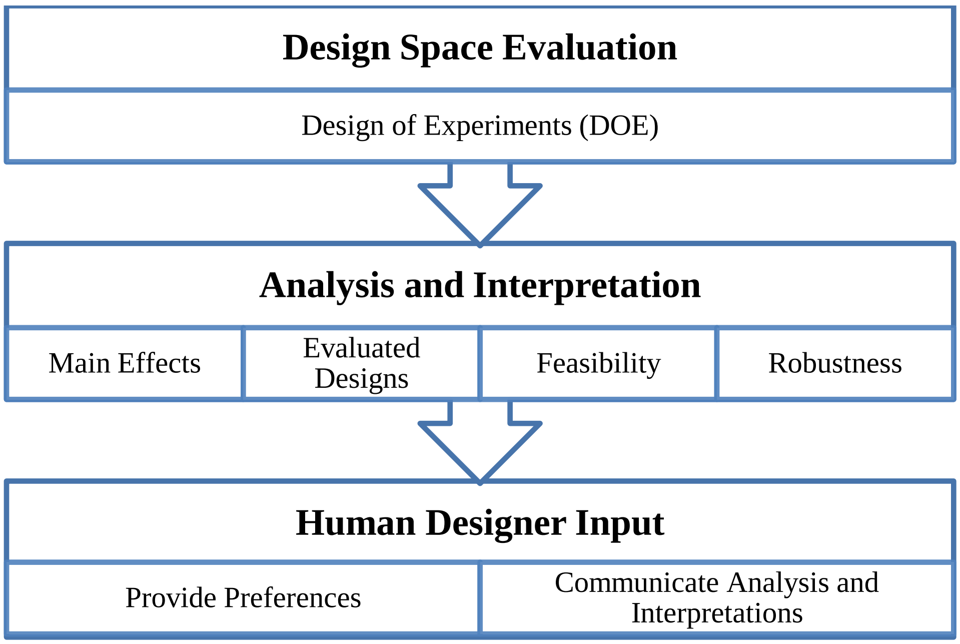


Figure 4.8: Design Facilitation Tool Framework

The overall goal of the facilitation tool is to improve how functional design groups generate preferences and determine what information should be communicated to aid in set reduction. This is achieved through the development of a tool that facilitates design space evaluation and analyzes and interprets that data within the SBD method. The first step is design space evaluation, which for this tool, is completed using Design of Experiments (DOE). Analysis and interpretation is next and identifies various metrics, some rooted in DOE theory, to understand the design space and design interactions. The final and most essential step is when the human designer takes the available information and converts it to variable preferences. Additionally, helpful information for set reduction can be passed along to the chief engineer or design managers.

4.3.1 Design Space Evaluation

There are many different techniques for conducting design space exploration or evaluation, including generating response surfaces, Monte Carlo simulations, DOE, and optimization. While automated evaluation of the design space can be an effective tool, complete automation of preference generation from this evaluation is not recommended. Input from human designers and their evaluation of the design space is essential in a SBD method, or in any design-related activity. While various techniques can provide information on the design space, the designer must effectively evaluate this information to communicate and provide preferences to the chief engineer. Part of the reason why SBD can be difficult to implement is because it requires a shift in the cognitive processing and communication of data from discrete values to sets of values. Execution of this shift requires re-training engineers and designers to think in a set-based manner. In an effort to facilitate the transition to set-based thinking, the design facilitation tool uses a combination of DOE and a custom-made analysis tool. Studies using the analysis tool within the SBD method also reveal important considerations regarding set-based communication.

Determining the relationships between variables and functional design objectives throughout the design space is of significant importance in the SBD method. Each functional design group is tasked with exploring the design space to determine a feasible region and provide preferences for values within that region based on their objective, for example, minimizing resistance. DOE can be used to understand which variables most greatly affect the calculated objective and determine the relationships between variables and the objective (Antony, 2003).

One of the most common types of DOEs, which was used in the design facilitation tool discussed in this section, is a full factorial experiment (FFE). A FFE evaluates all possible combinations of levels for all factors. The number of levels refers to the amount of times a variable is evaluated within a given set. The total number of experiments for studying k factors or variables at two levels is 2^k (Antony, 2003).

4.3.2 Analysis and Interpretation

Analysis and interpretation was developed using an example functional design group in order to apply DOE techniques to design space exploration at the functional level. A planing craft design was selected as the overall design with a seakeeping functional design group. The objective of the seakeeping group is to minimize vertical accelerations. Wave impact accelerations were estimated using a method described by Savitsky (1985). There are certain limitations to this method, including a restriction on the acceptable length-to-beam ratio. Also, the American Bureau of Shipping (ABS) Guidelines on vertical accelerations for a planing craft were used to provide additional constraints (ABS, 2007).

Along with selecting a method to calculate the design group's objective (vertical accelerations), inputs and variables used by the method to perform the FFE needed to be identified. Design requirements that were input into the tool included speed (V_k) and significant wave height ($h_{1/3}$). The negotiated variables were selected for the planing craft design based on their influence on the design itself, and whether they were required for calculation by the functional design group. The number of variables was limited to those needed by the empirical method used by the seakeeping group and potential conflicts between other groups. The selected variables were length (L), beam (B), deadrise (β), and full load displacement (Δ). Trim (τ) was considered an input parameter to seakeeping calculations.

After defining the calculation method, inputs, and variables used by the seakeeping functional design group, a FFE was conducted over the design space for each negotiation round. By reevaluating the design space as set-ranges converge, the analysis becomes dynamic. Initial ranges are typically defined by the chief engineer or engineering manager and provided to the functional design group. For this study, the selected set-ranges were based on typical values for small planing craft. This section discusses the different DOE and developed metrics that aid in the analysis and interpretation stage.

4.3.2.1 Main Effects

The first and most basic DOE metrics that can be calculated are main effects. A Main Effect Plot (MEP) for each variable describes the influence of that variable on the functional design group's objective. A MEP is "a plot of the mean response values at each level of a design parameter or process variable" (Antony, 2003, p. 34). It is important to look at both the sign and magnitude of a MEP. The sign shows the direction of the effect, whether the average response or objective value increases or decreases. The magnitude shows the strength of the effect (Antony, 2003).

Figure 4.9 shows a MEP for each variable that the seakeeping group negotiates, or for which it has a preference. The *x*-axis on each plot displays the set-range for that variable. The *y*-axis for all plots describes the average values of the objective, which is vertical acceleration. First, the slopes can be used to determine the direction of the main effects. For example, as deadrise increases, the average vertical accelerations decrease, which is logical from a ship design perspective. Also, a level slope, like the length MEP, indicates that there is no relation between length values and vertical acceleration.

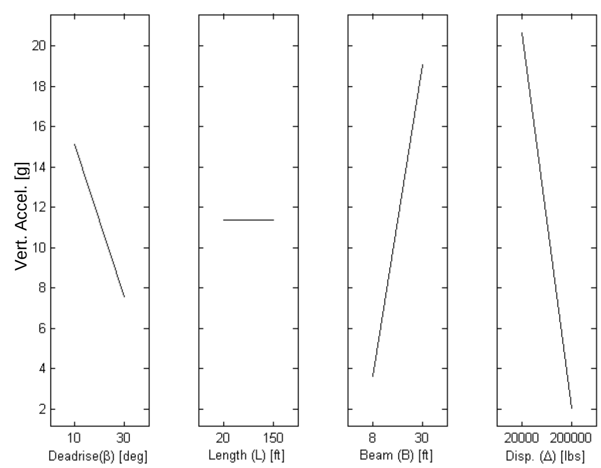


Figure 4.9: Main Effects Plots for Seakeeping Functional Design Group

The plots in Figure 4.9 were created by first calculating the vertical acceleration for every combination of variable values dictated by the FFE formulation. The average of the resulting accelerations for specific variable values is then plotted.

The magnitude of the MEPs is also important because it shows which variable has the greatest effect on the objective. It is evident in Figure 4.9 that displacement and beam have the largest effect, while length has no effect. The effect of a variable can be mathematically calculated using the following basic equation:

$$E_f = F_{(+1)} - F_{(-1)} \tag{4.1}$$

where $F_{(+1)}$ is the average objective value at high level setting of a factor, and $F_{(-1)}$ is the average objective value at low level setting of a factor (Antony, 2003).

MEPs can be easily generated within the DOE framework and can help designers determine the importance of variables based on the current model being used. Also, functional designers can use the slopes of the MEPs to determine general trends when initially developing their preferences. While this information is valuable to some degree, MEPs do not fully encompass variable importance at the functional design level. Simply because an MEP shows that a variable has little effect on the objective does not necessarily mean it is not a major factor in design. Main effects of variables should not be the only factor when determining the importance of variables.

To provide an example regarding misleading variable effects, consider a containership design with a Cargo functional design group. One of the most important variables for the Cargo group is the beam, which should have a value that corresponds to a multiple of the width of a standard container unit. If the beam value does not directly match one of these multiples, there will be wasted space that cannot be utilized to store containers. While the Cargo MEPs might show that beam does not have a large impact on the objective, the desire to not waste useable cargo volume could be a major factor in design that is not captured.

4.3.2.2 Evaluated Points and Feasibility

While MEPs are useful to determine general trends and basic relationships, they do not provide enough detailed information to generate preferences for a range of variable values. Also, a more detailed analysis should be conducted to determine the actual drivers of the functional design group. As part of the MEP calculations, evaluations of the objective (vertical acceleration) were completed. Using these evaluations, a better understanding of the design space can be accomplished.

A plot of all the evaluated points within the design space can be generated to provide additional information to a functional designer. Figure 4.9 shows a plot of all the points evaluated throughout the design space. The *x*-axis is the set-range for displacement and the *y*-axis is the corresponding vertical acceleration, which is different from a MEP. Based on the FFE procedure, each displacement value is held constant, while all other variable values are evaluated at each corresponding level. This plot shows a FFE with 10 levels. A much larger spread at lower displacements is observed because these values produce the largest vertical accelerations. As the displacement values increase, the vertical acceleration range is reduced. It is important to note that at each displacement value, the same number of points is being evaluated, which means that they are much more concentrated at higher displacement values.

Figure 4.10 provides the basic layout of the design space for displacement, but it is more important to see how the feasible points vary depending on displacement values. Figure 4.11 is a plot of only the feasible points from Figure 4.10. Feasibility is determined based on constraints defined by the functional design group and the limitations of the calculation method. When compared to Figure 4.9, the vertical acceleration range in Figure 4.11 is much smaller. The plotted line is the average feasible vertical acceleration. The feasible vertical acceleration is shown to decrease as displacement increases in a more descriptive manner than the MEP. This information can be used by the functional designer to provide preferences on variable values. The larger displacement values would be preferred because the objective is minimized in that area.

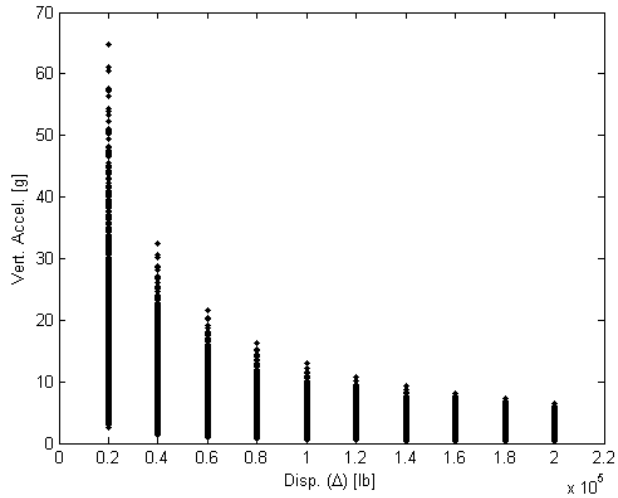


Figure 4.10: All Evaluated Points for the Seakeeping Displacement Variable

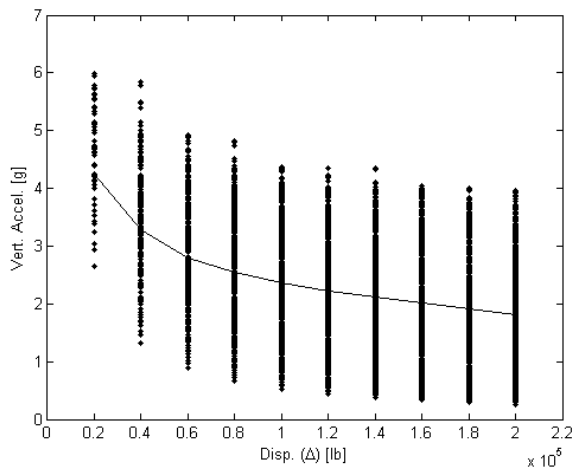


Figure 4.11: Feasible Points for the Seakeeping Displacement Variable with Average Feasible Vertical Acceleration Line

Corresponding to the plots in Figure 4.10 and Figure 4.11, the percentage of feasible points at each displacement value can also be determined. Figure 4.12 shows the percent feasibility for the seakeeping displacement variable. At lower displacement values, there are significantly fewer feasible points than at higher values. Also, the maximum percentage of feasible points is only a little more than 40%. The trend in Figure 4.12 can be useful to determine the more constrained areas of the design space. While lower displacement values have lower feasibility, it does not mean that they should be eliminated at this point.

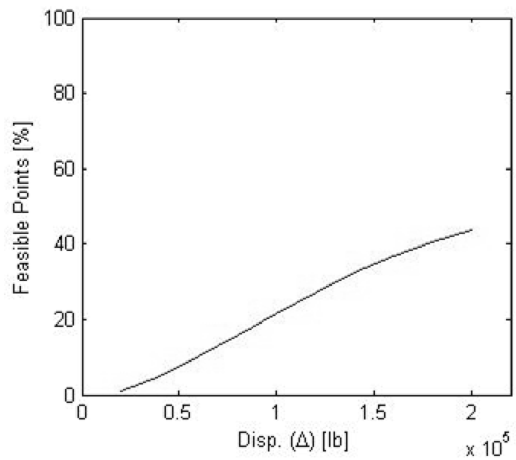


Figure 4.12: Percent Feasibility Plot for Seakeeping Displacement Variable

One way the information provided in Figure 4.12 can be used is to aid a designer in making set reduction. There is a higher probability of reduction in the more feasible regions. While the lower feasibility regions should not be ignored, effort should be focused in the areas that have a higher probability of reduction. There is a potential conflict when there are high feasibility regions with less-preferred objective values. The example provided in Figure 4.10 and Figure 4.11 show similar trends assuming higher feasibility is more preferred, but this is not always guaranteed.

Therefore, it seems that some combination of the average objective value and percent feasibility could be used to aid in preference generation. There is a potential concern that sets will not converge if focus is placed solely on the objective value. The importance of feasibility and optimizing the objective depends on the current stage of the design. At the earlier stages of design, greater focus should be placed on the higher feasibility regions, while at later stages it would be legitimate to focus on lower percentage regions with more optimal objective values. This first ensures feasibility and then focuses on optimizing the functional design objective.

4.3.2.3 Robustness

The design facilitation tool can also determine how a requirement change further constrains the design space and in what areas. By identifying the highly constrained areas, a more robust decision can be made where changes do not affect the design as much as others. As discussed earlier, SBD can handle changing conditions through the negotiation of set-ranges. Regardless of the method used, requirement changes affect, and in most cases constrain, the design space. These effects can be visualized using the design facilitation tool by evaluating the feasibility of various changes. Figure 4.13 shows a series of percent feasibility plots for the same seakeeping displacement variable as earlier, but at various significant wave heights. As the significant wave height requirement is increased, the percent feasibility decreases. While the slopes are similar, there is no direct linear relationship between the different feasibilities. This demonstrates that requirement changes can further constrain the design in certain areas more than others.

Along with the percent feasibility plots, the average feasible vertical accelerations associated with the requirement changes can also be calculated. Figure 4.14 shows these relationships for changes in the significant wave height requirement. As the significant wave height increases, the average vertical accelerations also increase. Due to constraining the design further, the more preferred objective values are no longer obtainable.

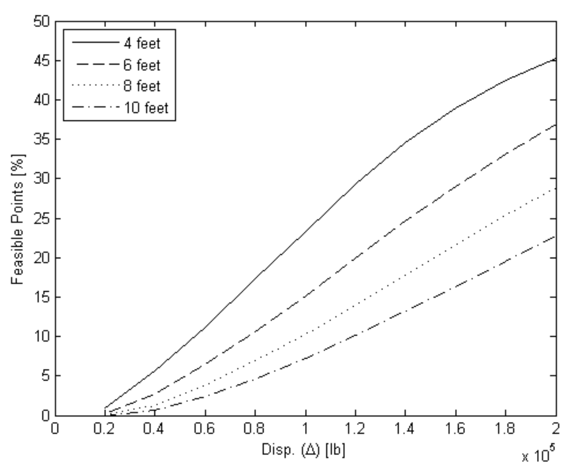


Figure 4.13: Seakeeping Displacement Variable Percent Feasibility Plots for Significant Wave Height Requirement Changes

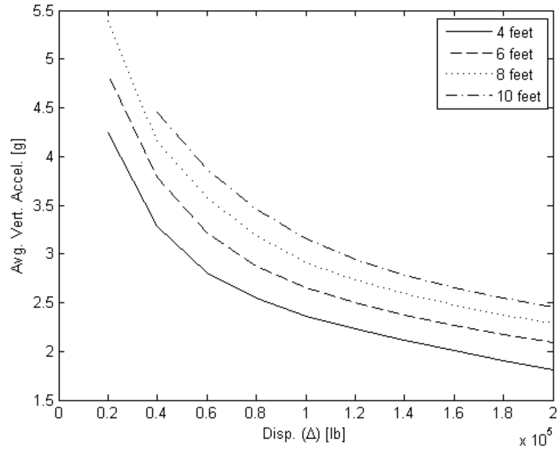


Figure 4.14: Seakeeping Displacement Variable Average Feasible Vertical Accelerations for Significant Wave Height Requirement Changes

The designer can use the information provided in Figure 4.13 and Figure 4.14 to evaluate design requirement set-ranges instead of discrete requirements. For example, if the significant wave height requirement was defined as the set [4, 10], then Figure 4.13 and Figure 4.14 can be used to show designers how this affects the design space. It is important to reiterate that the significant wave height is a requirement; therefore, it cannot be a negotiated variable for which design groups have preference. While the lowest displacement value in Figure 4.14 is feasible for significant wave heights 4–8 feet, it is infeasible at 10 feet. This shows the designer that the design is more constrained at these lower displacement values.

Percent feasibility plots can take many different forms and the example provided in Figure 4.13 is by no means representative of all types of variables, functional design groups, or requirement changes. Various shapes and sizes can provide the designer with information that can be communicated to the chief engineer to better guide set reduction.

4.3.3 Human Designer Input

While gathering data on the design space is the first step towards preference generation, the analysis and interpretation of the data is much more difficult to accomplish. Input from human designers and their evaluation of the design space is essential in the SBD method.

The developed design facilitation tool aids designers in understanding the required information to both provide preferences and communicate during SBD. Variable impacts on functional design objectives have proven to be beneficial, but do not consider all aspects of a situation that a designer requires. The tool can analyze the evaluated points, the feasible regions, and the average objective values. The designer can then take the analysis results and apply them to preference generation while understanding that an optimal objective value is sometimes not as important as the percent feasibility. The method can also be used to determine how the design space becomes constrained under requirement changes. Though the information used by the designer can be generated multiple ways, the types of analysis provided within this tool can help transition a designer to a set-based mentality that can improve communication and set reduction during the SBD method.

4.3.4 Method Limitations

While the developed design facilitation tool can aid a designer in preference generation and transitioning to set-based thinking, the ability of its analysis to understand design relationships and their impact on the reduction process is lacking. The tool is used at the functional design level, meaning that similar analysis is being conducted by other groups with different design perspectives. For simple problems, such as the one presented in this section, the design relationship analysis was able to provide a good understanding of the impact of variables on functions and the feasibility of solutions. However, in order to link the analysis of different functions together and determine the same design relationships for larger-scale problems, an increased level of synthesis and decreased level of fidelity of analysis would be required. This can take the human designer out of the design process, and can also lead to the requirement of lower fidelity models that oversimplify analyses.

As one of the major goals of this research was to develop a structure that supported concurrent engineering, this research direction was not extensible. After identifying the limitations of the design facilitation tool for understanding large-scale design relationships for team-based design, the explicit goal of identifying relationships through the use of an alternative method, perhaps using only variable preferences, was defined.

4.4 Chapter Summary

The previous chapter highlighted the current challenges associated with SBD execution, as well as the limitations of current research on SBD execution. Two major areas of interest were defined, including understanding design relationships and the temporal dynamics associated with the guidance of set reduction. Building on research completed by Singer (2003) and Gray (2011), the initial case study and the use of the design facilitation tool provided additional insight on the two focus areas.

Through the evaluation of Singer (2003) and Gray's (2011) research, potential areas of further development were identified. Most importantly, the guidance of the set reduction process was heuristic, yet reduction decisions greatly impacted the feasibility of a design. Also, the success of a design during the reduction process and under changing conditions was not defined, except for an evaluation of feasibility. Finally, certain design relationships were ignored, including the relationship between design variables and functions of variables (objectives or requirements). A set reduction framework that considers changing design relationships and reduction decision impacts is desired.

An initial case study revealed that providing preferences can be a difficult challenge without any support. Also, without any support, apart from preferences and expertise, the chief engineer had to make reduction decisions. A design facilitation tool, developed by the author, was then presented to address the problem of understanding design relationships and improve the preference generation process. While this tool can facilitate the transition to set-based thinking and preference generation, it is not extensible for larger scale problems without increasing the level of synthesis and decreasing the level of fidelity of analysis. Due to both issues being counter to the original goal of supporting CE, the need for an alternative method to understand design relationships was determined.

It has been identified that SBD is able to handle changes and that the set reduction path plays a role in the outcome, but the specific links for certain situations between reduction and outcome has not been established. The next chapter completes a more in-depth analysis of the set reduction process by developing metrics that can be used to describe the reduction process and conducting design experiments to better understand design relationships under changing conditions.

Chapter Citations

1. ABS. (2007). *Rules for Building and Classing High Speed Naval Craft*.
2. Antony, J. (2003). *Design of Experiments for Engineers and Scientists*. New York: Butterworth Heinemann.
3. Gray, A. W. (2011). *Enhancement of Set-Based Design Practices Via Introduction of Uncertainty Through the Use of Interval Type-2 Modeling and General Type-2 Fuzzy Logic Agent Based Methods*. (Doctoral dissertation). University of Michigan, Ann Arbor, MI.
4. Gray, A.W., & Singer, D. J. (2011, October 25-27). *Applied Set-Based Communications and Negotiation System*. Paper presented at ASNE Human Systems Integration Symposium, Vienna, VA.
5. McKenney, T. A., Kemink, L. F., & Singer, D. J. (2011, September). Adapting to Changes in Design Requirements Using Set-Based Design. *Naval Engineers Journal*, 123(3), pp. 66-77.
6. Savitsky, D. (1985). Planing Craft. *Naval Engineers Journal*, 97(2), pp. 113-141.
7. Singer, D. J. (2003). *A Hybrid Agent Approach for Set-Based Conceptual Ship Design Through the Use of a Fuzzy Logic Agent to Facilitate Communications and Negotiation*. (Doctoral dissertation). University of Michigan, Ann Arbor.
8. McKenney , T. A., & Singer, D. J. (2012, February). *Determining the Influence of Variables for Functional Design Groups in the Set-Based Design Process*. Paper presented at American Society of Naval Engineers Day 2012. Arlington, VA.

Chapter 5: Detailed Design Experiment

The anecdotal conclusions from the initial case study provide an increased understanding of how the SBD method operates and is able to handle changes. The developed design facilitation tool extended upon this basic understanding by identifying critical information for designer generated preferences and set reduction. A detailed design experiment, which is discussed in this chapter, was conducted to determine the link between reduction path, variable preferences, and the ability to handle design changes. By identifying lag indicators from the experiment associated with the ability to handle changes, the development of lead indicators that can potentially avoid unfavorable set-range combinations can be achieved. The formulation of the detailed design experiment and a presentation of its initial results are described in McKenney, Gray, Madrid, and Singer (2012). A FL design tool, described in the previous chapter, was utilized to simplify communication between design variables and solutions within the SBD environment by automating aspects, such as data collection and analysis, while allowing for human designer input. Multiple SBD experiments instituting varying magnitudes and timings of design changes were conducted using the FL SBD tool. By documenting how the SBD method handles changes in designer preferences, the impact of design requirement changes were determined and a link between reduction path and the ability to handle changes was established.

Additionally, before analyzing the experiment's results, multiple metrics were developed to better describe set reduction through the identification of trends in the data. These metrics can improve the ability to evaluate experimental or actual results of a SBD effort and can be a used as a starting point in the guidance of set reduction decisions. This chapter focuses first on the detailed design experiment and its associated design, a planing craft. Experimental results and their associated implications for guiding set reduction are then presented.

The novel contributions presented in this chapter are:

- A demonstration of the robustness of the SBD method through its ability to handle design changes of varying magnitude at various stages of the reduction process
- The development of metrics that improve the understanding and analysis of set-range reduction and changing preferences through time

5.1 Experiment Preparation

After selecting a planing craft design for the experiment, a basic mission profile and requirements were developed. Also, planing craft functional design groups and variables were selected. Finally, a computational design tool was developed for each functional group.

5.1.1 Representative Mission

The basic mission profile and general requirements for the planing craft design were based on the Mark V Special Operations Craft. The Mark V is mainly used to carry Special Operation Forces such as Navy SEALs into and out of operations. Secondary missions include coastal patrol and interruption of enemy activities. A typical detachment consists of two Mark V crafts that can be transported by two C-5 cargo plane or launched from a well or flight deck (U.S. Navy, 2009). The general characteristics of the Mark V were used to verify the developed design tools and helped to generate the initial ranges for the variables. The basic design requirements adapted from the Mark V mission profile included speed, range, payload, and sea state (Federation of American Scientists, 2010).

5.1.2 Functional Design Groups

The initial stages of a SBD approach require the determination of functional design groups (i.e. weights, stability, etc.) for the planing craft design. The functional groups for these experiments were selected based on general components of most planing craft. The selected functional groups include:

- Resistance,
- Seakeeping,
- Dynamic Stability, and
- Weights.

For the purposes of the experiments discussed in this paper, these four functional groups, represented as design agents in the SBD tool, provide enough information about the craft to simulate a set-based preliminary design. For a more detailed analysis, additional functional groups could be added in areas such as propulsion, arrangements, and structures.

Each functional design group had an objective that they hoped to achieve while incorporating all aspects of their focus area. Their objectives are:

- Resistance: minimize the resistance of the hull
- Seakeeping: minimize vertical accelerations for the given sea state requirement
- Dynamic Stability: minimize trim to reduce porpoising effects
- Weights: minimize a weight criteria value that ensures displacement is greater than the weight estimate

Resistance of the hull describes the effort required to move the ship through the water and is directly related to the power required to attain certain speeds. Vertical accelerations, especially on high-speed small craft, are of major concern for both the safety of the crew and vessel, and their ability to operate. A particular concern for small craft when planing is dynamic instability. Porpoising is the dynamic coupled pitch-heave oscillations that should be avoided. Finally, the most basic consideration naval architects have to consider is if the ship can float, which is determined through a hydrostatic analysis of weight and displacement of the hull.

While each group has a specific objective, there are other factors that should be considered when providing their preferences. The additional non-quantitative components of design are considered by designers when generating preferences. For example, a designer might have an understanding of the limitations of the methods they are using to calculate their objectives. If a result does not appear logical, then the designer can modify their preference to reflect the most appropriate estimate.

5.1.3 Variables and Requirements

Variables and parameters were selected for the planing craft design based on their influence on the design itself, and whether or not they were required by the agents. Using the four design agents, variables were selected based on the possibility of conflicting preferences between two or more agents. A preference can be defined as the degree to which certain design variable values favored. For a SBD, negotiated design variables usually include the principal dimensions of the craft, because most agents have preferences for these values. The number of variables was limited to those needed by the mainly empirical methods used by the design agents and with the purpose of simplifying the experiments. The selected design variables were length (L), beam (B), deadrise (β), longitudinal center of gravity (LCG), and full load displacement (Δ). The five variables were chosen to represent the values with the most significant impact on the planing craft design. Negotiation of a design variable is only required when functional agents prefer different values. For displacement, higher values increase resistance while lowering vertical accelerations. A higher deadrise increases resistance but decreases vertical accelerations. For the longitudinal center of gravity, an LCG further from the stern increases resistance while reducing trim. These trade-offs dictate the negotiation of these design values.

There are also design requirements based on the representative mission that are provided to the design agents. These requirements include speed, range, payload, and a representative wave height associated with a sea state. While ranges of design requirements would normally be used in a full SBD, this experiment used single, discrete, requirement values. A single value was chosen because the SBD approach was being utilized to determine the potential design space for a planing craft preliminary design, as opposed to searching for a single feasible solution. Another aim of the experiment was to test the robustness of the SBD process rather than the value of SBD. The benefits of SBD have already been discussed at length in Chapter 2. The negotiated variables and design requirements can be seen in Table 5.1.

Table 5.1: List of Negotiated Variables, Requirements, and Interactions

	Unit	Resistance	Seakeeping	Stability	Weight
Variables					
Length (L)	ft	N	N		N
Beam (B)	ft	N	N	N	N
Deadrise (β)	deg.	N	N	N	N
Long. Center of Gravity (LCG)	ft from stern	N		N	
Full Load Displacement (Δ)	lbs	N	N	N	N
Requirements					
Speed (V_k)	kts	In	In	In	In
Range	nm				In
Payload	lbs				In
Significant Wave Height ($h_{1/3}$)	ft		In		
		In = Input		N = Negotiated	

5.1.4 Tool Development

Each design agent needs a tool to conduct analysis for the functional component of the design. These tools could range from a simple spreadsheet to sophisticated software. A large part of the preparation for the experiment included determining which tools to use for each design group. All tools were developed based on accepted methods from the planing craft field. Some tools used first principles while others were empirically-based equations. Also, a design methodology was developed to aid the design agent in charge of using the tool. In an attempt to make the experiments run as smoothly as possible, substantial effort was put into making sure the agent evaluation process was as clear and user-friendly as possible. The developed tools automated the design space exploration to ensure that a large sample of combinations of variable values was evaluated. This was previously introduced as the design facilitation tool in Chapter 4, and was used during the experiments to evaluate the design space for each design group. Each subsection will discuss the tools in more detail and provide the references used.

After defining the tools used by the design agents, the inputs can be identified to form a better idea of how the variables and requirements interact between agents. Selecting the agents' tools also dictates which inputs are required. Table 5.1 provides the interactions between the variables and requirements of the agents. This table also provides an overview of the inputs and outputs of each agent, as well as a glimpse into which variables and requirements are important to the agents.

5.1.4.1 Resistance Tool

The objective of the resistance agent is to minimize the resistance of the planing craft. Savitsky's method was used to estimate the calm-water resistance of the planing craft design for this research (Savitsky, 1964). Using additional resources on Savitsky's method, an existing MATLAB program was modified for the Resistance agent to use during the experiments (Doctors, 1982). Due to the small impact on the estimated resistance, values for the vertical center of gravity (VCG) and shaft angle were assumed and held constant. Constraints on the objective function were related to the limitations of the method used. These constraints included restrictions on trim (τ), average wetted length-to-beam ratio (λ_w), and beam Froude number (Fn_B).

5.1.4.2 Seakeeping Tool

The objective of the seakeeping agent is to minimize vertical accelerations. The wave impact accelerations were estimated using a method described by Savitsky (1985). There are certain limitations to this method, including a restriction on the acceptable length-to-beam ratio. Also, the American Bureau of Shipping (ABS) Guidelines on vertical accelerations for a planing craft were used to provide additional constraints (ABS, 2007). This was the same tool used as a case study when describing the design facilitation tool discussed in Chapter 4.

5.1.4.3 Dynamic Stability Tool

The objective of the dynamic stability agent is to minimize trim to reduce porpoising effects. Porpoising has been shown to depend strongly on trim angle (Celano, 1998). A critical trim value can be calculated to estimate when porpoising will occur (Sun & Faltinsen, 2011). In order to stay away from this region, calculated trim should remain below this value. Trim calculations were made using methods provided in Faltinsen's "Hydrodynamics of High-Speed Marine Vehicles" (Faltinsen, 2005). The critical trim value was used as a constraint for the dynamic stability agent.

5.1.4.4 Weight Tool

The objective of the weight agent is to minimize a weight criteria value that ensures displacement is greater than the weight estimate. The lightship weight estimation uses a modified Karyayanis method (Grubisic, 2008; Karyayanis, Molland, & Sarac-Williams, 1999). Fuel weight is calculated by using the provided speed and range. The payload weight is provided as an input, and the total estimated weight is compared to the full load displacement. The first constraint restricts the total buoyancy to a particular positive value. The second constraint restricts the draft to be within a small percentage of the chine height. The draft is then calculated using the geometric properties of the planing craft and the full load displacement associated with those dimensions.

5.2 Screening Experiment

Typically, before a large experiment is completed, a smaller-scale screening experiment is used to better understand important factors and aspects. When there are many different potential factors involved in an experiment, screening can be used to reduce the number of design parameters. This is done by identifying important design parameters that affect the overall goal of the experiment (Antony, 2003). For this research, there were four main goals in completing a screening experiment:

1. Determine reasonable initial ranges and ensure feasible regions exist
2. Determine how long an experiment takes

3. Determine how many rounds are typical for this type of experiment
4. Determine what type of change should be implemented for the experiment

Before the screening experiment could begin, a complexity metric had to be defined to describe the various design changes that would be implemented. The first three goals are discussed in Section 5.2.2, and the final goal is discussed in Section 5.2.3.

5.2.1 Complexity Metric

The complexity metric used for the experiment was initially presented in Chapter 2 when discussing cost escalation and its relation to increasing system and design complexity. When discussing the complexity of a design change in this paper, it is referring to the change to the design process, not the change in complexity of the planing craft design itself. Identifying how complexity affects a design process is important because complexity usually leads to fragile designs that are sensitive to small perturbations (Colwell, 2005). For the purposes of this experiment, a general complexity metric can be identified using basic dependencies between design activities, or agents in our experiments. Maier and Fadel (2004) describe an approach to measuring complexity "…based upon the coupling between design targets and design variables. The underlying assumption here is that the more coupled the design problem, the more complex it is" (p. 3).

By looking at the coupled nature of the planing craft design problem, a complexity metric can be used to identify different levels of design changes. A change impacting only one agent is not as complex as a change impacting every agent. Additionally, if two changes affect an equal number of agents, the higher complexity change is the one that constrains the design more and makes it more sensitive to failure. For example, if two changes impact the same number of design groups, the one with the greater magnitude is more complex. This was tested and concluded to be valid during the screening experiment.

5.2.2 Initial Design Space Exploration

The initial design space exploration was used to ensure that there were feasible regions of the design space. For logistical purposes, the experiment length and the number of rounds needed for reduction were also identified. A round is defined as a completed negotiation on every design variable. Once all agents provide preferences for each variable, a chief engineer determines updated set-ranges, which initiates another round of negotiations. After completing the screening experiment, it was determined that feasible regions do exist within the design space, each experiment takes about one hour, and five rounds is the typical number of rounds required for reduction.

5.2.3 Design Change Selection

There were two general types of changes that were tested in the screening experiment. The first type of change was increasing the magnitude of a design requirement. The design requirements that could be used were speed, range, payload, or significant wave height. The second type of change was restricting a region of the variable space. For example, a requirement for the planing craft to be transported in a C-5 cargo plane would restrict the beam. Another change could institute a weight limitation for craning. The impact of each type of change (speed increase and beam restriction) was tested in the screening experiment. In order to test the hypothesis that the SBD method is robust enough to handle design changes, the selection of a design change was based on its total impact on all agents. An increase in speed was selected as the final design change for the experiments due to the larger total impact on agents and how preferences shifted after a speed change was implemented.

5.3 Design of Experiments

The hypothesis developed to guide the design of experiments was that the SBD approach is robust enough to handle design changes of varying complexity at different times. There were two design parameters considered for the experiments: timing and magnitude of a change. The three levels associated with timing were early, middle, and late. These levels corresponded to a change at the beginning of round three, four, and five, respectively. The levels associated with the complexity of a change, which was defined earlier as an increase in magnitude of the speed requirement, were no change, moderate change, and large change. For the experiments, the speed was initially set to 45 knots. The second level was set to 47 knots followed by a third level set to 50 knots.

Due to a simplified design of experiments, replications of the experiments could be readily completed. “Replication means repetitions of an entire experiment or a portion of it, under more than one condition” (Antony, 2003, p. 9). The major condition change between replications was that different human designers were used. It is worth noting that the unchanged experiments were considered a baseline test rather than an actual level of magnitude. This means that the unchanged magnitude did not have to be tested at all three timings. With this is mind, there were seven different types of experiments, with three replications of each type of experiment, meaning a total of 21 experiments were conducted. Table 5.2 provides a list of the experiments conducted.

Table 5.2: Detailed Design of Experiments

Replication 1			*Replication 2*			*Replication 3*		
Experiment	**Magnitude**	**Timing**	**Experiment**	**Magnitude**	**Timing**	**Experiment**	**Magnitude**	**Timing**
1	Unchanged	-	8	Unchanged	-	15	Unchanged	-
2	Moderate	Early	9	Moderate	Early	16	Moderate	Early
3	Moderate	Middle	10	Moderate	Middle	17	Moderate	Middle
4	Moderate	Late	11	Moderate	Late	18	Moderate	Late
5	Large	Early	12	Large	Early	19	Large	Early
6	Large	Middle	13	Large	Middle	20	Large	Middle
7	Large	Late	14	Large	Late	21	Large	Late

The response characteristic for the experiments was robustness, which is defined as the observed number of times the current set-ranges could not handle a design change, or “failure opportunity.” The process is able to continue after a failure opportunity occurs by reopening set-ranges to regain feasibility.

5.4 Reduction Visualizations and Metrics

Interpreting the experimental results was initially challenging, due to the fact that there are 420 preference curves available for review (21 experiments, 5 rounds, and 4 variables). In an effort to expedite the analysis of experiment results, a visualization technique and reduction metrics were developed. These techniques provide the ability to analyze and understand set reduction efforts in a simple and easy-to-understand format.

As part of the work completed in collaboration with Gray, Madrid, and Singer (2012), a three-dimensional visual representation of a set reduction through time was developed. Figure 5.1 provides an example of reduction visualization for the beam variable. The three axes show the beam values, the JOP level, and the round number. Starting from the back of the figure in round one and moving forward to round five, the narrowing of the set-ranges can be seen. This visualization can provide a designer with a good understanding of a reduction for a single variable and experiment.

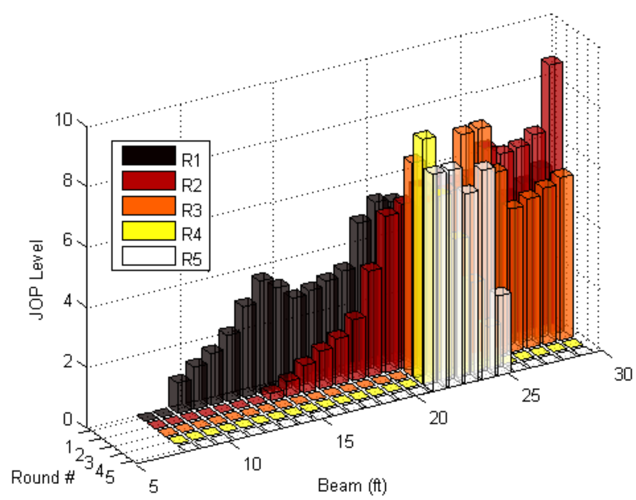


Figure 5.1: Beam Reduction with No Design Change (Exp. 15)

While this visualization technique reduces the amount of figures to analyze due to the consideration of the preferences through time, 84 of these figures exist for the experiment results. To reduce the amount of figures further, weighted mean and standard deviation metrics were developed to provide a quantitative assessment of a reduction process. These metrics can then be plotted for all three replications of a variable at the same time. This would reduce the total number of figures to 28, a much more manageable number than a total of 420 initially. These metrics can be used both during an actual SBD process as an intermediate reading of where the design is going or as a post-processing technique to evaluate what led to a specific result.

The first step in the development of the metrics was being able to accurately describe the preferences of a JOP curve. This was done using a weighted mean that, in a sense, finds the variable value that is associated with the center of the area under the JOP curve. Next, a standard deviation using the weighted mean can be calculated to describe the spread of the JOP curve around that weighted mean. By evaluating how these two values change between rounds, both the direction the design is heading and the rate of reduction can be determined in a quantitative manner.

For the weighted mean calculation, the design variable values are defined as data points (x) and the weights (w) are defined as the corresponding JOP levels. The weights are normalized to sum to one to simplify the calculations. For the non-empty data set $\{x_1, x_2, \dots, x_n\}$ with non-negative weights $\{w_1, w_2, \dots, w_n\}$, the weighted mean is:

$$\bar{x} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} = \frac{w_1 x_1 + w_2 x_2 + \cdots + w_n x_n}{w_1 + w_2 + \cdots + w_n}. \tag{5.1}$$

If the weights are normalized such that they sum to one ($\sum_{i=1}^{n} w_i = 1$), the normalized mean equation simplifies to:

$$\bar{x} = \sum_{i=1}^{n} w_i x_i. \tag{5.2}$$

The weighted standard deviation can be calculated using the equation:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} w_i (x_i - \bar{x})^2}{\sum_{i=1}^{n} w_i}}. \tag{5.3}$$

When the weights are normalized, the equation simplifies to:

$$\sigma = \sqrt{\sum_{i=1}^{n} w_i (x_i - \bar{x})^2}. \tag{5.4}$$

An example of weighted mean and standard deviation values for the unchanged design scenario (three experiments) for the beam variable for all five rounds is provided in Figure 5.2. Each line corresponds to a specific experiment. There were three unchanged experiments; therefore, there are three lines. Rather than interpret each individual three-dimensional JOP plot, one figure can be used to represent the same information in a simplified format. It can be seen, for example, that there are two reduction paths taken by the three experiments: two converged to lower beam values, while one converged in a much different manner to higher beam values. Also, the reduction rate can be visualized much easier using the standard deviation plot.

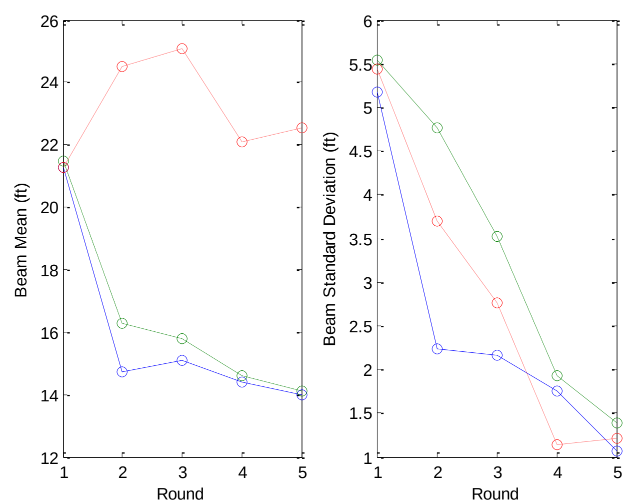


Figure 5.2: Weighted Mean and Standard Deviation Reduction Plots

Additional metrics based on the weighted mean and standard deviation calculations can also be introduced, including the slope and intercept of both between rounds. This would identify a specific reduction rate and direction the design is heading in. The development of these metrics are reserved for future work.

5.5 Experiment Results

The SBD experiments were conducted over the course of three days with the help of eight volunteers. Volunteers were rotated to multiple agent positions depending on the ability to change the conditions of each experiment replication. Experiment organizers completed the chief engineer role for each experiment, as a detailed understanding of the SBD approach was needed for this role. As mentioned earlier, a total of five rounds of negotiations occurred during every experiment. At the end of each round, the chief engineer made a decision to reduce the variable set-ranges. These decisions dictated the starting set-ranges of the next round. After completing the experiments, initial results regarding confirmation of convergence, agreement between replications, and handling design changes could be identified. There were also a few special cases where a failure opportunity occurred after a change was implemented, which are discussed individually to identify root causes.

5.5.1 Confirmation of Convergence

Before looking at how the implemented design changes affected the SBD approach, it is important to identify the baseline experimental results without a design change. Three tests were conducted without implementation of a design change. Figure 5.3 shows a general reduction for the variable beam with no design changes implemented (experiment 15). The three axes show the beam values, the JOP level, and the round number. Starting from the back of the figure in round one and moving forward to round five, the narrowing of the set-ranges can be seen. Also, as certain values of the variables became infeasible and the chief engineer reduced the sets, the preference levels changed based on updated evaluations by the agents involved; this too can be seen in Figure 5.3. Even though there seems to be a preference for higher beam values in round two, the preferences change in the next round. The change in preference is a result of the other design variable set-ranges changing and the updated overlapping feasible regions existing between agents.

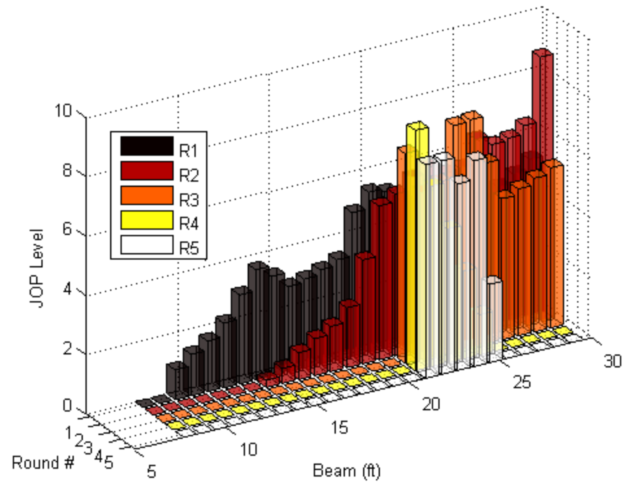


Figure 5.3: Beam Reduction with No Design Change (Exp. 15)

Narrowing of the set-ranges for every design variable occurred at the end of each round in all experiments, to varying degrees. For example, larger changes that greatly impacted preferences resulted in wider final set-ranges due to the effort taken to resolve the issues associated with the change. Set reduction was controlled by the chief engineer agent. The rate of reduction varied for each variable, which is due to the impact of that variable on the agents' objectives. For instance, the deadrise remained open longer than the other variables. This was because most deadrise values were initially feasible and deadrise did not substantially influence the objectives. As the other variable set-ranges narrowed, fewer deadrise values were feasible, which caused it to narrow to a smaller range of values.

5.5.2 Agreement between Replications

Although narrowing occurred for all variables in every experiment, the reduction rates and final variable set-ranges for replications of the same experiment type varied. These outcomes highlight the nature of the design space; most notably, that it is relatively unconstrained. This can be seen by analyzing the final set-ranges for a given experiment type. Figure 5.4 and Figure 5.5 are the other two replications of the experiment type discussed in the previous section for the beam with no design change (the first replication can be seen in Figure 5.3). The final set-ranges shown in Figure 5.4 and Figure 5.5 are in the same general region between 12-17 feet. The final set-range for the other replication (Figure 5.3) is in the region between 20-25 feet. Both regions are feasible and show high preferences, but are in different areas of the design space. This same occurrence can be seen for other variables and experiment types. In a more constrained design space, dictated mainly by the initial requirements, there would be fewer feasible areas that the set-ranges could converge towards.

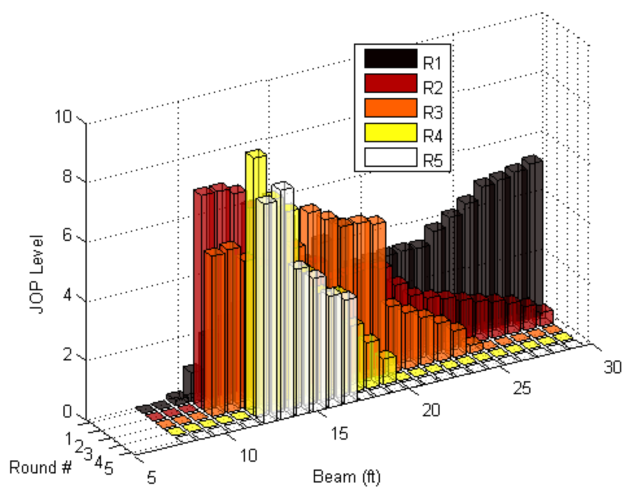


Figure 5.4: Beam Reduction with No Design Change (Exp. 8)

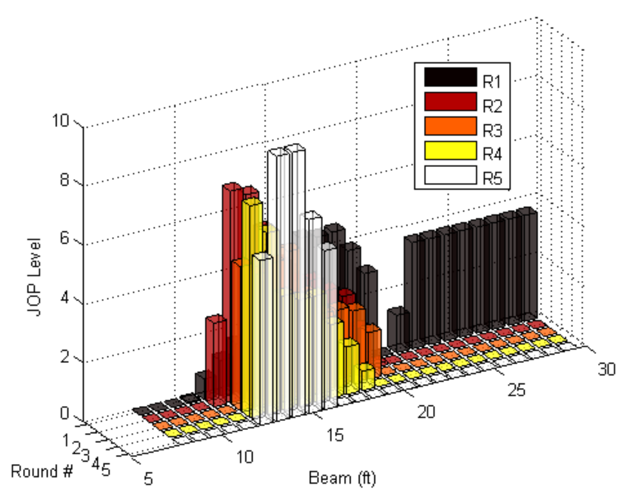


Figure 5.5: Beam Reduction with No Design Change (Exp. 1)

Agreement between replications is not a necessity when evaluating whether set-ranges converge and how design changes are handled. During experiments conducted by Gray (2011), the unconstrained design scenarios resulted in a wider range of final set-ranges, while the constrained design scenario led to either a more specific set-range area or a failure occurred. It is important to note that the results of the experiments are not invalidated by a difference in where the set-ranges are reduced. In the experiments, emphasis was placed on the ability to converge in a feasible region and manage design changes, and not on identifying agreement between replications.

5.5.3 Design Changes

The main objective of the experiments was to evaluate how the SBD process handles design changes at various times during the design process. As the two magnitudes of speed change, the change in timings affects the process in different ways. Also, the design changes impact the preferences of agents for certain variables more than others. A general evaluation of trends related to both timing and magnitude are first discussed, including how agent preferences are modified when a design change is implemented. The next section focuses on the specific experiments that had interesting results to identify the potential causes of these failure opportunities.

5.5.3.1 Effects of Varying Magnitudes

There were a series of observations in evaluating the impact of varying magnitudes of changes. Two important factors to look for are the reduction path taken and the final set-range values. By looking at the reduction path, a potential link can be identified between set reduction decisions made by the chief engineer and the ability to manage changes. Also, more general observations were made on how large or small final set-ranges are under the various conditions. Another factor to look for is how preferences of variable set-ranges are modified after a change occurs. By looking at an increasingly more complex change that is instituted, one can better understand how a set-based approach handles these changes.

A good example that can be used to better understand the two factors discussed in the previous paragraph is looking at the length JOP for three experiments with varying magnitudes of design change. It is important to note that the design changes all occur at the beginning of round four. Figure 5.6, Figure 5.7, and Figure 5.8 show the JOP plots for three separate experiments. The first experiment (Figure 5.6) does not have any design change implemented. This can be used as a baseline. The second experiment (Figure 5.7) corresponds to a moderate speed change from 45 to 47 knots at the beginning of round four. The third experiment (Figure 5.8) corresponds to a large speed change from 45 to 50 knots at the beginning of round four. These figures can be used to form some basic observations.

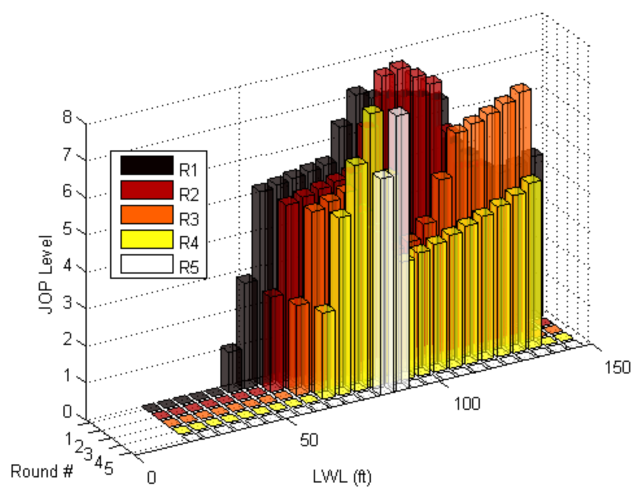


Figure 5.6: Length JOP Plot with No Change (Exp. 1)

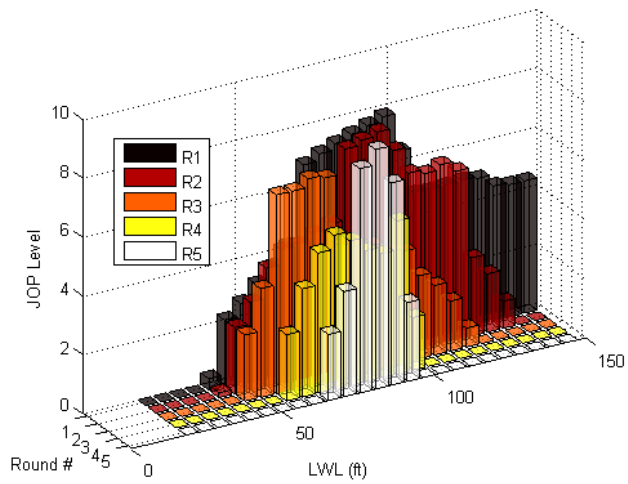


Figure 5.7: Length JOP Plot with Moderate Change in R4 (Exp. 17)

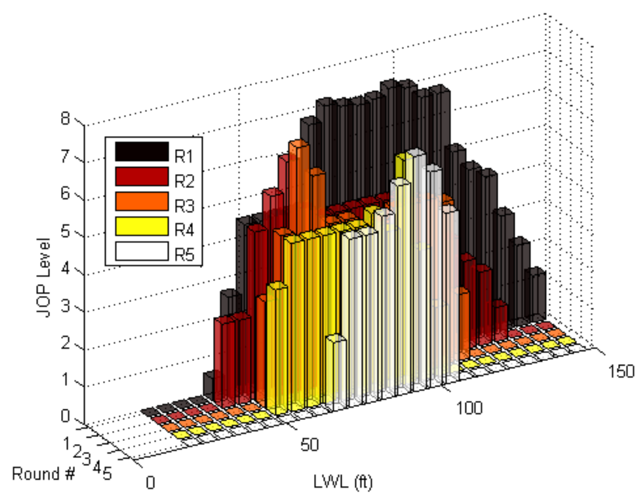


Figure 5.8: Length JOP Plot with Large Change in R4 (Exp. 20)

The first observations focus on the reduction paths and final set-range values. Initial observation of the figures identify that round one preferences were similar for all three experiments. It is evident that, while there were higher preferences for larger and smaller values for the no change experiment, all three experiments converge towards the same general region. In the moderate and large change case, the impact of that change can be seen by looking at the JOP plot for round four. This shift in peak preference values is more distinct for the large change than the moderate change, which would make sense because the large change should more greatly impact the solution space.

While analyzing the JOP curves is the easiest way to identify the impact of design changes, taking the analysis a step further by evaluating each design group's membership functions (MFs) can provide additional insight. The MFs generated by each agent are combined through the FL system to make the JOP curves used by the chief engineer who then reduces the set-ranges. After using the assigned tool to evaluate the design space within the set-ranges, the agent generates MFs to define preferences for regions of the set-range.

Figure 5.9 shows MFs generated by the resistance agent for the length variable throughout several negotiation rounds, including the implementation of a major change in required design speed during round four. Starting from the top,
Figure 5.9 shows the resistance agent's MFs from round three through round five for the length negotiation. Solid lines represent the boundaries of preferred regions; dotted lines represent marginal regions; and dashed lines represent unpreferred regions. The labels P, M, and U also correspond to the regions described above.

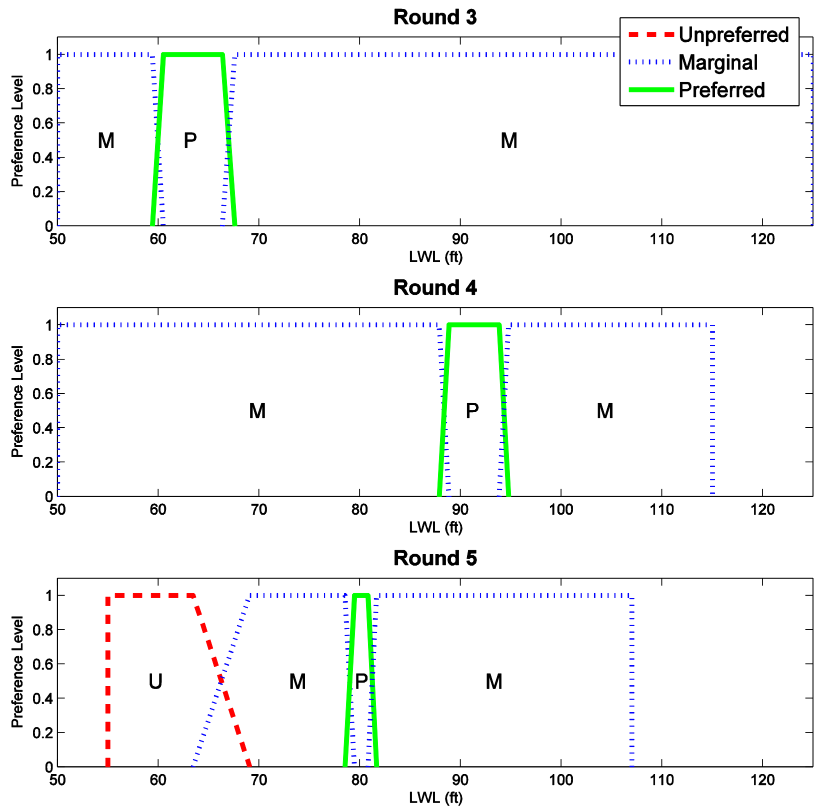


Figure 5.9: Resistance Membership Function for Length

It can be seen in Figure 5.9 that there is a strong preference towards values roughly between 60 and 70 feet in round three. After the major design change was implemented in round four, the preference region shifted to between 90 and 95 feet. After further negotiation in round five, an unpreferred region develops and the preferred region moves slightly towards a value of 80 feet. The scales for length on each round plotted in Figure 5.9 are the same. This shift in preference can also be seen in the JOP plot in Figure 5.8. The resistance agent had the most influence in the shift seen in Figure 5.8. This is reasonable from a ship design perspective because, as the speed requirement increases, resistance can be further reduced by increasing the length.

Another interesting observation is the final set-ranges for each case. For the no change experiment, the final set-range was 70-90 feet (a range of 20). This is much narrower compared to the other two experiments. The moderate change experiment final set-range was 64.5-95 feet (a range of 30.5) and the large change experiment final set-range was

55-107 feet (a range of 52). This seems somewhat counterintuitive because one would likely reason that as the change became larger, the solution space would be further constrained; however, when thinking about the true impact of change, the role of the chief engineer and their reduction decisions become more significant. After a change is implemented, the chief engineer would want to keep the set-ranges open longer than normal to understand the impact of that change and redirect the reduction path towards the new preferred region. A larger change requires more time to figure out its actual impact, which can be an explanation for the round five set-range values being larger as the design change becomes larger. This translates to a shift in the rate of reduction while the impact of the design change is identified and set reduction continues; however, this could be a function of the set-range values of a particular variable at the time a design change was implemented. Additional discussion of this topic is presented in the next section.

While these observations provide insight, there are other experiments that do not identify such a clear impact of design changes on their JOP plots and the set reduction process. The other replications of the same scenarios discussed earlier were also evaluated to better understand this difference. Figure 5.10 and Figure 5.11 are the length JOP plots for the other two replications of the no change scenario, Figure 5.12 and Figure 5.13 are the length JOP plots for the other two replications of the moderate change scenario, and Figure 5.14 and Figure 5.15 are the length JOP plots for the other two replications of the large change scenario. Figure 5.14 does not have any JOP for round four due to all set-range values being infeasible for one of the agents. This will be discussed in Section 5.5.4 on special cases.

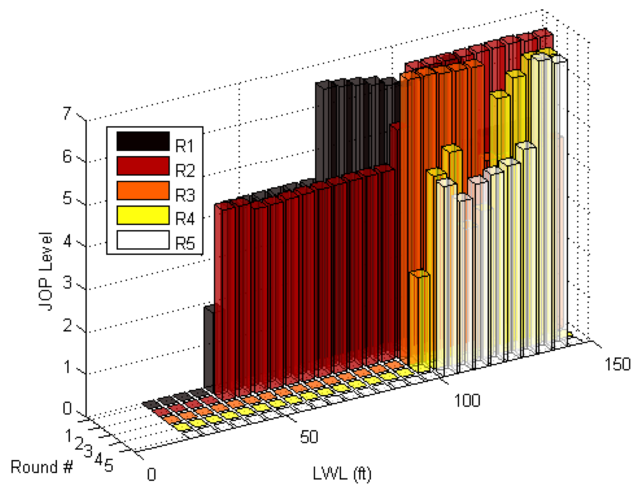


Figure 5.10: Length JOP Plot with No Change (Exp. 8)

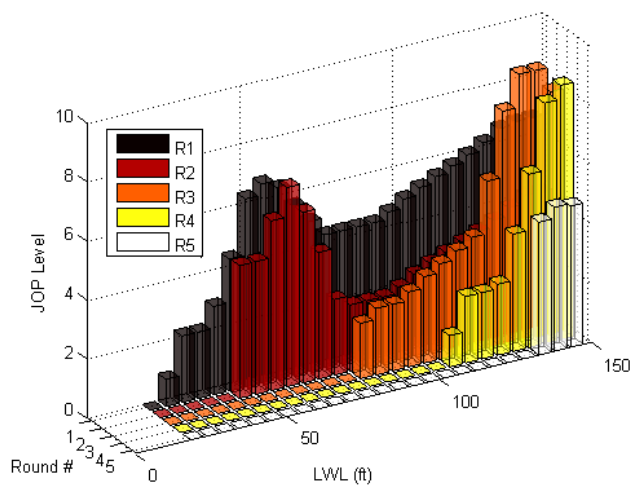


Figure 5.11: Length JOP Plot with No Change (Exp. 15)

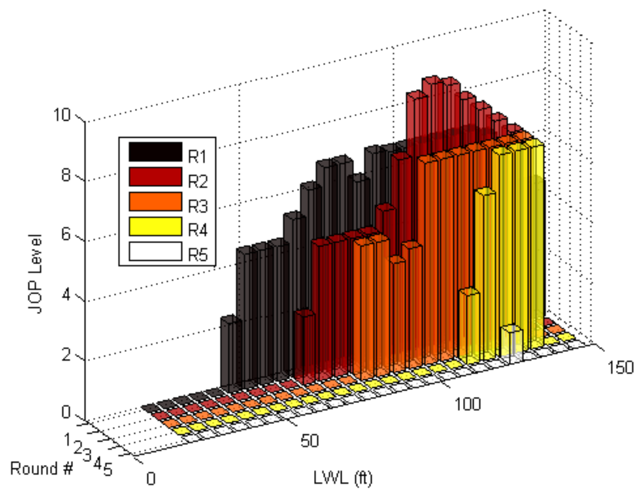


Figure 5.12: Length JOP Plot with Moderate Change (Exp. 3)

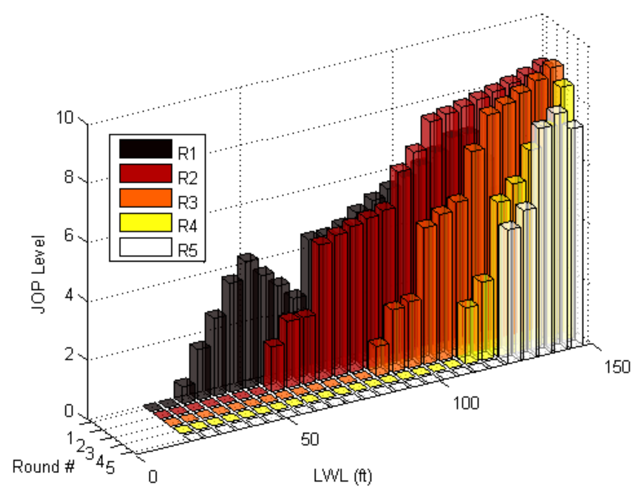


Figure 5.13: Length JOP Plot with Moderate Change (Exp. 10)

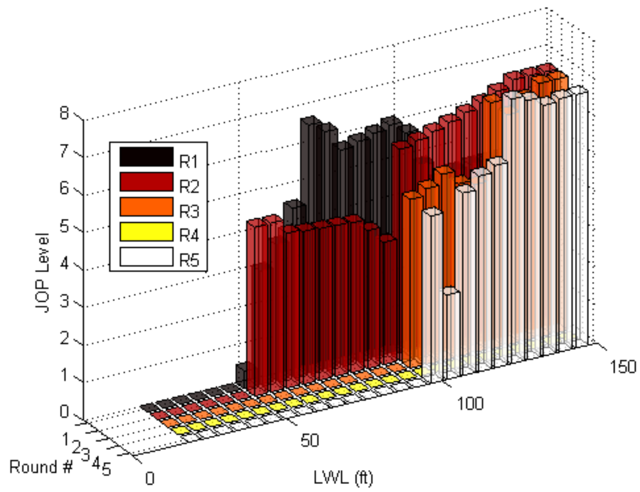


Figure 5.14: Length JOP Plot with Large Change (Exp. 6)

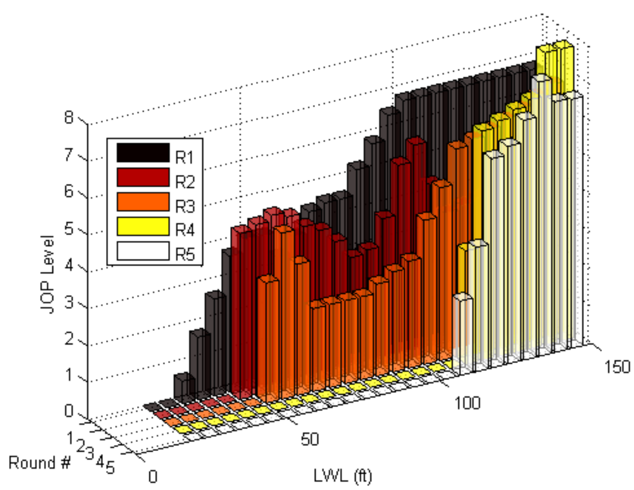


Figure 5.15: Length JOP Plot with Large Change (Exp. 13)

As mentioned in the explanation of agreement between replications of the same scenario in Section 5.5.2, it was determined that the design space was relatively unconstrained (i.e. there were multiple feasible combinations of final variable values). This can be validated again when looking at the replications of the length of JOP plots. Figure 5.6, Figure 5.7, and Figure 5.8 identified length values converging towards set-ranges between 70-100 feet. Figures 5.10-5.15 identify length values converging towards set-ranges between 100-150 feet. This is not too unexpected given the unconstrained nature of the design problem, but what is interesting when looking at this alternative reduction path is the impact of design change on the preferences for set-range values.

While slight shifts in preferences can be seen on some of the figures, most do not show any dramatic changes. One explanation for this is that this alternative reduction path was able to accommodate change better than the one converging towards the lower length values. Higher length values provide an opportunity to handle increased speeds by reducing resistance. From an impact standpoint, it can be seen that certain reduction paths lead to less of a change in JOPs, which can be interpreted as a more robust path to changing conditions.

The ability to handle design changes is theoretically based on the use of set-ranges as opposed to discrete values. Similar to being able to better manage changes based on the reduction path taken, observations also show that set-ranges with larger ranges can better manage design changes. Using the same length JOP plots used throughout this section, corresponding to nine total experiments associated with three scenarios, the set-ranges in round four can be identified. Table 5.3 highlights these values.

Table 5.3: Length Round 4 Set-Range Values and Ranges for Round 4 Changes

	Length (Round 4)		
	Min	**Max**	**Range**
No Change			
Exp. 1	65	135	70
Exp. 8	98	140	42
Exp. 15	95	150	55
Moderate Change			
Exp. 17	53	100	47
Exp. 3	80	139	59
Exp. 10	98	150	52
Large Change			
Exp. 20	50	115	65
Exp. 6	119	150	31
Exp. 13	50	150	100

The first experiment under both the moderate change and large change section is associated with the initial reduction experiments discussed, and are associated with reduction to the lower set-range values between 70-100 feet. The remaining two below are associated with reduction towards the higher length set-range values that handled the changes better. For the moderate change, the range of the length set was larger for the second alternative reduction path. Also, excluding experiment six, the range of the length set was much larger for experiment 13 compared to experiment 20, which highlights the potential advantage of having larger set-ranges when a change occurs. The range of the length set for experiment six was much smaller than experiment 20, but this resulted in no feasible region during round four negotiations. This will be discussed more in Section 5.5.4, but it highlights the importance of set-range values when a change occurs. At a higher level, the rate of reduction directed by the chief engineer is considered important. For the cases that resulted in a visible impact, the set-ranges were smaller, while little impact was seen for larger set-ranges. This observation again highlights the importance of the chief engineer and the set reduction decisions that he/she makes.

5.5.3.2 Effects of Varying Timings

Both the reduction path taken and how the set-ranges manage design changes can also be evaluated for the timing of a change. When looking at the trends associated with the timing of a change, impacts are not as obvious as a change in magnitude, but valuable observations can be made. A good example to show basic observations is how displacement in JOP plots change for three experiments due to the difference in timing. The magnitude of the change was held constant for this analysis at a large change level. Figure 5.16 shows the displacement JOP plots for an early change instituted at the beginning of round three, Figure 5.17 shows the displacement JOP plots for a middle change instituted at the beginning of round four, and Figure 5.18 shows the displacement JOP plots for a late change instituted at the beginning of round five.

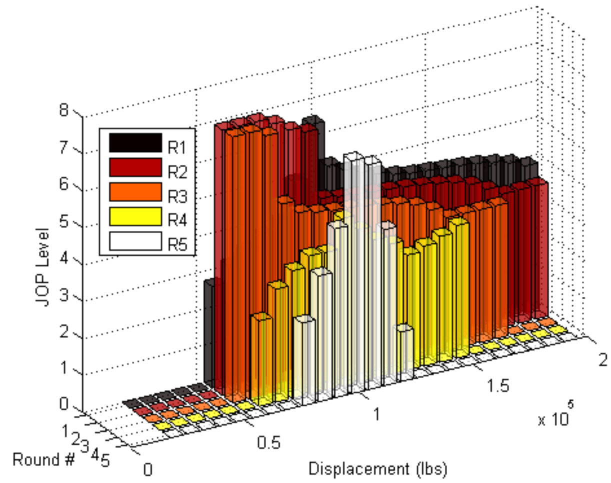


Figure 5.16: Displacement JOP Plot with Early (R3) Change (Exp. 5)

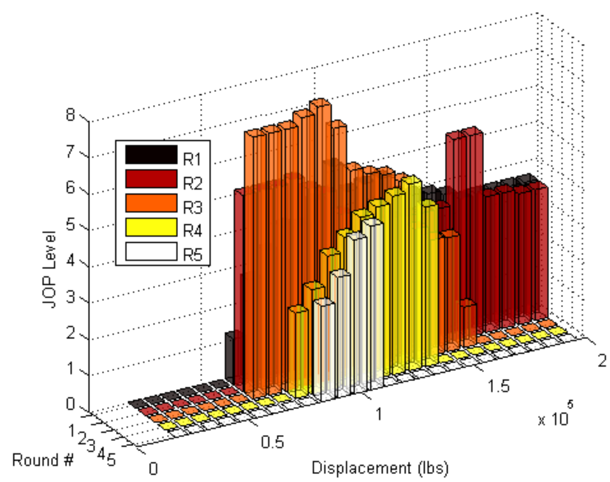


Figure 5.17: Displacement JOP Plot with Middle (R4) Change (Exp. 20)

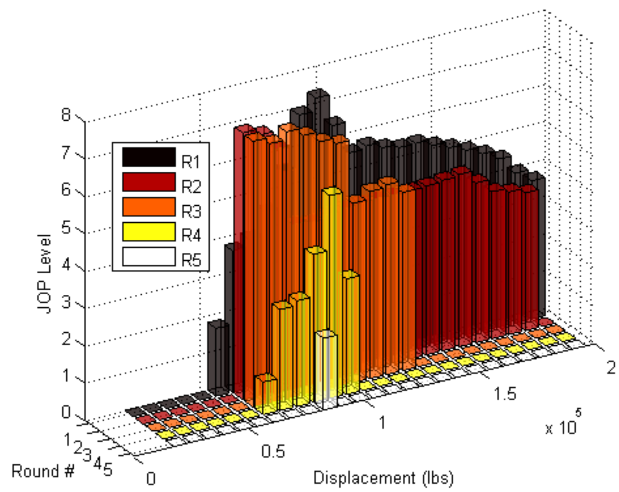


Figure 5.18: Displacement JOP Plot with Late (R5) Change (Exp. 7)

All three experiments converge towards the same region around 100,000 pounds. Starting with Figure 5.16, the early change in round three shows little or no impact of a change at this time. Preferences did shift slightly towards lower displacement values, but for the most part the large set-range was able to manage the change. A shift in preferences can be identified for a middle change, as seen in Figure 5.17, from lower values to higher, but reduction continued without any major issues. The late change, as seen in Figure 5.18, shows the set-range reducing greatly to a small region. This substantial reduction was dictated based on the feasibility of the other regions after the speed change was implemented.

When looking at the final set-ranges, an interesting and somewhat counterintuitive observation to previous analysis can be made. The early change experiment had a larger final set-range and the late change had the smallest final set-range. In this situation, the observation can be explained based on the reasoning for the reductions. For the displacement variable, reductions after the middle and late changes were based on infeasibility, which led to a substantial reduction. It can also be seen that the reduction rate for the middle and late changes was faster leading up to the changes being implemented, while the early change was much slower. This again highlights the importance of the reduction rate and how it effects how the set-ranges handle a design change.

5.5.4 Failure Opportunities

In three of the experiments, design changes led to either a complete or partial failure opportunity. As mentioned earlier, a failure opportunity occurs when the current set-ranges cannot handle a design change. It is considered a failure *opportunity* because feasibility can potentially be regained by reopening the variable set-ranges.

5.5.4.1 Functional Design Failure (Experiment 6 and 16)

At some point a design change will be too large for the current set-ranges to manage. This is represented as a completely unpreferred JOP. There are, however, different ways a JOP becomes unpreferred. The first case, which occurred in experiment 6 and 16, is when one functional design group is completely unpreferred for all variable set-ranges. Experiment 6 is the design scenario with a large speed change implemented in round four. Experiment 16 is the design scenario with a moderate speed change implemented in round three. Important considerations that should be accounted for include how the preferences changed from before the failure opportunity and after, as well as the reduction path taken leading up to the design change being implemented.

First, the impact of the failure opportunity on design preferences using variable JOPs can be determined. Experiment 6 will first be evaluated. Figure 5.19 shows the beam preference with a failure opportunity occurring in round four after a speed change from 45 to 50 knots. The first three rounds are similar to the preferences in the unchanged case provided in Figure 5.3. Round three preferences are mainly centered on values between 20 and 25 feet, which is the same preferred range from the unchanged experiment. After the speed increase is implemented, the resistance agent held no preference for values in the set. This meant that the narrowed set was completely infeasible.

Nevertheless, even when a failure opportunity occurs, the SBD process can still be used to redirect the design to a feasible region. This is done by reopening the sets to previous values that were feasible. During experiment 6, when the failure opportunity occurred, the chief engineer reopened the set-range to the previous round three values and asked agents to re-negotiate the variables. Figure 5.20 shows the beam preference with failure and then the reopening and re-negotiation of the set in round five. The round five data shows that by reopening the sets, a feasible region can be found. Although the preferences are again found in a feasible region, the lower beam values are now preferred, showing a large shift. This experiment resulted in the largest and most obvious impact of a design change. From a ship design perspective, speed increases would correspond to preferring lower beam values.

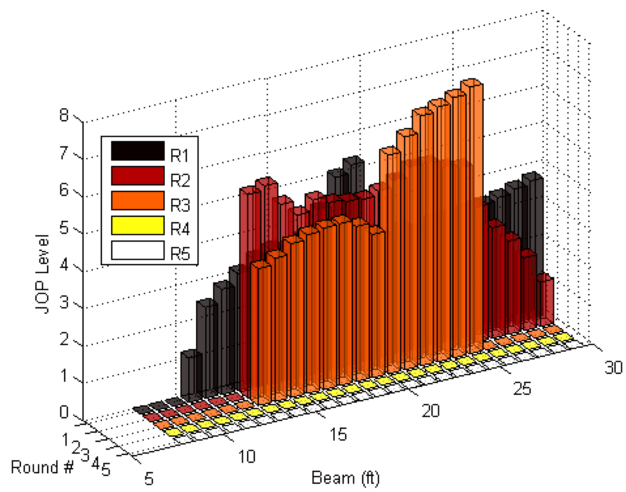


Figure 5.19: Beam JOP with Failure (Exp. 6)

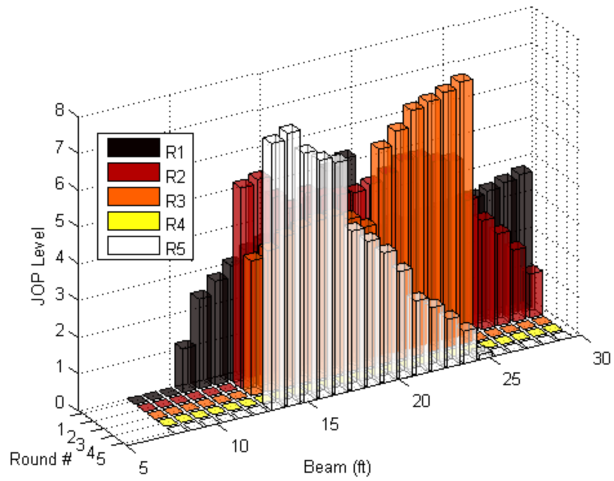


Figure 5.20: Beam JOP with Failure and Re-Negotiation (Exp. 6)

While the reduction paths were similar to the unchanged case leading up to the failure opportunity, the set-range reduction decisions by the chief engineer can provide additional insight into potential causes. Figure 5.21 shows beam reduction plots, the set-range values associated with each negotiation round, for both experiment 6 (failure opportunity) and experiment 20, which was able to handle the same type of change. Round one is at the top of the plot. The design change occurred in round four. Based on round three JOP plots, it is evident that the chief engineer decided to reduce the beam set-range significantly for the round four negotiations. When the design change was implemented, the smaller set-range was unable to handle the change, which led to the failure opportunity. Experiment 20, which handled the design change, reduced the set-ranges much more gradually and consistently. Figure 5.22 shows a similar occurrence from the reduction plots for the length variable.

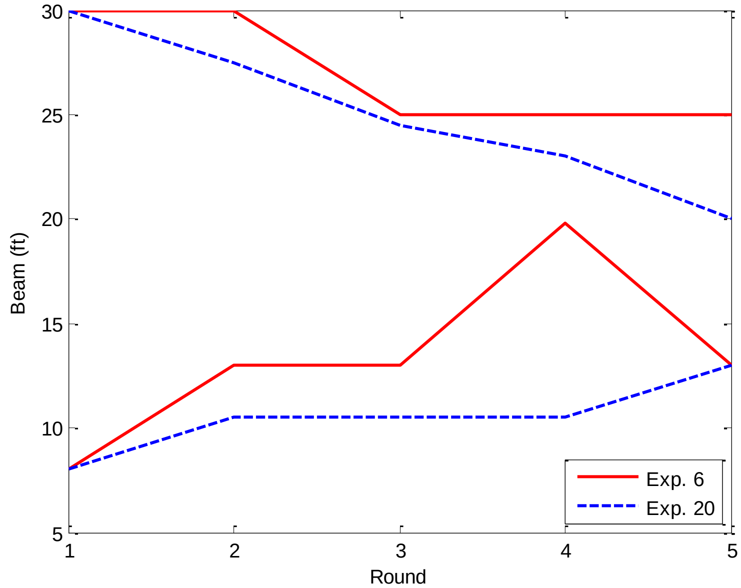


Figure 5.21: Beam Reduction Plots (Exp. 6 and 20)

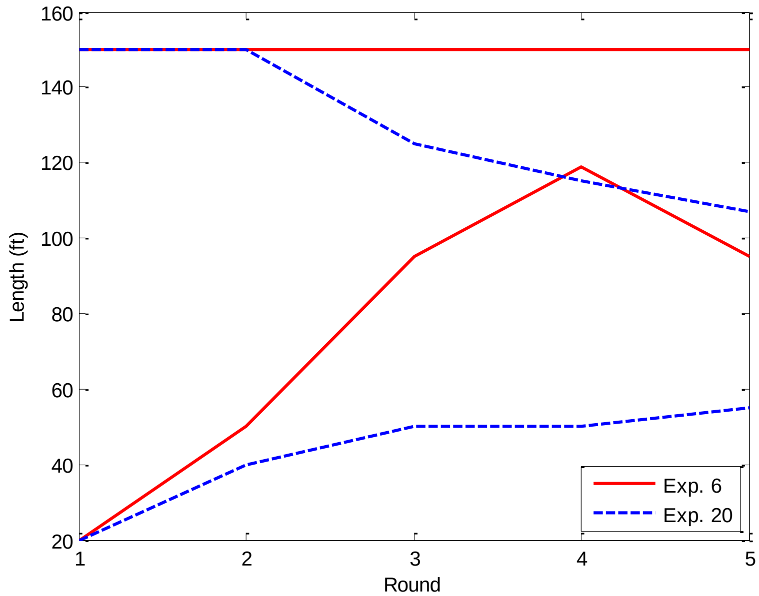


Figure 5.22: Length Reduction Plots (Exp. 6 and 20)

Experiment 16 also identified similar observations to those of experiment 6. Again, resistance was the agent that unpreferred all variable set-range values. This suggests that resistance might be the limiting factor in this design and should be focused on during the reduction process. Figure 5.23 and Figure 5.24 show how preferences are modified after the set-ranges are reopened when a failure in round three (orange) occurs. These figures show similar shifts in the JOP shapes after a design change and failure occurs.

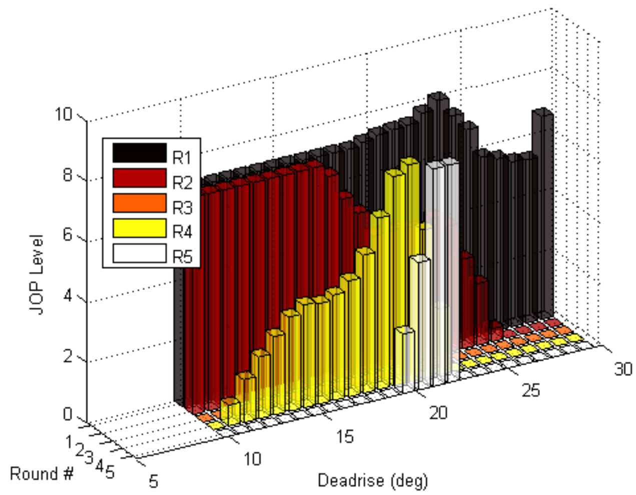


Figure 5.23: Deadrise JOP with Moderate Early Change (Exp. 16)

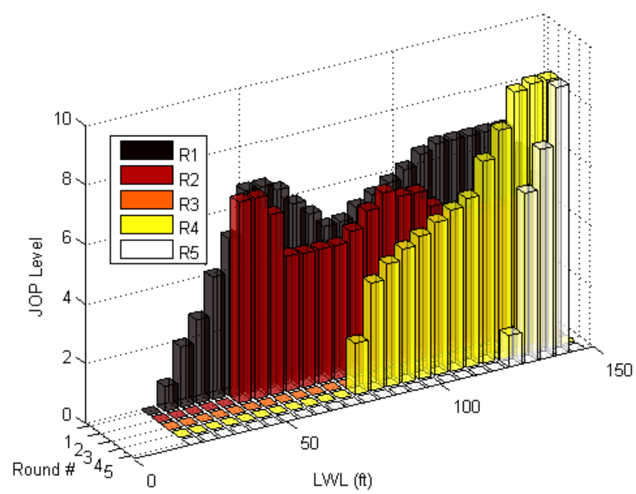


Figure 5.24: Length JOP with Moderate Early Change (Exp. 16)

After examining the reduction path and set-range values for experiment 16, similar observations to the experiment 6 results can be seen. Figure 5.25 shows the deadrise reduction plot for experiment 16 and experiment 2, an experiment with the same design scenario that handled the design change in round three. Figure 5.26 shows the same reduction plot, but for the length variable. The reduction plots associated with experiment 2 show relatively smooth reduction and no major shift after the design change is implemented. Deadrise set-range values are reduced substantially for round three negotiations when the design change was implemented. Length set-range values are also reduced at a faster rate when compared to experiment two reduction. This again leads to the observation that reduction path and set-range values are critical for the success of a SBD process.

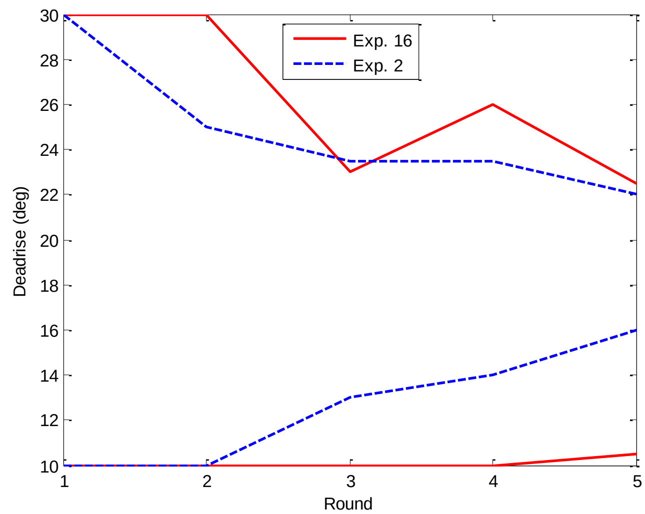


Figure 5.25: Deadrise Reduction Plots (Exp. 16 and Exp. 2)

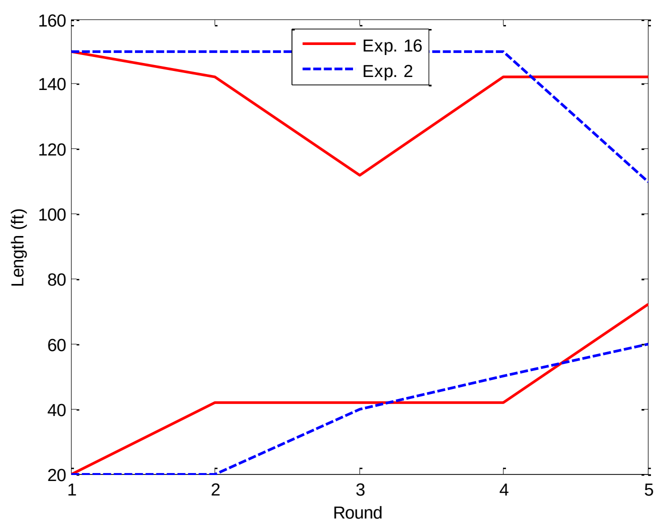


Figure 5.26: Length Reduction Plots (Exp. 16 and Exp. 2)

Identifying failure opportunities and how the SBD process handles these situations are important components of a set reduction strategy. By examining the reduction plots associated with a SBD process, the significance of the set reduction path taken can be determined. Also, avoiding failure opportunities would be a primary concern for the chief engineer guiding the process. If a failure opportunity occurs, however, the process can regain feasibility by reopening the set-ranges. While expanding sets during the SBD process is not recommended, special exceptions, such as a good improvement idea, an error, or requirement change might dictate its use.

5.5.4.2 Single Variable Failure (Experiment 13)

Similar to a functional design failure, a single variable failure occurs when only one variable set-range is completely infeasible. This typically happens when multiple MFs have unpreferred regions that when combined make the whole set-range unpreferred. During experiment 13, a single variable failure occurred for deadrise in round four, when a major design change was implemented. Figure 5.27 shows the JOP plot for deadrise. As mentioned earlier, deadrise was a relatively open variable, and preferences were generally indifferent when other variable set-ranges remained open; however, when other influential variables, such as length or beam, are reduced significantly, preferences for deadrise are impacted.

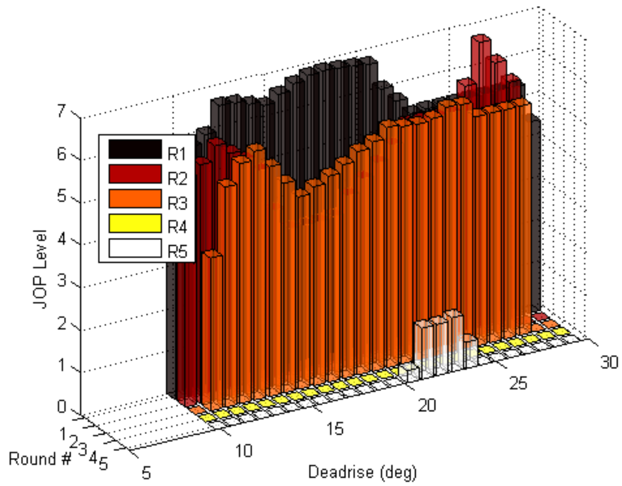


Figure 5.27: Deadrise JOP with Major Middle Change (Exp. 13)

Set-range values for the variables other than deadrise greatly reduced prior to the round four design change; however, the ranges were able to manage the change. Due to the dramatic shift in preferences and narrow set-range values, round four preferences for deadrise signaled multiple unpreferred regions. The two functional design groups that conflicted were the resistance and weight groups. While both had feasible and preferred regions, their unpreferred regions combine to make the whole set-range unpreferred. Figure 5.28 shows the resistance MF for deadrise in round four. The unpreferred region is relatively large and goes up to values around 22 degrees. Figure 5.29 shows the weight MF for deadrise in round four. Its unpreferred region starts around 22 degrees and goes to the maximum set-range value. When this type of overlap occurs, the JOP curve for the entire deadrise set-range must be zero. This causes a failure opportunity for the specific variable, in this case deadrise, where the unpreferred regions combine to make the whole set-range unpreferred.

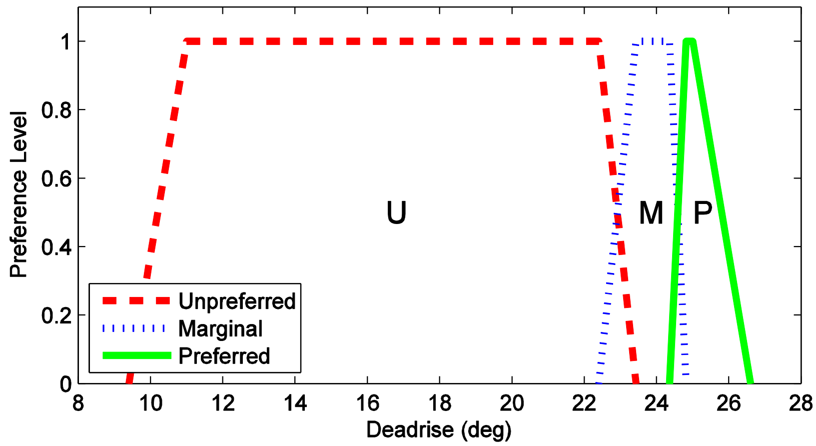


Figure 5.28: Resistance Membership Function for Deadrise (Round 4-Exp. 13)

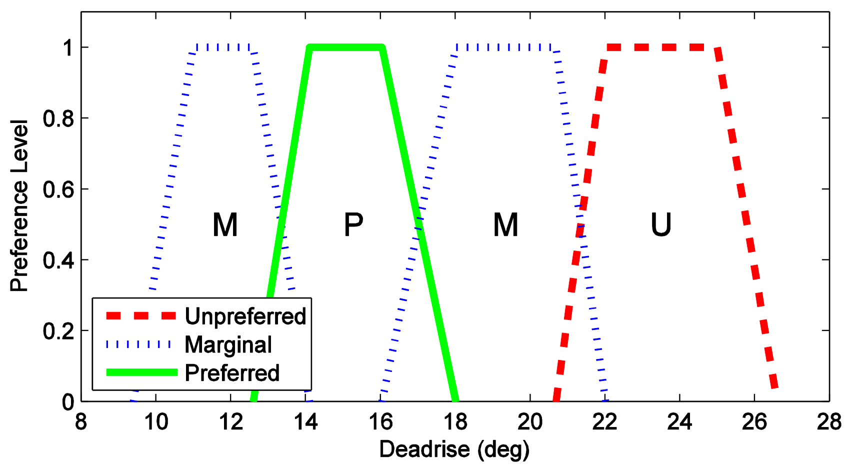


Figure 5.29: Weight Membership Function for Deadrise (Round 4-Exp. 13)

The single variable failure opportunity that occurred in experiment 13 highlighted the impact of conflicting preferences and the importance of all variables in the set reduction process, even ones that seem to have indifferent preferences early on. In some cases, JOPs do not provide all the information necessary to understand the causes of failure opportunities. Individual functional design group MFs describing their preferences for set-range values can be used to understand specific types of failures, such as overlapping unpreferred regions. Also, the impact of reducing all variable set-ranges should be considered, as well as how a reduction could potentially impact a variable's feasibility later in the process.

5.6 Experiment Conclusions

The results of the experiments show how the robustness of the SBD process can manage design changes. This robustness comes from the ability to delay decisions and keep sets open longer. Also, by being able to reopen sets after a failure opportunity occurs, feasible regions can be located and the new design direction can be found. The experiments show that more impact comes from 1) more complex design changes and 2) later-stage design changes. One of the most important conclusions made from the experimental results is that regardless of the complexity and timing of a design change, the SBD process can demonstrate how a change affects the design and where the new design direction should be.

Beyond the basic, and intuitive, conclusions, there are certain observations regarding specific types of scenarios that merit further discussion and analysis. These scenarios are related to both the reduction path taken and the rate of reduction; both of which are identified as potential factors in how changes in design impact the process.

First, due to the unconstrained nature of the design problem, multiple reduction paths could be taken to achieve a reduced feasible region. However, it was identified from the experiments that some paths were able to handle design changes better than others. This has major implications for the importance of the reduction path taken and the crucial role of the chief engineer in the set reduction process.

Second, the experiments identified the importance of reduction rate and the range of the set when a design change is implemented. From this observation, there were two types of situations that led to different reduction rates. The first was the observation that larger magnitude changes resulted in larger final set-ranges than smaller magnitude changes for the length variable. The second was the observation that the early change experiment had the largest final set-range and the late change had the smallest final set-range for the displacement variable. The difference can potentially be explained by looking at the reduction paths for each scenario and the rate of reduction. There are two basic situations that can occur when a change is implemented: 1) preferences might change, but the feasible region stays relatively similar and a reduction is not forced or 2) the change leads to an infeasible region to develop, forcing a reduction. These two situations have the opposite effect on results, even if the same type of change and timing is implemented. It can also be different for each variable. These observations emphasize the importance of the reasoning a chief engineer uses to reduce sets.

Finally, the experiments identified special occurrences during the SBD process defined as failure opportunities, which require additional research to understand. If such occurrences can be predicted and what triggers them can be identified, a designer can make more educated set reduction decisions, including which reduction path to take and the rate at which to reduce set-ranges. By understanding the causes of these failure opportunities, chief engineers can guide the set reduction process in such a way that avoids these potential scenarios to begin with.

5.7 Chapter Summary

This chapter focuses on detailed design experiments conducted to identify more concrete conclusions regarding the ability of SBD to handle design changes. A total of 21 experiments were conducted. There were seven design scenarios with three replications of each design scenario. A design scenario consists of a magnitude of change of the speed requirement (no change, moderate, and large) and what round of negotiations the design change was implementing (early, middle, and late).

Based on initial difficulty associated with analyzing the experiment results, a visualization technique and a series of reduction metrics were developed to aid in the understanding and analysis of SBD reduction efforts. The developed metrics can be used during a SBD execution to understand the current reduction characteristics of the effort.

The experiment results were broken down into three aspects: the effects of varying magnitudes, the effects of varying timings, and the special cases that resulted in failure opportunities. Overall, the results of the experiments show how the robustness of the SBD process can handle design changes. The robustness of the process comes from the ability to delay decisions and keep sets open longer. Also, by being able to reopen sets after a failure opportunity occurs, feasible regions can be located and the new design direction can be found. The experiments show most impact comes from more complex design changes and later-stage design changes. One of the most important conclusions made from the experimental results is that regardless of the complexity and timing of a design change, the SBD process can show how a change affects the design and where the new design direction should be.

There were also certain observations regarding specific types of scenarios that identified additional conclusions. It was seen from the experiments that some paths were able to handle design changes better than others. This has major implications for the importance of the reduction path taken and the crucial role of the chief engineer in the set reduction process. The experiments also identified the importance of reduction rate and the range of the set when a design change is implemented. There are two basic situations that can occur when a change is implemented: preferences might change, but the feasible region stays relatively similar and a reduction is not forced, or the change leads to the development of an infeasible region, forcing a reduction. The outcomes of these two situations are the opposite even if the same type of change and timing is implemented. It can also be different for each variable. These observations emphasize the importance of the reasoning a chief engineer uses to reduce sets.

Finally, failure opportunities were observed and the ability to manage these scenarios requires additional research to understand. If failure opportunities can be predicted and their triggers identified, a designer can make more educated set reduction decisions, including which reduction path to take and the rate to reduce set-ranges. By understanding the causes of these failure opportunities, chief engineers can guide the set reduction process in such a way that avoids these potential scenarios to begin with.

The major observations and conclusions that can be formed from conducting the detailed experiment provide insight into the set reduction process. However, using the developed reduction metrics and observations seen from the experiment results are considered lag indicators. The reduction process had to occur before these metrics could be calculated and observations seen. In an attempt to avoid the situations that led to failure opportunities and remain in an area of the design space that is robust to change, there is a requirement for lead indicators. These indicators would guide the designer in making set reduction decisions with the intention of avoiding areas of the design space that can lead to potential failures.

Chapter Citations

1. ABS. (2007). *Rules for Building and Classing High Speed Naval Craft*.
2. Antony, J. (2003). *Design of Experiments for Engineers and Scientists*. New York: Butterworth Heinemann.
3. Celano, T. (1998). *The Prediction of Porpoising Inception for Modern Planing Craft*. Trident Scholar Project Report, United States Naval Academy.
4. Colwell, B. (2005, October). Complexity in Design. *Computer*, 38(10).
5. Doctors, L. (1982). *Hydrodynamics of High-Speed Small Craft*. Department of Naval Architecture and Marine Engineering, University of Michigan.
6. Faltinsen, O. (2005). *Hydrodynamics of High-Speed Marine Vehicles*. New York: Cambridge University Press.
7. Federation of American Scientists. (2010). *Mark V Special Operations Craft*. www.fas.org.
8. Grubisic, I. (2008, September). *Reliability of Weight Prediction in the Small Craft Concept Design*. Paper presented at the 6th International Conference on High-Performance Marine Vehicles.
9. Karyayanis, T., Molland, A. F., & Sarac-Williams, Y. (1999). Design Data for High-Speed Vessels. *Proceedings of the 5th International Conference on Fast Sea Transportation*, pp. 605-615, Seattle, WA.
10. Maier, J. R. A., & Fadel, G. M. (2004, May 16-21). *Understanding the Complexity of Design*. Paper presented at The New England Complex Systems Institute Fifth International Conference on Complex Systems, Boston, MA.
11. McKenney, T. A., Gray, A. W., Madrid, C., &Singer, D.J. (2012, October-December). The Use of a Fuzzy Logic Set-Based Design Tool to Evaluate Varying Complexities of Late-Stage Design Changes. *Transactions of the Royal Institution of Naval Architects Part A: International Journal of Maritime Engineering*, 154(A4), pp. 179-189.
12. Savitsky, D. (1964). Hydrodynamic Design of Planing Hulls. *Marine Technology*, 1(1), pp. 71-95, 1964.
13. Savitsky, D. (1985). Planing Craft. *Naval Engineers Journal*, 97(2), pp. 113-141.
14. Sun, H., & Faltinsen, O. (2011). Predictions of Porpoising Inception for Planing Vessels. *Journal of Marine Science and Technology*, 16, pp. 270-282.
15. U.S. Navy. (2009). *Mark V Special Operations Craft U.S. Navy Fact Sheet*. www.navy.mil.

Chapter 6: Decision Support Framework

The previous chapters have introduced SBD as a potentially advantageous design method, but a method that has been characterized by a number of execution challenges. The difficulties of conducting early-stage design efforts in today's environment are clear, and there are no simple solutions for the complex issues that arise throughout a design effort. SBD execution for organizations such as the U.S. Navy is of particular interest. For example, how do you effectively manage a large-scale, team-based design process for complex systems that are difficult to fully understand? Utilizing the developed tools and experiment results discussed in the previous chapters, a set reduction decision support framework, which is presented in this chapter, is created.

This chapter begins by identifying insights gained from previous research and the formulation of the problem statements used to guide the remainder of the work presented in this dissertation. Next, an overview of the methodologies used is presented, including the longest path problem, the Markov Decision Process, design space mapping, and sensitivity analysis using preference structure simulations. Finally, visual representations of the methodology's results are highlighted, which can be utilized by a designer to make more informed design reduction decisions within a SBD environment.

6.1 Problem Formulation

The three research problems presented in Chapter 1 are revisited in this section to demonstrate a clear understanding of their implications through initial research insights and to show how the developed decision support framework addresses each problem. It is also important to consolidate and understand the implications of previous work completed by other researchers.

6.1.1 Insights from Previous Research

The overarching insight gained from previous research, which is demonstrated by reviewing current SBD research and completing the initial research discussed in the previous chapters, is that the guidance of set reduction is a critical element of SBD execution for large-scale, team-based design efforts and remains an open research problem. The majority of SBD research currently focuses on different research areas including design optimization techniques, multi-objective Pareto fronts, and automated reduction methods. Additionally, the U.S. Navy's execution of SBD for the SSC identified that while advantages were seen, extension to larger-scale design efforts would be challenging. Both the initial case study and detailed experiment revealed that more heuristic set reduction decision making can result in different reduction paths and outcomes for the same design scenario. These collective observations identify the guidance of set reduction as an important and open research area.

The two components of set reduction efforts that have been identified as major influences on the design outcome are time-dependent design relationships and determining robust decision paths. A major observation seen both in the practical setting of the SSC SBD execution and the academic setting of the design experiments was the lack of design relationship understanding. Even more significant is the understanding of these design relationships as they change over time. Design relationships change as the fidelity of analysis increases, variable set-ranges are reduced, or requirement changes are implemented. Additionally, there is a lack of understanding associated with the impact of reduction decisions. A reduction decision made early can greatly impact the ability of a design process to handle changing relationships later in the process. Also, it was identified that reduction path and rate have a major impact on handling a design change. While SBD has been shown to be change resilient, the design experiments revealed that the reduction process can still be restricted to the point of potential failure.

In summary, the four major insights gained from previous work include the need for:

1. A method to aid in SBD execution for large-scale, team-based design
2. A more formal set reduction decision making framework
3. A better understanding of time-dependent design relationships and the potential impact of current decisions on the design process
4. The identification of robust decision paths that avoid failure opportunities, while considering reduction path and rate

6.1.2 Problem Statements

The insights outlined in the previous section have shown that there is still a substantial need for SBD execution support, especially in how decisions should be made to reduce the design space, while considering total design process impacts. This involves understanding relationships as the design process progresses and understanding design reduction decisions. The insights obtained through design research and the previous work completed, as outlined in the previous two chapters, led to the development of three major problem statements. The work presented in the remainder of this dissertation focuses on these three statements and the development of a framework to aid in their solution. Table 6.1 summarizes the three research problems and questions, followed by the proposed solutions.

Table 6.1 Research Problem Statements and Proposed Solutions:

Problem	Research Question	Proposed Solution
Time-dependent design relationships	How can a designer understand changing dependencies as the design progresses?	Extension of Design Space Mapping
Determining impact of reducing certain areas of the design space	How can a designer organize reduction decisions to account for total design process impacts?	Longest Path Problem (LPP) formulated as a Markov Decision Process
Identifying robust decision paths	What decision paths are flexible to changing design conditions?	Preference Change Simulations

The first research problem is the issue of time-dependent design relationships and how to handle changing dependencies as the design process progresses. Design space mapping can be used to determine relationships between the various design spaces, including variable, constraint, and objective spaces. These mapping techniques can also facilitate human designer preferences for variable and function values. Using the preferences provided at each time step, a series of mappings can be completed to determine the influence of variables at different set-ranges. At each time step, preferences are updated and the mappings can be repeated to get an updated view of design relationships.

The second research problem builds on the first by acknowledging the difficulty of determining when and where to make design reduction decisions. The Longest Path Problem (LPP) formulated as a Markov Decision Process (MDP) is proposed to aid in design reduction decision making. This proposed method is able to balance the risk and reward of reducing certain areas of the design space and can determine the impact of these decisions on the overall design process. Using the information provided by the design space mappings, the MDP can be used every round of the SBD process to identify optimal decision paths. The MDP results can provide the design manager, or chief engineer, with valuable guidance on how to reduce the design space from the perspective of the identified function. This process can be completed for multiple functions of interest to provide a clearer design reduction strategy for the overall design process.

The third research problem focuses on the identification of robust decision paths. The goal is to avoid failure opportunities and potential situations where the current set-ranges cannot handle a changing design relationship. Identifying potential decision paths that are more flexible to changing design conditions would be preferred. Preference change simulations can be used to identify these robust decision paths. The LPP MDP formulation can also be used with various design preference structures representing potential future changes in preferences. Additionally, the likelihood of a certain path being able to handle varying magnitudes of changing conditions, including preference and requirement changes, can be determined.

6.2 Execution Strategy

Before introducing the components of the developed framework, it is important to understand how the framework can be used within a SBD effort and by whom. As mentioned previously, the chief engineer's role of managing the set reduction process is critical to the success of a design effort. An overview of the set reduction process is provided in Figure 6.1. After functional design groups are provided with the initial variable set-ranges from the chief engineer, they conduct engineering analysis and generate their preferences. JOPs are then calculated and sent to the chief engineer. At this point, the developed framework is used by the chief engineer to evaluate potential reduction decisions. Based on the framework results and any other considerations a chief engineer desires, the decision to reduce is made and the new set-ranges are sent to the functional design groups. At this point, the process begins again.

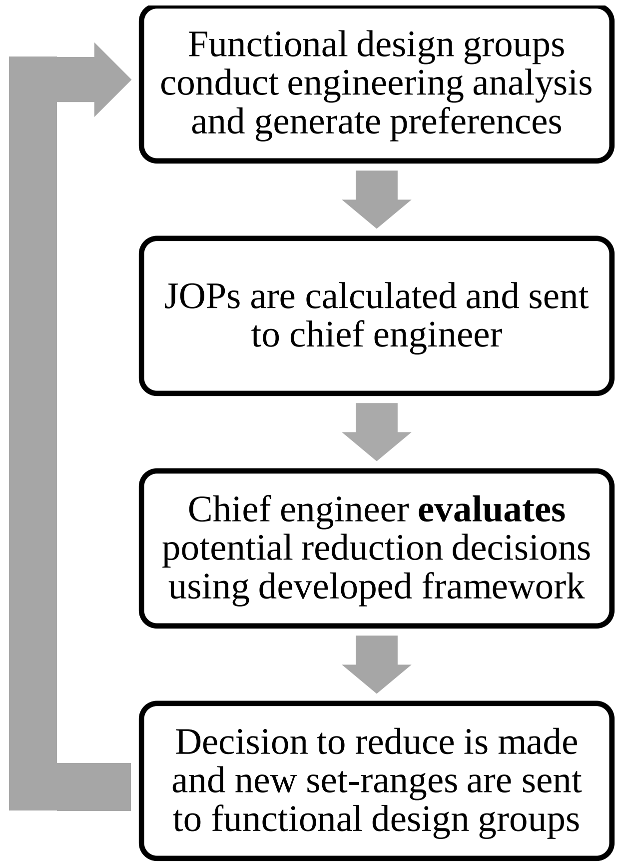


Figure 6.1: Set Reduction Overview

The research problems presented in the previous section lend themselves to a sequential decision making framework that uses preference information from teams of designers as a basis for making design space reduction decisions. Again, an assumption made for the work presented in this dissertation is that JOPs are initially provided and adequately represent the current design problem. The ability of JOPs to describe designer preferences has been explicitly shown by Singer (2003) and Gray (2011). This section presents a mathematical framework for reduction decision making within a SBD environment that combines DM, the LPP formulated as an MDP, and simulation.

This section initially provides an overview of how the three methods are combined into a cohesive execution strategy. The required inputs and how each is used within the developed framework are discussed as well as the links between the three major methods proposed. The execution strategy can be broken down into a series of distinct steps that occur during a single round of negotiation, or time-step in the decision making process.

The developed framework is designed for use at every negotiation round. After a set reduction decision has been selected during a given round, the method is used to reevaluate the remaining reduction process using updated variable preferences provided by the functional design groups.

For each negotiation round, there are a number of important inputs that are required to use the developed framework. These include:

- Variables and associated set-ranges,
- Number of set-range partitions for each variable,
- Function,
- Function preference,
- Variable preferences,
- Simulation variation strategy (how preference structures vary), and
- Type of reward.

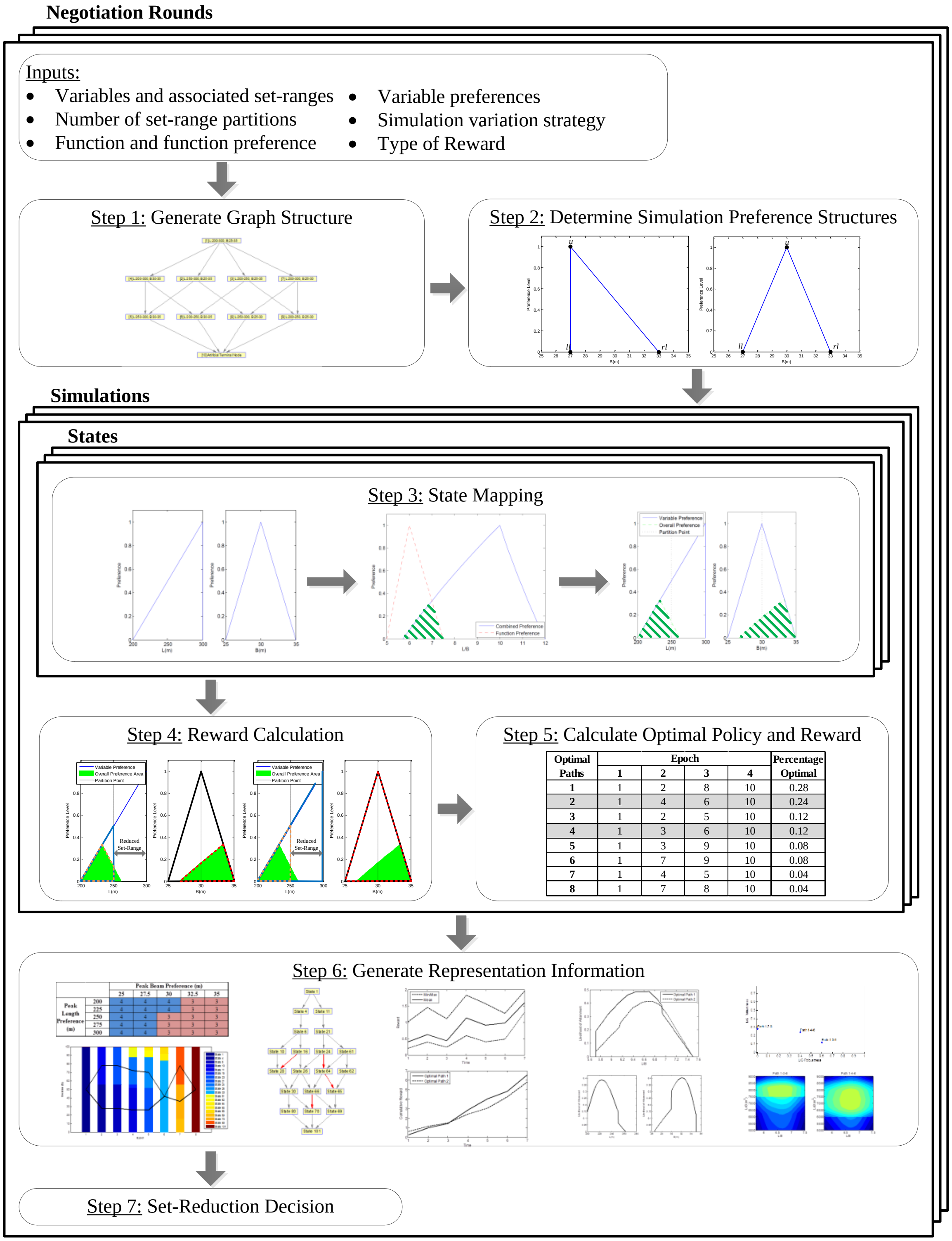
The first inputs are the variables and their associated set-ranges. A set-range is the minimum and maximum variable values being considered. These will change for each negotiation round as the set reduction process continues. The number of partitions that each variable set-range should be divided into is also an input and is based on the level of detail required or how complicated the preference functions are. If smaller reductions are desired, a larger number of partitions should be selected. Also, if the JOPs have multiple modes or complicated curvatures, additional partitions can provide a more accurate representation of the different regions. A variable partition region is a specific area of a set-range. For example, if there are two partitions for a given set-range, there will be two variable partition regions: the lower region and upper region. The function of interest is required along with a preference for particular function values or regions.

Variable preferences are also required, which are in the form of JOPs based on analysis conducted by the functional design groups. How the preference structures should vary for the simulations is also important and guidance is needed to determine how many variations of the assumed preference structure are required. Finally, the type of reward, which is based on design space mapping (DM) information, is required. The developed reduction metrics that are used to calculate the reward are discussed after the DM presented.

A complete overview of the execution strategy is now presented. Figure 6.2 may be referenced for further explanation as the steps are described. Step 1 is the generation of the graph structure. The graph structure is determined based on variable set-ranges and the number of partitions. One such structure is the single reduction scenario that is focused on in this dissertation. Next, step 2 determines the number of simulations required and their associated preference structures. Using the simulation variation strategy, initial preference structures can be determined. The initial preferences of all the simulations are the provided JOPs. All subsequent state preferences are based on the assumed preference structure for the specific simulation. The total number of simulations is based on the number of variables and preference structure variations.

For every simulation within a negotiation round, a series of calculations needs to be completed. First, a design space mapping is completed using the determined variable preferences, function, and inputted function preference for every state in the structure associated with a given simulation. The outputs from the state mappings are used to calculate the reward and risk metrics. These metrics are calculated for every outgoing graph connection, or feasible reduction, based on state mapping inputs. The final step for every simulation is calculating the optimal reduction policy, or path, and reward. Using the MDP LPP formulation, the optimal policy and associated reward is recorded for every simulation.

Back at the negotiation round level, various representations of the simulation results and recorded information are generated. This information includes the optimal strategy, robust decision paths, alternative paths, reward over time, likelihood of attainment, and multi-objective trade-offs. The decision-maker uses these representations to make a set reduction decision. The set-ranges are reduced and functional design groups receive updated set-ranges to continue their analysis. As mentioned previously, a visual depiction of this execution strategy is provided in Figure 6.2.



Optimal Paths	Epoch 1	2	3	4	Percentage Optimal
1	1	2	8	10	0.28
2	1	4	6	10	0.24
3	1	2	5	10	0.12
4	1	3	6	10	0.12
5	1	3	9	10	0.08
6	1	7	9	10	0.08
7	1	4	5	10	0.04
8	1	7	8	10	0.04

Figure 6.2: Execution Strategy Overview

The overall reduction process from the initial to the final reduced variable set-range values can be completed in different ways. Using the inputs defined earlier in this section, the designer can specialize each round's analysis based on current conditions. For this dissertation, a structured reduction approach is assumed. The number of negotiation rounds is dictated by the number of partitions and variables. This means that for the variable that has a region reduced, the next round's analysis for that variable will have one fewer partitions. For example, if a two-partition variable is reduced, a single partition remains. The region does not get partitioned again into two regions. This then dictates the number of negotiation rounds associated with the reduction process. This reduction structure can be considered valid for the relatively simple triangular preferences assumed in this dissertation. For more complex preferences, additional partitioning might be required.

The following novel characteristics of the developed framework include:

- The extension of design space mapping (DM) methods to include multiple metrics that can be used to aid design reduction
- Provides a mathematical framework for team-based SBD reduction that captures changing conditions as the design progresses, including designer input
- Applies the longest path optimization problem and the Markov Decision Process (MDP) to early-stage design reduction decision making efforts

6.3 Methods

The remainder of this section introduces the methods used within the execution strategy. The reduction path MDP formulation is first discussed to provide an overview of the major problem structure. Next, the DM method is presented and its relation to the MDP formulation is provided. Sensitivity and simulation that uses the combination of the MDP and DM is then presented. Novel approaches to representing the results of the complete framework are also discussed. How each component fits into the overall reduction process and execution strategy is provided along the way. First, however, an example problem is presented to be used throughout the remainder of the chapter as an illustrative aid in describing the methods used.

6.3.1 Example Problem

For this chapter, a function of two variables is used to demonstrate how each element of the methodology is implemented. The function selected is the length-to-beam ratio (*R*), which is used in naval architecture to describe the slenderness of a hull. Larger length-to-beam values signify a longer and more slender hull, while smaller values signify a shorter, wider hull. The variables are length (*L*) and beam (*B*). The equation for the function *R* is:

$$R = \frac{L}{B} \tag{6.1}$$

While a simple function, it is able to illustrate how the developed methodology can be utilized. In the following sections, the length-to-beam ratio will be continually referenced.

6.3.2 Reduction Path Optimization

There are a series of key decisions that must be made during any design reduction process, most importantly what area of the design space should be focused on (or eliminated in the SBD case) and when that decision should be made. The design reduction process is also stochastic in nature due to many unknown and changing relationships, an incomplete description of the solution space, and potential external influences resulting in design changes (i.e. requirement changes). One of the main objectives when guiding design reduction is to maximize the reward associated with eliminating a certain area of the design space while considering the risk associated with that decision. The reward is based on DM information, and is explicitly defined later in this chapter. This section first introduces the Canadian Traveler Problem to gain a better understanding of the reduction path problem. A novel approach to generate graph structures is then discussed, followed by an introduction to longest path problems.

Finally, a Markov Decision Process (MDP) formulation that models the reduction path problem is introduced.

6.3.2.1 Understanding the Reduction Path Problem

As identified in Chapter 2, one of the main challenges associated with design decision making is that there is a large amount of incomplete information, especially at the early stages. The designer does not know what future analysis or preferences are going to be, therefore, they are forced to make decisions based on the best information they have available. After the decision is made, the designer can potentially evaluate whether that decision was appropriate. The types of decisions that are made differ depending on the design approach taken. For example, for the set reduction decision making process, the graph can be known before the process begins if the number of partitions is assumed from the start.

A similar type of problem arises in the extensive literature associated with the shortest-path problem (SPP). The SPP is the problem of finding a path from one node in a graph to another by minimizing the sum of the edge weights between nodes. Applications of the SPP in a geometric setting have identified a variant that deals with certain edge weights or nodes being unknown. Examples of this type of SPP application include the movement of a robot through an area with various obstacles (Papadimitriou & Yannakakis, 1991) and robot navigation under sensor uncertainty (Briggs, Detweiler, Scharstein, & Vandenberg-Rodes, 2002). Papadimitriou and Yannakakis (1991) state, "It is sometimes natural to assume, both in the graph-theoretic and the geometric contexts, that the planner initially has incomplete information about the graph or scene, and such information is acquired in a dynamic manner, as the search for a good path evolves" (p. 127). While this is in reference to robot navigation, the same principles can be applied to design.

The special case of the SPP where the graph structure is known is called the Canadian Traveler Problem (CTP). The CTP describes a typical scenario for certain travelers in Canada: only when a driver reaches an intersection can he or she identify if the roads leading out are snowed in or not. This is a problem in which the weight of an edge is learned only when arriving at the next node. After arriving to an intersection, the traveler can determine whether a road is snowed in and can decide in which direction to continue (Nikolova & Karger, 2008). The simplest implementation of this problem is to resample edge weights each time a new node is visited. This formulation fits nicely for the set reduction decision making process because the resampling of edge weights can be synonymous with negotiating reduced set-range values.

In an effort to make the reduction formulation more intuitive, the longest path problem (LPP) can be used instead of the SPP. The LPP was selected based on the intuitive nature associated with maximizing a reward associated with a decision path as opposed to minimizing a defined cost. The LPP, a component of graph theory, is the problem of finding a path from one node in a graph to another by maximizing the sum of the edge weights between nodes. While solving a LPP compared to a SPP can be more challenging and take additional time, there are multiple methods for solving both types of problems. The LPP can be formulated as a SPP by multiplying edge weights by negative one. Before an LPP problem can be solved, however, a graph structure must be defined including its associated nodes and arcs.

6.3.2.2 Generation of Graph Structure

One of the prerequisites for solving a LPP is a defined graph structure that describes the sequential decision making scenario. After providing the required inputs, the generation of the reduction graph structure is the first step. The goal of the graph structure generation step is to identify potential reduction decisions. The required inputs to generate a graph include the number of variables, variable set-range values, and the number of partitions for each variable. There are three general structures that can be used to describe the set reduction decision making process, each with increasing degrees of detail and complexity. These structures include single reduction, multiple reductions, and potential reopening. For this dissertation, the single-reduction scenario is used. The multiple reductions and potential reopening scenarios are discussed as future work in Chapter 9.

The first scenario, defined as single reduction, is when only one variable partition region (set-range) can be reduced at a time. There is no ability to reduce multiple variable set-ranges or reduce multiple partition regions at the same time. This provides a simple structure that can be easily understood through inspection for basic problems. Figure 6.3 shows the graph structure for the length-to-beam single reduction problem with two partitions for each variable set-range. The bracketed numbers are the states and each node is associated with the shown set-range combinations. This is a directed acyclic graph (DAG), which allows for easier solution methods compared to both undirected and cyclic graphs. Each row of nodes is associated with a specific epoch or time-step. For this graph structure, a total of two decisions would need to be made in sequence, which is based on the fact that there are two variables with two partition regions. For the single reduction structure, the number of time steps is dictated by the number of variables and partitions. The goal is to reduce to one partition region for each variable. This corresponds to four potential combinations of final partition regions. An artificial terminal node is added for two reasons: to aid in the solution of the SPP by defining one start node and one terminal node and to account for potential rewards associated with being at a final node.

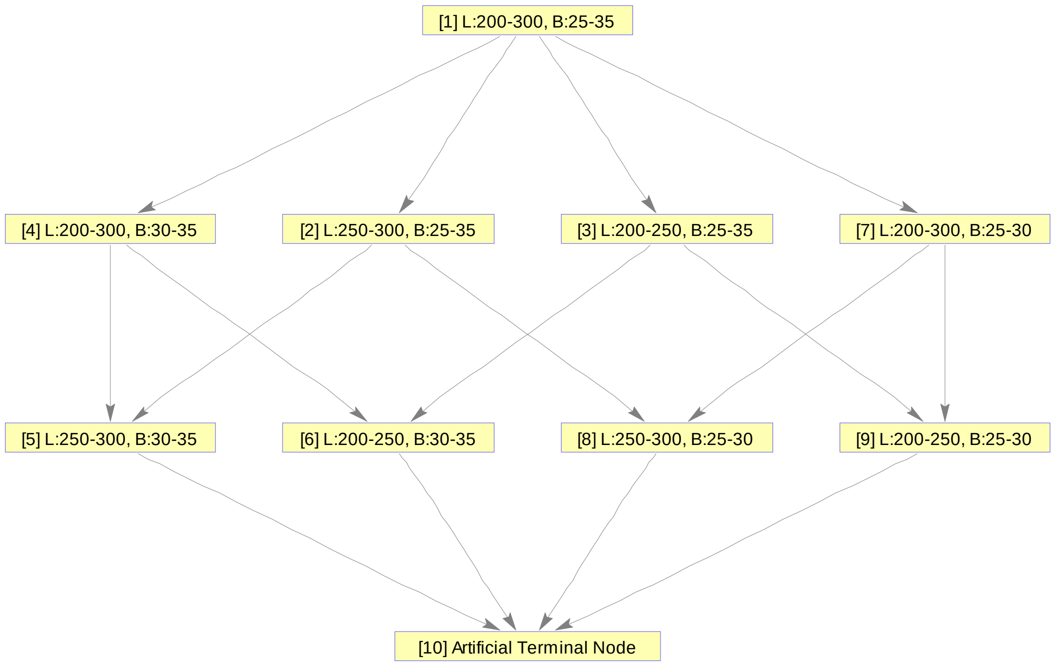


Figure 6.3: Length-to-Beam Single Reduction Graph (Two Partitions)

While the graph in Figure 6.3 can be manually generated for the simple length-to-beam problem, larger problems would require substantial time and effort for graph generation. Therefore, a novel approach to automatic graph generation for the set reduction decision making problem was developed. The goal of this approach is to develop a transition matrix that describes the relationships between the set-ranges associated with each state. The transition matrix is calculated using principles from design of experiments (DOE), specifically a full factorial experiment (FFE) setup. The calculation process combines the total number of reduction steps, defined as levels, for each variable (defining the nodes) with determining how set-range combinations are related (defining the directed edges).

The first step is determining the number of states (or nodes) required to describe the set reduction process. The total number of states can be calculated using the number of levels associated with each variable and then the possible combinations between variables. The number of levels for a variable is based on the number of partitions. A simple example is when the number of partitions, defined as P, is equal to two. The set-range with two partition regions is one level, and each individual partition region is another level, for a total of three levels. This is considered a triangular number, which counts the number of objects that can form an equilateral triangle. The formula for a triangular number, with notation changed for the levels calculation, is provided in Equation 6.2.

$$L_P = \sum_{k=1}^{P} k = 1 + 2 + \cdots + P = \frac{P(P+1)}{2} \tag{6.2}$$

To determine the total number of states by calculating the combination of all variable levels, the number of levels for each variable can be multiplied together. This can be described as a FFE. If the number of partitions is the same for every variable, the total number of nodes, T, can be calculated using Equation 6.3. The total number of variables is defined as N.

$$T = \left(\frac{P(P+1)}{2}\right)^N \tag{6.3}$$

For the length-to-beam example with $P = 2$ and $N = 2$, the total number of nodes would be equal to $3^2 = 9$. Notice that the artificial terminal node does not count towards this total node value.

After the number of states has been calculated, the relationships between the states need to be determined. Reduction occurs when moving from a higher level to a lower level for each variable. A higher level set-range is a variable set-range that is larger than a lower level set-range. Moving from a higher level to a lower level is associated with eliminating a particular variable partition region. DOE principles can again be used, but in a different way. A FFE can be set up where the factors are the beginning and end partition regions that describe a variable set-range. The levels for each factor are the number of partitions for that specific variable. FFE results for length in the length-to-beam problem with two partitions are provided in Table 6.2.

Table 6.2: Length Variable Two-Partition FFE

Set-Range	*Partition Region*	
	Begin	**End**
200-250	1	1
300-200	2	1
200-300	1	2
250-300	2	2

Partition region "1" in Table 6.2 corresponds to the variable region 200-250 and partition region "2" corresponds to the variable region 250-300. By numbering the partition regions in this manner, a rule can be added to determine if the set-ranges are valid, which is that the end partition region number is greater than or equal to the beginning partition number. As shown, not all of the resulting FFE is valid based on how the problem is set up. For example, the shaded row in Table 6.2 shows an infeasible partition region. The 1-2 region represents the initial set-range of both partitions, the 1-1 region represents the lower set-range partition, and the 2-2 region represents the higher set-range partition.

After infeasible and redundant partition regions are eliminated from the FFE, the relationships between the variable partition regions can be determined. A series of logical arguments are used to identify where connections exist. For every permutation (order *does* matter) of the variable partition regions (*PR*s), the logical arguments in Equation 6.4 are used to identify if a connection exists. The starting partition region is defined as PR_i, and the potential reduced region is defined as PR_j. The subscripts *B* and *E* stand for the beginning and ending region for a particular partition region, respectively.

$$\begin{gathered} PR_{j_B} = PR_{i_B} + 1 \; \boldsymbol{AND} \; PR_{j_E} = PR_{i_E} \\ \boldsymbol{OR} \\ PR_{j_E} = PR_{i_E} - 1 \; \boldsymbol{AND} \; PR_{j_B} = PR_{i_B} \end{gathered} \tag{6.4}$$

The first logical argument identifies whether a lower partition region is eliminated and the upper region remains the same. The second logical argument does the opposite: it identifies if a higher partition region is eliminated and the lower region remains the same. If either logical argument is true, then a connection exists. A good example is determining if a connection exists between the region 1-2 and both regions 1-1 and 2-2 shown in Table 6.2. By identifying what each region represents, it can be easily determined that there should be a connection between the initial region 1-2 and the other two reduced regions. For the reduction from region 1-2 to 2-2, the first argument holds. For the reduction from region 1-2 to 1-1, the second argument holds. It is important to note that these logical arguments only hold for a single reduction scenario. After reordering the partition regions from largest to smallest, a transition matrix can be determined for each variable. The transition matrix for the length variable with two-partitions is provided in Table 6.4 for a reordered FFE shown in Table 6.3. Note that partition regions shown in Table 6.4 are connected to themselves. This is because every variable region does not have to be reduced every time-step.

Table 6.3: Length Variable Reordered Two-Partition FFE

Set-Range	*Partition Region*	
	Begin	**End**
200-300	1	2
250-300	2	2
200-250	1	1

Table 6.4: Two-Partition Variable Transition Matrix

		Set-Range		
		200-300	**250-300**	**200-250**
Set-Range	**200-300**	1	1	1
	250-300	0	1	0
	200-250	0	0	1

The final step in the graph generation process is to define the set-range values for each node, which is a combination of all the variable regions. The variable transition matrices are used in a similar way as the variable partition FFE results are used to determine partition region connections. By looking at all the permutations of the variable partition regions, the number of regions that remain the same and the number of regions that are at the next level for all variables are determined. Again, using a similar series of logical arguments associated with both ensuring that only one variable and a single region is reduced at a time, the states and relationships (arcs or connections between nodes) can be automatically generated. The automatic graph generation method developed can be used to determine a graph structure that is then used as an input to the LPP.

6.2.2.3 Longest Path Problem

The LPP provides the structure to evaluate potential future outcomes and sets the problem up so steps 3-5 in Figure 6.2 can be completed. With a complete generation of the graph structure, the information outputted from the DM can be used to describe the desire to take certain reduction paths within a LPP framework. The LPP can be formulated as a linear programming problem. Given a graph $G = (V, E)$ where V is the set of nodes and E is the set of edges and start node $s \in V$, let c_{uv} be the cost (weight) of an edge $(u, v) \in E$. The total cost of path p is $c(p) = \sum_{(u,v) \in E_p} c_{uv}$ where $E_p \subseteq E$ is the set of edges in path p. The longest path length $\delta(s, v) = c(p^*) = \max_{p \in P_{sv}} c(p)$ where P_{sv} is a set of paths from s to v. The traditional SPP and LPP have been solved using dynamic programming methods, including the popular Dijkstra's and Bellman-Ford algorithms. Dijkstra's algorithm solves the single-source SPP for a graph with non-negative edge weights, and the Bellman-Ford algorithm can accommodate negative edge weights, which can correspond to a LPP. The LPP is solved using the Bellman-Ford algorithm for the research presented in this dissertation.

The traditional LPP provides a valuable framework to begin to understand set reduction decisions, but there are some limitations to its current formulation. These limitations include:

1. Being unable to capture the stochastic nature of the reduction process,
2. The inability to understand the potential impacts of decisions at various time-steps
3. Future edge weights and probabilities are unknown.

In an effort to improve upon the first limitation introduced above, stochastic shortest and longest path problem (SSPP, SLPP) formulations can be used to add a probability distribution at each node over all possible successor nodes (Bertsekas & Tsitsiklis, 1991). Examples of SSPP applications include automobile route planning with stochastically changing road congestion levels, vessel routing with uncertain weather conditions, and robot navigation through a random environment (Polychronopoulos & Tsitsiklis, 1996). A SLPP formulation can address the first limitation of the basic LPP, however, a traditional application does not translate directly. A risk-adjusted reward between each node is calculated and the basic LPP is solved using the modified risk-adjusted reward calculations. Using this formulation, the modified edge weight is now defined as $p_{uv}c_{uv}$. The risk-adjusted reward calculation is discussed further in Section 6.3.4. A more detailed formulation that handles the stochastic nature of the problem in an improved manner is discussed as future work in Chapter 9.

6.3.2.4 Markov Decision Process Formulation

The LPP can be formulated as a Markov Decision Process (MDP). MDPs provide a structured way to evaluate decision making by modeling the relationships between present and future decision and outcomes (Puterman, 1994). A MDP is closely related to optimization problems and is also known as sequential dynamic programming. The second limitation of traditional path problems, the inability to understand the potential impacts of decisions at various time-steps, can be handled using an MDP framework. LPPs require the specification of a start and end node as inputs and solution methods typically only output the optimal path and distance. There is no regard to other potential paths, distances from other nodes, and cumulative distances as the graph is traversed. MDPs provide additional information than simply the optimal path and distance, which can provide decision-makers with a better understanding of the problem at hand. This section introduces MDPs and how they are solved starting with a description of their structure, then a discussion on how optimality is determined, and finally an introduction to the solution method used in this research.

6.3.2.4(a) Structure

Regardless of the type of problem, an MDP structure consists of the same elements. The sequential decision making model representation is provided in Figure 6.4. Puterman (1994) describes the process as follows:

> *At a specified point in time, a decision maker, agent, or controller observes the state of a system. Based on this state, the decision maker chooses an action. The action choice produces two results: the decision maker receives an immediate reward (or incurs an immediate cost), and the system evolves to a new state at a subsequent point in time according to a probability distribution determined by the action choice. At this subsequent time, the decision maker faces a similar problem, but now the system may be in a different state and there may be a different set of actions to choose from (p. 1).*

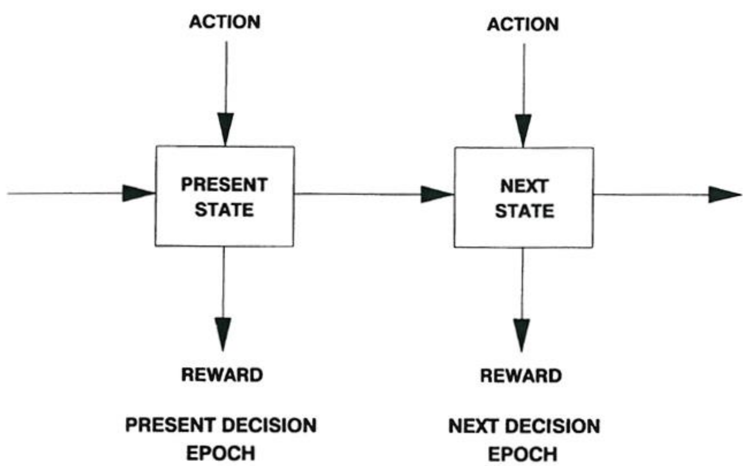


Figure 6.4: Sequential Decision Making Problem Representation (Puterman, 1994)

A fully observable MDP has five major components, defined by Puterman (1994):

- Design epochs, t
- System states, $S = \{s\}$
- Available actions, $A_s = \{a\}$
- State and action dependent rewards, $R_t(s, a)$

- State and action dependent transition probabilities, $P_t(s'|s,a)$

Design epochs are the time steps that decisions are made at; states are where an agent can exist, actions are the decisions an agent can make, rewards are what an agent gets by making a certain decision in a specific state, and transition probabilities describe the likelihood that an agent will move to a certain state if a specific action is taken in a given state. It is assumed that all components are known when a decision is made.

One important property of MDPs, known as the Markov property, states that the current optimal policy is independent of previous state policies. This is derived from that fact that the probability distribution of future states depends only on the present state. In relation to the reduction decision making process, the Markov property makes intuitive sense. The current set reduction decision is not conditional on a previous decision and is only based on the observed state information and future opportunities. This is one of the main reasons that an MDP framework was selected over a more conditional structure, such as Bayesian networks.

An MDP solution, defined as a policy, specifies an action that should be taken, and is denoted as π. The quality of a policy is determined using the total utility of the states a policy represents. An optimal policy is denoted as π^*. Utility will be defined explicitly in the next section, but represents the total risk-adjusted reward for a specified policy (or path) that traverses different regions of the design space.

A special class of MDPs is the LPP defined as a deterministic dynamic problem. In a deterministic dynamic program, choice of an action determines the future state with *certainty*. For example, if a chief engineer decides to take an action to reduce a certain area of the design space, the subsequent state will be, with certainty, the area remaining after the reduction. For the MDP model to take this into account, a transfer function is used instead of a transition probability matrix. To formulate a LPP as a MDP, nodes represent states, arcs characterize actions, a transfer function represents transition probabilities, and edge weights symbolize rewards. For the LPP, traditional MDP transition probabilities do not correlate. If a decision is made in a MDP, there is a certain likelihood that the system will end up in multiple states. With a directed graph, the system knows with certainty that the future state will be determined by the action taken. Therefore, instead of having a transition probability matrix, a transition probability function is defined:

$$P_t(j|s,a) = \begin{cases} 1 & if\ \tau_t(s,a) = j \\ 0 & if\ \tau_t(s,a) \neq j \end{cases} \tag{6.5}$$

where $\tau_t(s,a)$ is a function that "specifies the system state at time *t* + 1 when the decision maker chooses action $a \in A_s$ in state *s* at time *t*" (Puterman, 1994, p. 42). In a deterministic dynamic program, the total reward is used to identify optimal routes, which is equivalent to a LPP.

6.3.2.4(b) Optimality

The MDP performance measure, utility, can be calculated in many different ways. While additive rewards are the most common way, there are variations that are required depending on the type of problem that needs to be solved. The first issue to resolve is whether the problem has a finite or infinite horizon. A finite horizon is associated with a problem where there is a fixed time *N* that dictates when the decision making process must end. This means that an optimal action for a given state could change over time. A non-stationary policy is a policy that depends on time. An infinite horizon is where there is no fixed time limit, which means that the optimal action only depends on the current state and *not* the time step. The optimal policy in this case is called stationary. The typical output of a MDP is a decision matrix that provides the optimal actions for a given state and epoch (or time-step). An example of a non-stationary decision matrix is provided in Table 6.5. For stationary policies, there would only be one row because time does not matter. It is important to note that not all infinite horizon problems have infinite state sequences. It only means that there is no fixed deadline to which the process must adhere. For example, the single reduction formulation has fixed sequences with terminal states, but is considered an infinite-horizon problem. The multiple reduction formulation does not have fixed sequences or a fixed time limit; therefore, it is an infinite-horizon problem as well.

Table 6.5: Example Decision Matrix (Niese, 2012)

	State 1	State 2	…	State n
Epoch 1	Action A	Action A	.	Action A
Epoch 2	Action B	Action C	.	Action C
Epoch 3	Action C	Action A	.	Action A
…	.	.	.	.
Epoch m	Action D	Action B	…	Action A

The next step is determining how to calculate the utility used to identify optimal policies. Derived from multi-attribute utility theory, there are two ways to define the utility of sequences: additive and discounted rewards. The additive and discounted rewards utility calculations are shown in Equation 6.6 and Equation 6.7, respectively.

$$U([s_0, s_1, s_2, \dots]) = R(s_0) + R(s_1) + R(s_2) + \cdots \tag{6.6}$$

$$U([s_0, s_1, s_2, \dots]) = R(s_0) + \gamma R(s_1) + \gamma^2 R(s_2) + \cdots \tag{6.7}$$

The discount factor, γ, in Equation 6.7 is a number between 0 and 1 and places emphasis on current rewards over future rewards. Values of γ close to 0 indicate that future rewards are increasingly insignificant. When γ is equal to 1, rewards at all times are equally significant, which is equivalent to additive rewards. A discount factor of γ is associated with an interest rate of $(1/\gamma) - 1$. The main issue with infinite-horizon problems is that if there are no terminal states that can be reached in finite time, or if a terminal state is never reached, policies are infinitely long and rewards converge to infinity (Russell & Norvig, 2003).

For the single reduction case, terminal states exist and it is guaranteed that one will be reached in finite time. This is known as a proper policy. Additive rewards ($\gamma = 1$) can typically be used for proper policies without any issues. The research presented in this dissertation assumes a discount factor equal to one, due to the fact that a proper policy exists for the single reduction scenario. When the discount factor is equal to one, the utility calculations are equivalent to additive rewards. This calculation equally weighs all states that make up a sequence.

The final step in a MDP is to determine how to compare between and select policies. The value of a policy for the LPP is the sum of the discounted rewards. In a stochastic problem where transition probabilities exist, the value of a policy would be the *expected* sum of the discounted rewards. An optimal policy π^* satisfies Equation 6.8.

$$\pi^* = \text{argmax}_\pi \sum_{t=0}^{\infty} \gamma^t R(s_t) \tag{6.8}$$

For this dissertation, value iteration is used to find the optimal policy, which is discussed in the next section.

6.3.2.4(c) Value Iteration

The value iteration algorithm, developed by Bellman (1957), can be used for MDPs to calculate the optimal policy or path to the terminal state. The utility of each state is calculated and then the state utilities are used to select an optimal action in each state (Russel & Norvig, 2003). The utility of a state is the additive rewards associated with an optimal policy from that state. Using the maximum expected utility principle, the optimal action is defined as the action that maximizes expected utility, or basic utility for the LPP. The utility at each state for the LPP is:

$$U(s) = \max_a P_t(s'|s,a)\big(R_t(s,a) + U(s')\big) \tag{6.9}$$

The utility of a given state is the discount factor multiplied by the maximum utility associated with all potential future paths. The future path utilities are calculated by first validating that a connection between two states exists, which is determined by using a P_t value of 0 or 1. If a valid connection exists, the utility is calculated by the reward associated with moving from one state to another, plus the utility associated with the second state. Notice that there is no immediate reward associated with being in a given state. This is because of the specialized formulation associated with a deterministic dynamic program and the LPP. The utility of a state is only associated with the path going forward that has the maximum value.

The optimal policy, π^*, can be calculated by taking the argument of the maximization in the utility equation:

$$\pi^*(s) = \text{argmax}_a P_t(s'|s,a)\big(R_t(s,a) + U(s')\big) \tag{6.10}$$

The value iteration algorithm is based on the Bellman equation (Bellman, 1957). For *n* possible states, there are *n* equations that contain *n* unknowns, which are the utilities of each state. Unfortunately, the equations become nonlinear due to the *max* operator. An iterative approach is required because the equations cannot be solved using linear algebra. The utility of each state is updated based on the previous iteration's utility values until each utility value converges. If $U_i(s)$ is the utility at state *s* and the *i*th iteration, the Bellman update, or iteration step, is:

$$U_{i+1}(s) \leftarrow \max_a P_t(s'|s,a)\big(R_t(s,a) + U_i(s')\big) \tag{6.11}$$

It has been proven that this process converges to a fixed point given initial state utility values of zero (Briggs, Detweiler, & Scharstein, 2004). Based on a specified maximum error allowed for the utility of every state, a termination condition can be developed to determine the proper number of iterations (Russel & Norvig, 2003). An example termination condition is provided in Equation 6.12.

$$\|U_{i+1} - U\| < \varepsilon \tag{6.12}$$

The majority of longest and shortest path problems, including the problem presented in this dissertation, can be solved by directly using dynamic programming methods such as the value iteration algorithm while more complicated formulations require the use of approximation algorithms.

6.3.3 Design Space Mapping

Design space mapping is used to determine relationships between function and variable preferences. This is step 5 in the execution strategy. As discussed in the previous section, the MDP requires inputs for the transition probabilities and rewards. For the formulation used in this research, a transfer function and a risk-adjusted reward is used. The reward is based on a DM that is completed for every state in the graph structure for a given MDP problem. This section presents the DM method and how the results can be used within the MDP formulation. A detailed discussion of various developed metrics that directly link the mapping results to the MDP rewards is presented in the next chapter.

As mentioned in Chapter 2, traditional design methods require decisions to be made early that typically have a large impact on the final cost. While being able to handle imprecise information would be valuable at the early stages of design, most methods and tools require precise information. SBD allows the use of imprecise information, including preferences, for design variables of interest. DM enhances preference-based reasoning by identifying the impacts of variables on key functions of interest, such as performance objectives. One of the major assumptions associated with the work presented in this dissertation is that variable JOPs have already been determined, for example, using the fuzzy logic systems developed by Singer (2003) and Gray (2011). DM uses these variable preferences as an input and maps them to a function space. The mapping of designer preferences is best described using the Method of Imprecision, or MoI (Antonsson & Otto, 1995).

MoI first identifies design variables, d_i, and an initial range of valid variable values, X_i, which is a subset of the design variable space (DVS). For each design variable, a designer provides a preference function on X_i, denoted as $\mu_{d_i}(d_i)$. Performance variables, p_j, are identified next including their mapping f_j such that $p_j = f_j(d)$. The mappings can be any type of calculation where the performance variables are a function of the design variables. The range of valid performance variable values, Y_j, for p_j is a subset of the performance variable space (PVS). Figure 6.5 shows the basic steps of a mapping from the DVS to the PVS. In the PVS, MoI also identifies a preference function that represents a functional requirement, which could be considered a customer's preference for performance variable values, p_j (Antonsson & Otto, 1995).

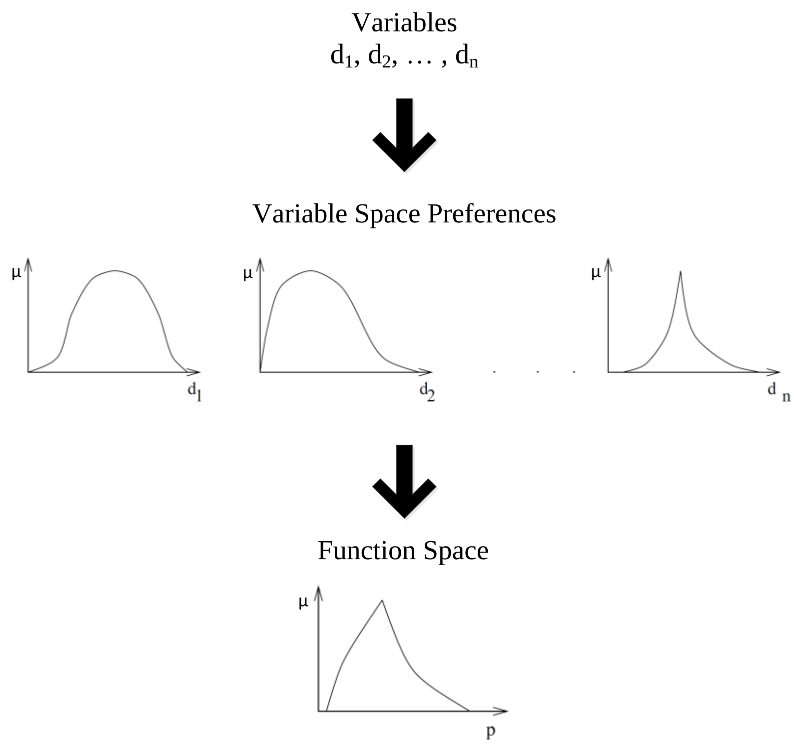


Figure 6.5: Design Space Mapping from DVS to PVS (Adapted from Wood, Otto, & Antonsson, 1992)

Design variable preferences are then mapped from the DVS to the PVS to calculate the preference of a performance variable using Zadeh's extension principle (Zadeh, 1965). The extension principle was initially developed to complete operations of independent fuzzy variables. The extension principle for a discrete-valued function is:

$$\mu(p_j) = \begin{cases} \max\{\min\{\mu(d_1), \ldots, \mu(d_N)\} | d_1, \ldots, d_N : p_j = f_j(d_1, \ldots, d_N)\} \\ 0 \quad if \; \{d_1, \ldots, d_N \; | p_j = f_j(d_1, \ldots, d_N)\} = 0 \end{cases} \tag{6.13}$$

where $d_1, \ldots, d_N$ are variable values, $p_j = f_j(d_1, \ldots, d_N)$ is a function of the variables or objective, and $\mu(d_i)$ is the preference level for the variable value d_i (Wood, Otto, & Antonsson, 1992). The extension principle equation means that the achievable performance preference, $\mu_d(\vec{p})$, from the mapping is the least upper bound of the minimum of all design variable preferences at a specific performance value. For continuous-valued functions, the maximum (max) operation is replaced by the supremum operation (sup).

A simple one-dimensional example can be used to understand the extension principle more clearly, which is shown in Figure 6.6. For the one-dimensional case, the extension principle equation can be reduced to:

$$\mu_d(p) = \max\{\mu_d(d) | d: p = f(d)\} \tag{6.14}$$

For every mapping combination of the design variables, the minimum preference level of the design variable values is associated with that mapped performance variable, which is calculated using the function *f* (a basic curve in this example). The associated preference level, $\mu_d(\boldsymbol{d})$, in the DVS is then mapped to the PVS to determine $\mu_d(\boldsymbol{p})$. If there are multiple mappings for the same function value, the maximum preference level is used. In this one-dimensional example, if the function was horizontal at a particular point, then there would be multiple performance values that are the same for different variable values (and preference levels). In this case, the maximum preference level would be used.

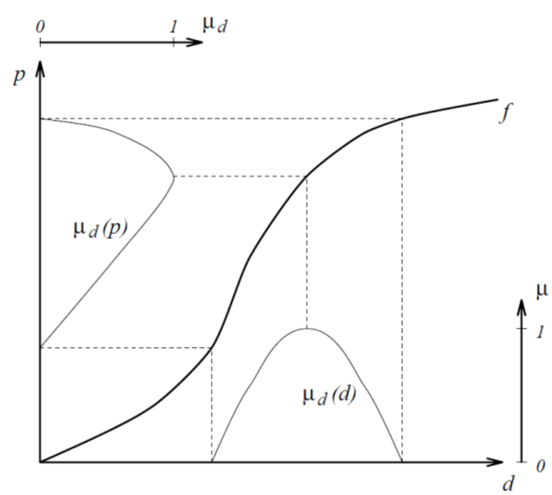


Figure 6.6: Zadeh's Extension Principle (Antonsson & Otto, 1995)

In multi-dimensional problems, the extension principle calculations become more complicated. Every combination of design variable values must be mapped to the PVS and the minimum preference level for the design variables should be recorded. After the minimum operations are completed, the maximum preference level at every performance variable value becomes the final preference level of the mapped preferences. A more detailed example can be used to describe the steps for DM. First, an important note on nomenclature is required. If X is a collection of objects denoted generically by x, then a fuzzy set $\tilde{A}$ in X is a set of ordered pairs defined by:

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) | x \in X\} \quad (6.15)$$

where $\mu_{\tilde{A}}(x)$ is called the membership function of x in $\tilde{A}$. If x and y are real numbers defined by sets $\tilde{A}$ and $\tilde{B}$, respectively, the fuzzy set $\tilde{C}$ representing the real numbers z given by $z = x^2 + y^2$ can be calculated. $\tilde{A}$ and $\tilde{B}$ are defined as the following sets:

$$\tilde{A} = \{(0,0), (1,0.1), (2,0.6), (3,0.8), (4,0.9), (5,0.7), (6,0.1), (7,0)\} \quad (6.16)$$

$$\tilde{B} = \{(0,0), (1,1.0), (2,0.7), (3,0.5), (4,0.2), (5,0.1), (6,0.0), (7,0)\} \quad (6.17)$$

Figure 6.7 shows plots of sets $\tilde{A}$ and $\tilde{B}$. Also, the x and y values can be identified as $x = \{0,1,2,3,4,5,6,7\}$ and $y = \{0,1,2,3,4,5,6,7\}$. Other values of interest include $x^2 = \{0,1,4,9,16,25,36,49\}$ and $y^2 = \{0,1,4,9,16,25,36,49\}$.

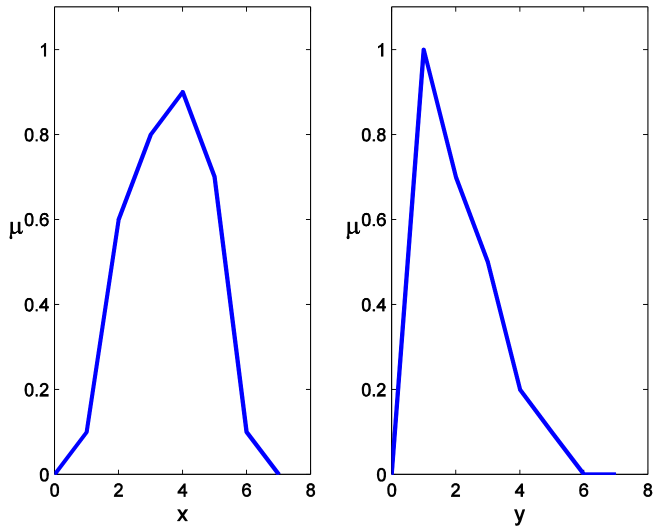


Figure 6.7: Example Plots of Fuzzy Sets

Table 6.6 shows x and y values and their associated membership function values. Referring back to Equation 6.13, the mapping operations can be completed. Initially, the set $\tilde{C}$ can be defined, as seen in Equation 6.18. For notational purposes, the mapped membership function value is above the horizontal line and the mapped function value is below the line (the line does *not* signify a division operation). Also, the plus signs between evaluations do not signify the addition of these values, but the combination of all the mappings for the set $\tilde{C}$. For example, the first mapping is associated with $x = 0$ and $y = 0$. The membership function values for both *x* and *y* are equal to zero, which is why the mapped membership function value is $\min(0{,}0)$. The second mapping is associated with $x = 0$ and $y = 1$. The membership function value for *x* is zero and for *y* is one.

Table 6.6: Values for *x* and *y* and their Associated Membership Function Values

		x,y							
		0	1	2	3	4	5	6	7
μ	$\tilde{A}$	0.0	0.1	0.6	0.8	0.9	0.7	0.1	0.0
	$\tilde{B}$	0.0	1.0	0.7	0.5	0.2	0.1	0.0	0.0

$$\tilde{C} = \left\{\frac{\min(0,0)}{0} + \frac{\min(0,1)}{1} + \frac{\min(0,0.7)}{4} + \frac{\min(0,0.5)}{9} + \cdots + \frac{\min(0,0.1)}{25} + \cdots + \frac{\min(0.9,0.5)}{25} + \cdots\right\} \quad (6.18)$$

It can be seen in Equation 6.18 that sometimes the mapped function value is the same for different variable mapping combinations. For example, the last two mappings in Equation 6.18 have mapped function values equal to 25. These mapped function values are associated with $\{x = 0, y = 5\}$ and $\{x = 4, y = 3\}$.

The next step is performing the minimum operations seen above the line. Equation 6.19 shows the results of taking the minimum of the two variable membership function values corresponding to the variable values mapped. It is evident that there are still the two mappings with function values equal to 25, but the mapped membership function values are different. The final step in the mapping process is performing the maximum operations for the mappings that have the same mapped function values. In this case, the mapping with a mapped membership function value of 0.5 is retained. The resulting fuzzy set $\tilde{C}$ is plotted in Figure 6.8. While the meaning of this plot is insignificant for this example, it does highlight the type of result that the extension principle calculates.

$$\tilde{C} = \left\{\frac{0.0}{0} + \frac{0.0}{1} + \frac{0.0}{4} + \frac{0.0}{9} + \cdots + \frac{0.0}{25} + \cdots + \frac{0.5}{25} + \cdots\right\} \quad (6.19)$$

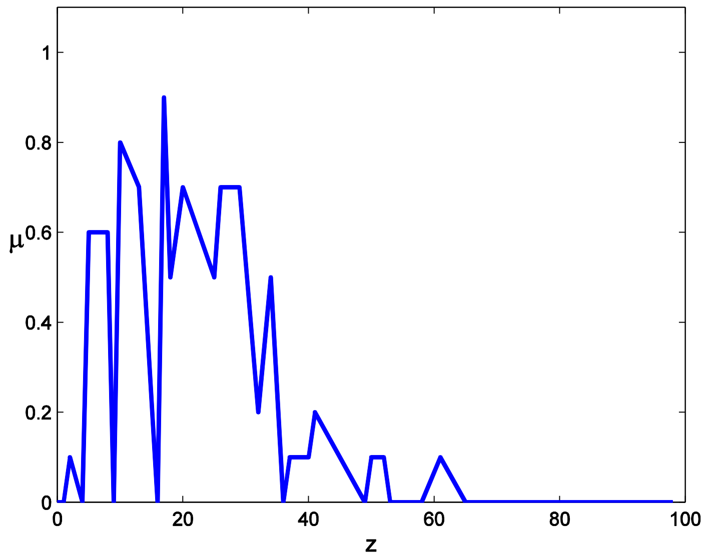


Figure 6.8: Example Plot of Mapped Function

The extension principle can be solved analytically, but requires the solution of a complicated non-linear programming problem. The preferred solution method is using a discrete numerical approach. Within the MoI, computation of the extension principle is done using the Level Interval Algorithm (LIA), also known as the vertex method. The LIA uses interval analysis by discretizing the design variable preference levels into a specified number of α-cuts. Wood, Otto, and Antonsson (1992) describes what the LIA algorithm does as "performing interval analysis for each α-cut and combining the resultant intervals, the output is a discretized fuzzy set, the performance parameter output of input preference functions for the case of a design calculation." There are a series of conditions related to the use of the LIA algorithm including:

- Preference functions must satisfy normality and convexity conditions
- Preference functions must be continuous,
- No singularities of the functions can occur (i.e. no division by zero or zero arguments), and
- Variable preference functions must be monotonic (Wood, Otto, & Antonsson, 1992).

Antonsson and Otto (1997) extended the LIA to handle internal extrema or non-monotonic variable preference functions.

The following LIA algorithm description is presented in Wood, Otto, & Antonsson (1992):

> The algorithm is as follows: for N real imprecise design parameters, $\tilde{d}_1, \ldots, \tilde{d}_N$, let d_i ($i \in [1, N]$) be an element of $\tilde{d}_i$. Given a performance parameter represented by the mapping
>
> $$p = f(d_1, \ldots, d_N) \qquad \forall d_i \in \tilde{d}_i$$
>
> respectively, let $\tilde{P}$ be the fuzzy output of the mapping. The following steps lead to the solution of $\tilde{P}$.
>
> 1. For each $\tilde{d}_i$, discretize the preference function into a number of α values, $\alpha_1, \ldots, \alpha_M$, where M is the number of steps in the discretization.
>
> 2. Determine the intervals for each parameter $\tilde{d}_i, i = 1, \ldots, N$ at each α-cut, $\alpha_j, j = 1, \ldots, M$.
>
> 3. Using one end point from each of the N intervals for each α_j, combine the end points into an *N-ary* array such that 2^N distinct permutations exist for the array.
>
> 4. For each of the 2^N permutations, determine $p_k = f(d_1, \ldots, d_N), k = 1, \ldots, 2^N$. The resultant interval for the α-cut, α_j, is then given by
>
> $$P^{\alpha_j} = [\min(p_k), \max(p_k)].$$

By implementing the LIA algorithm for a particular mapping, an achievable preference function in the PVS is found. This can be compared to the designer-inputted performance requirement to identify overlap. Figure 6.9 shows an example of the achievable preference function, $\mu_d(p)$, and the performance requirement, $\mu_p(p)$. Both functions are in the performance space. From these two functions, an overall preference function, $\mu_o(p)$, can be calculated by combining both preferences using either a compensating ($\mu_o = \sqrt{\mu_d \mu_p}$) or non-compensating ($\mu_o = \min[\mu_d, \mu_p]$) trade-off strategy. For this research, a non-compensating strategy, which maximizes satisfaction with the least satisfactory aspect of the design, is selected because it is a more conservative strategy (Law & Antonsson, 1994). After calculating the overall preference, the maximum preference level ($\mu_o^* = \max[\mu_o(\vec{p})]$) and α-cuts for the overall preference in the performance space ($P^o_{\mu_o^*}$) can be found to aid in the mapping back to the DVS.

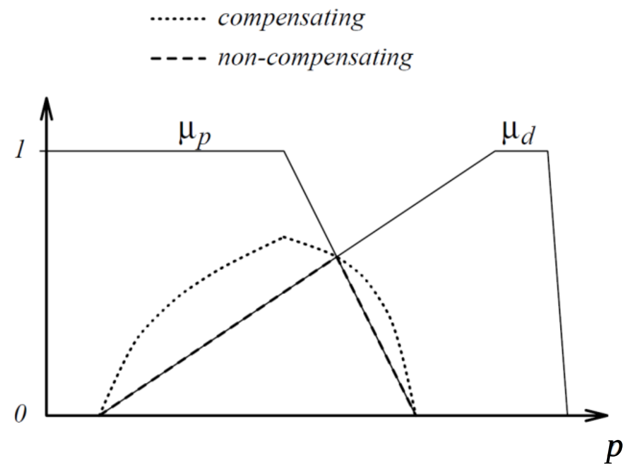


Figure 6.9: μ_o for compensating and non-compensating trade-offs (Antonsson & Otto, 1995)

After mapping design variable preferences to the PVS and calculating the overall preference, the overall preference can be mapped back to the DVS to identify what design variable values are in the overlapping region. An inverse mapping can be used to backward calculate α-cuts, if the inverse of the mapping function can be found. If the inverse mapping cannot be found, a revised extension execution can be used that does not require the function inverse by aggregating the overall preference in the DVS. In the current method, computations are carried out in both the DVS and PVS, and finally the overall performance preference is generated before the design variable overall preference, which is why the function inverse is required. In the revised method, the final aggregation for the overall preference is in the DVS. The revised method can be understood as applying the two-step current method at a finite number of design points, where the function inverse is well defined. The usage of the function inverse is avoided by transferring the information of the functional requirements in the PVS to the DVS by using the equivalent inverse of the function at individual points in the PVS (Wang, 2003).

The complete DM method is best explained through a simple example. Using the length-to-beam ratio example, the design space mapping method can be used to map preferences for the length and beam variables to the function space. Using the overlap between the combined preference and another introduced function space preference, the overall preference can be determined and mapped back to the variable space. First, nominal variable preference functions are generated for length and beam. These can be seen in Figure 6.10. The set-range values for the variables were selected based on reasonable length-to-beam values and naval architecture experience.

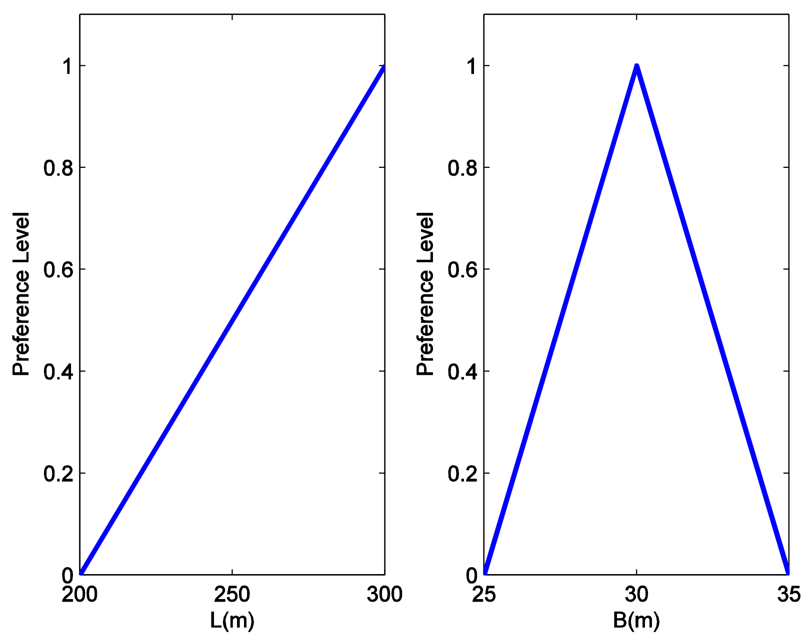


Figure 6.10: Variable Preference Functions for Length and Beam (Variable Space)

Using the LIA algorithm described earlier, the variable preference functions can be mapped to the function space to form a single combined preference function. The combined preference function can be seen in Figure 6.11 as the blue solid line. A function preference, which is inputted by the user, is the red dashed line. If this function preference were a requirement, it would be interpreted as preferring a length-to-beam value of six, but allowing it to be between five and 7.5. The green shaded area is the overall preference area and that can be identified as the overlapping region between the combined preference and the function preference. This area, once identified, can be mapped back to the variable space, identifying which variable set-range values are preferred.

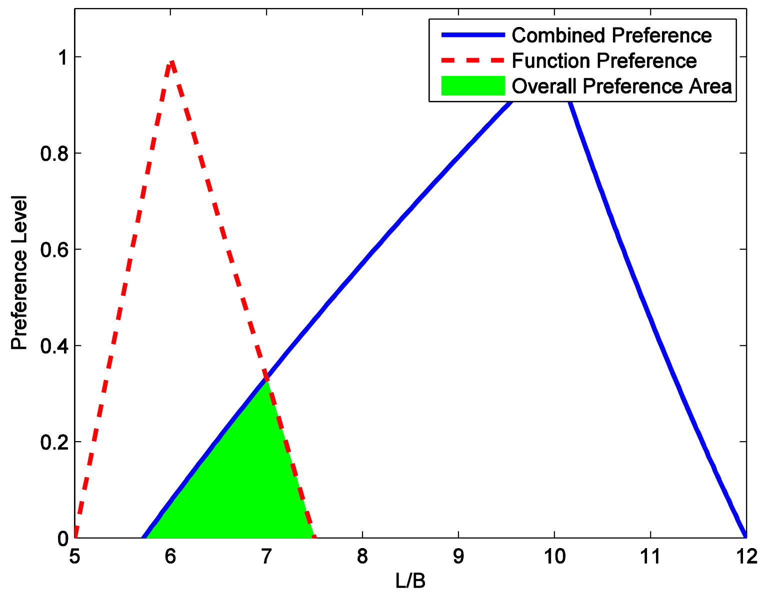


Figure 6.11: Combined Preference and Inputted Function Preference (Function Space)

The mapping back to the variable space utilizes the inverses of the original function from each variable's perspective. The same forward mapping calculation presented above can be completed using the inverse functions to map the overall preference to the variable space. For the length-to-beam problem, the inverses would be $B = L/R$ and $L = RB$. More importantly for the SBD approach, areas with little or no preference can also be identified. Figure 6.12 shows the variable preferences and the mapped overall preference function. It can be seen that general trends show preferences for lower length values and higher beam values.

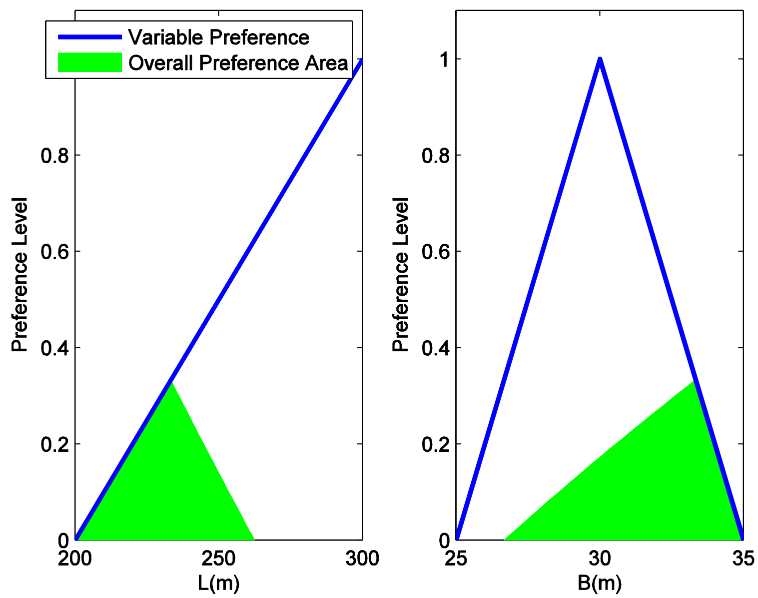


Figure 6.12: Variable Preferences and Mapped Overall Preference (Variable Space)

While DM provides an effective way to understand relationships between variable and function preferences, the method needs to be extended in order to be used as inputs in the MDP framework. To the knowledge of the author, there are currently no metrics that utilize DM information to aid designers in set reduction decisions. As the utilization of this information directly impacts the MDP results, selecting proper ways to use the mapping information is critical.

6.3.4 Reward Calculation

This section focuses on calculation of the rewards, based on mapping information, used as inputs into the SBD MDP framework. The goal is to determine the impact of reducing certain areas of the design space. This is step 4 in the execution strategy. A series of risk and reward reduction metrics are developed using the DM areas. Current SBD reduction methods are mainly heuristic and do not consider potential future outcomes. Focusing solely on current information can lead set reduction unintentionally in a direction with a high potential for failure (McKenny, Gray, Madrid, & Singer, 2012). By developing reduction metrics using DM information, additional information can be provided to the designer to make better set reduction decisions.

Before these metrics can be developed, it is important to identify the type of information designers desire when making set reduction decisions. While determining what a designer wants can become ambiguous, the discussion here is simplified in an effort to develop meaningful metrics. Every person, every day, makes decisions; and while each person does not always consciously analyze all of the potential options, the final decision is not developed arbitrarily. One way of analyzing decisions is using a basic risk versus reward evaluation. A person must be able to weigh the potential reward against the risk associated with the decision of pursuing that reward. In most scenarios, higher risk is associated with a larger reward, but also a lower likelihood of obtaining that larger reward. A good example of this risk versus reward scenario is thought process and calculations that go into deciding whether to invest in a stock. While risk can be high, the potential return is almost always higher than in lower risk options. People will make different decisions using the same risk and reward information available based of their personal beliefs and goals (whether they are risk adverse or reward seeking). Even though the decisions people make may be different, the underlying information used to make to those decisions should adequately express the nature of the risk versus reward evaluation process.

For a designer, risk and reward can be thought of in different ways. A fundamental conflict that arises during SBD reduction efforts is the desire to reduce the solution space while remaining in an unconstrained area of the design space, where many potential solutions exist. As mentioned in Chapter 2, selecting the "best" region, and eliminating the worst are not directly comparable. By selecting the "best" region, an assumption of where the boundary of that region is required. That assumption would most likely be based on infeasibility and/or dominance. Therefore, understanding the infeasible and dominant regions is still required. By solely focusing on these regions using elimination, there is no need for the identification of the best. For SBD, there are various forms of elimination criteria that can be used to reduce set-range values. During experiments conducted by Singer (2003) and Gray (2011), their elimination criterion was loosely based on a clipping method using the joint output preference (JOP) curves. For example, the regions where preference levels fell below a certain threshold, such as 0.2, were eliminated. With the addition of the design space mapping method and its associated design information, new elimination criteria have been developed to improve the inherent limitations with the methods developed by Singer (2003) and Gray (2011).

The first step in developing reduction metrics involves partitioning the design space into regions. As discussed in the previous chapter when introducing the set reduction graph structure, partitions are used to understand characteristics about specific areas of the design variable space.

Figure 6.13 is similar to a figure presented in the previous chapter when introducing the design space mapping method, however in this case each variable set-range is partitioned into two distinct regions. The number of partitions can vary depending on the specific problem and they do not have to be the same for every variable. The partitioned regions allow a designer to understand the impact of eliminating certain regions.

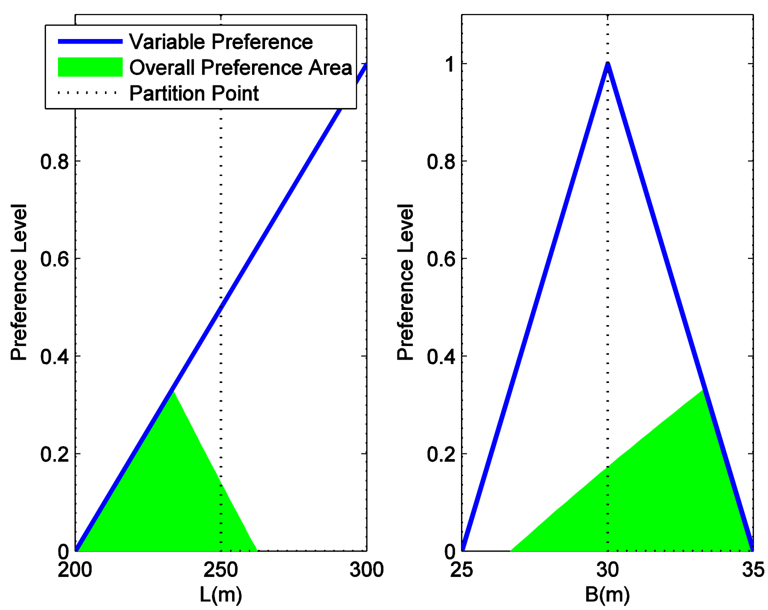


Figure 6.13: Mapped Variable Space with Partition Points

The remainder of this section introduces multiple types of risk and reward metrics. These metrics utilize not only DM information, but the inputted variable and function preferences associated with the problem of interest. The metrics are presented for the scenario in which a specific partitioned region is potentially being reduced. This analysis is conducted for every combination of potential reductions to calculate a metric value for each individual scenario. Each metric is described using the length-to-beam example problem introduced in the previous chapter and a potentially eliminated region of $L = [250,300]$. This translates to calculating the risk and reward associated with eliminating length variable values between 250 and 300. After the metrics are introduced, Section 7.2 discusses the evaluation and comparison of these metrics using the MDP framework.

6.3.4.1 Reward Metrics

Out of the two types of metrics, reward metrics describe the value associated with reducing a certain area of the design space. Two reward metrics were developed to investigate different approaches to the set reduction problem. The first reward metric, defined as satisfaction reward, utilizes the overall preference area in the variable space as a reward. In this case, the reward described the degree to which variable preferences are meeting the required function preference in the variable space. The second reward metric, defined as reduction reward, utilizes the difference in area between the variable preference and the overall preference in the potentially reduced region. This type of reward emphasizes reducing areas with large differences between obtainable values, and values that overlap with the function preference.

The satisfaction reward is calculated by determining the area of the overall preference mapped back to the variable space within the partitioned regions which remain after a potential reduction occurs. The ratio between the mapped area and the area produced by the variable preference in that same region can then be defined as the satisfaction reward. The satisfaction reward (*SR*) calculation is provided as Equation 6.20. For a total of *N* variables, the overall preference area in the variable space (P_{OV}) and the variable preference area (P_V) can be used to calculate the proper ratio. The subscripts *T* and *R* correspond to the total area and the reduced region area, respectively.

$$SR = \sum_{n=1}^{N} \left(\frac{P_{OV_T} - P_{OV_R}}{P_{V_T} - P_{V_R}} \right)_n \tag{6.20}$$

As the ratio increases, the overall preferred region in the remaining set-range increases. The calculated ratios for each variable are then summed together to form a single reward value. The maximum value of the final ratio is equal to the number of variables. Figure 6.14 shows the regions used to calculate the satisfaction reward and the calculation for the length-to-beam problem.

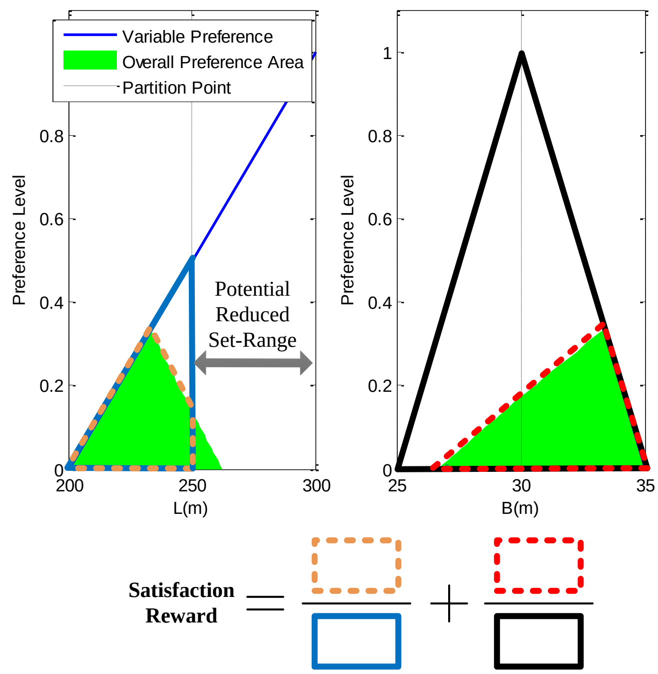


Figure 6.14: Example Satisfaction Reward Calculation

The reduction reward, unlike the satisfaction reward, only deals with areas from the region that is eliminated when a decision is made. The unpreferred area for the eliminated region, which is the variable preference area minus the overall mapped area in that region, is used. The ratio of the unpreferred area to the variable preference area for the eliminated region is then calculated. The reduction reward (*RR*) calculation is provided as Equation 6.21. The same areas and notations described for the *SR* calculation can be used for the *RR* calculation.

$$RR = \sum_{n=1}^{N} \left(\frac{P_{V_R} - P_{OV_R}}{P_{V_R}} \right)_n \tag{6.21}$$

Figure 6.15 shows the regions used to calculate the *RR*, as well as the calculation for the length-to-beam problem. It can be seen there is only one ratio used. This is because there is only a reduction in one variable at a time using the single reduction scenario, as described in the previous chapter.

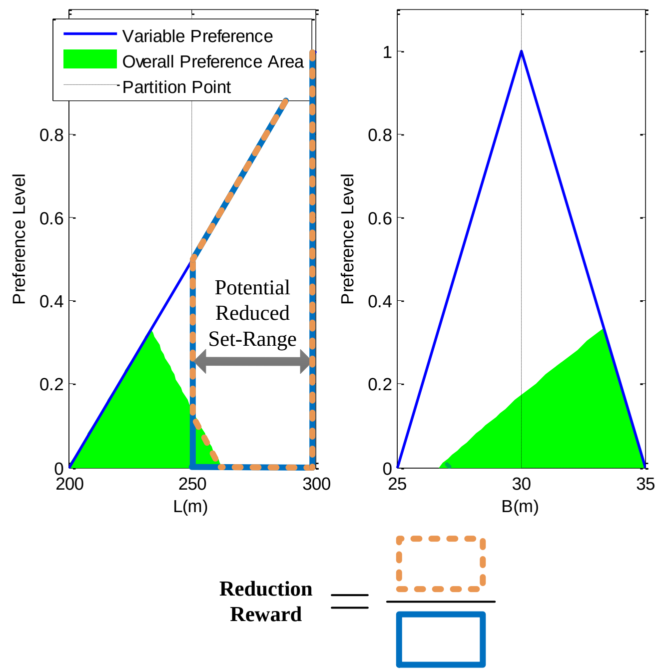


Figure 6.15: Example Reduction Reward Calculation

Both reward metrics are ratios of areas associated with either variable preferences, or the overall mapped preference, in the variable space. Beyond this fact, the calculations and the areas used are different and can produce different results if used when making set reduction decisions. While the satisfaction reward emphasizes variable values with large overall preference, and the reduction reward emphasizes the difference between obtainable and overlapping areas, both on their own are not adequate to describe all reduction considerations. For this reason, additional metrics are needed.

6.3.4.2 Risk Metrics

In an effort to describe the risk associated with not having a feasible solution, two risk metrics were developed. The first risk metric, defined as variable risk, utilizes ratios of the initial variable preferences to describe the probability of a solution existing. The second risk metric, defined as function risk, is based on the ratio of the overlapping area to the function preference area in the function space, which describes the likelihood of meeting the desired function values.

Variable risk (*VR*) describes the probability of a solution existing. *VR* places emphasis on attempting to remain in an unconstrained area of the design space. The metric is also used as a measure of how constrained an area of the design space is. The variable preferences are a combined description of what the different functional design groups feel is both possible and preferred based on the analysis that is conducted. However, it is important to note that the term "preferred" can mean different things depending on the scenario. For a traditional design emphasizing preferred regions, the variable preference can describe where the optimal solutions exist. For the SBD approach that emphasizes eliminating infeasible or dominated solutions, the variable preferences can describe the regions that have infeasible or dominated solutions.

VR is calculated by taking the ratio of the variable preference area of the remaining region after the reduction to the overall variable preference area. The ratios for each variable are then multiplied together to determine the overall risk value. This value will, therefore, always be between zero and one for each potential decision that is analyzed. *VR* can be calculated using Equation 6.22. Again, the same areas and notations described for the previous two metrics can be used for the *VR* calculation.

$$VR = \prod_{n=1}^{N} \left(\frac{P_{V_T} - P_{V_R}}{P_{V_T}} \right)_n \tag{6.22}$$

This metric multiplies the risk value for each variable together, as they can be considered independent events with probabilities between zero and one. Figure 6.16 shows the regions used to calculate variable risk and its calculation for the length-to-beam problem. Notice that *VR* does not depend on the mapped overall preference area. This is due to the fact that the probability of a preferred solution existing is not necessarily dependent on overlap between the combined preference and function preference, which determines the overall preference.

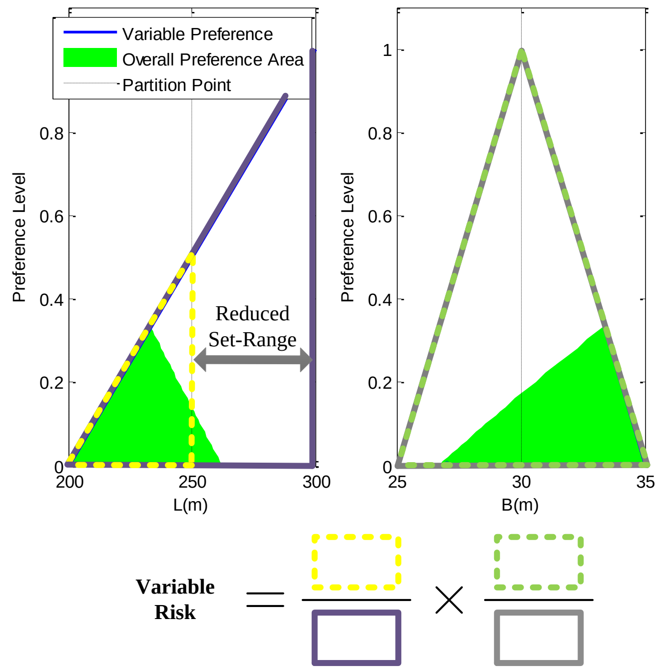


Figure 6.16: Example Variable Risk Calculation

On the other hand, function risk emphasizes maintaining a large overall area in the function space. Maintaining a large overlap with function preference values allow for adaptability to change during the design process. The function risk calculation describes the likelihood of overlap between the combined and function preference in the function space. This is calculated by dividing the function preference area by the overall preference area for the future state that a reduction will result in. This ratio, which will always be between zero and one, describes the probability of meeting the function preference based on a given reduction. The function risk (*FR*) calculation requires additional areas to be defined. The overall preference area in the function space (P_{OF}) and the function preference area (P_F) are required to calculate the ratio. The *FR* is calculated using Equation 6.23.

$$FR = \frac{P_{OF}}{P_F} \tag{6.23}$$

Figure 6.17 shows the regions used to calculate the function risk and its calculation for the length-to-beam problem. The value will fall between zero and one, and can be represented as a probability.

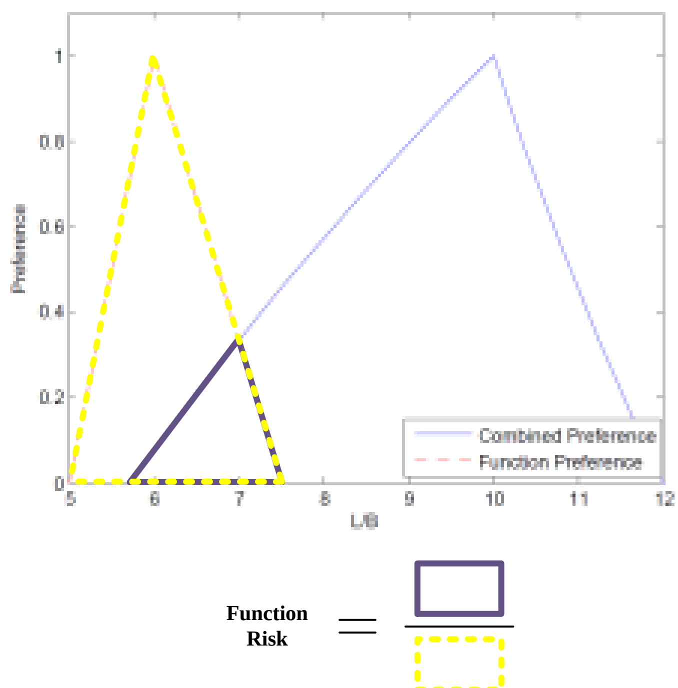


Figure 6.17: Example Function Risk Calculation

While both the risk and reward metrics can individually describe an aspect of a potential set reduction, the best combination of the individual risk and reward metrics need be evaluated to properly capture the tradeoffs inherent in a set reduction effort.

6.3.5 Sensitivity and Simulation

Before the framework results can be calculated, the types of preference changes to evaluate must be determined, defined as the simulation variation strategy, or step 2 in the execution strategy. The simulation variation strategy is first presented. The simulation output used to identify robust decision paths, step 5 in the execution strategy, is then discussed.

When using MDPs to solve sequential decision making problems, the parameters such as the rewards and probabilities are typically held constant. However, due to uncertain forecasts and environments, these values can vary from the estimates used as inputs. The third limitation of the basic LPP is that future edge weights and probabilities are unknown, especially for the reduction problem. Future edge weights and probabilities can be estimated based on current preferences, but these estimates do not account for the changing of dynamics associated with design relationships or potential requirement changes.

Niese (2012) identifies the important distinction between sensitivity and accounting for imprecise parameters. Imprecision replaces the constant parameter with a closed interval and determines the optimal policies (one to infinite) associated with the parameter intervals. There have been many proposed approaches to solving the imprecision problem, including using max-min techniques, perturbed dynamic programming, and robust dynamic programming (White & El-Deib, 1986; Hopp, 1988; Wallace, 2000; Tan & Hartman, 2011). Sensitivity uses the same constant parameters, but determines parameter bounds where the original optimal policy remains optimal (judge of solution stability). Tan and Hartman (2011) recommend using the Bellman equations instead of solving the problem for different parameter values to save computation time. Niese (2012) describes the overall approach where rewards are expressed as affine functions of uncertain parameters, which is similar to shadow price calculations in linear programming.

For the set reduction problem, emphasis should be placed on the link between changing preferences and the impact of changing rewards on the optimal reduction path. This would lend itself to the use of imprecision to identify the optimal policies associated with a range of changing preference structures. The issue with using the approaches discussed in the previous paragraph is that there is no way to determine preference structures from a change in the risk-adjusted rewards, which is associated with areas under the preference curves. Therefore, advanced and timesaving approaches are not possible based on the current formulation. The basic fundamentals of sensitivity analysis, however, can still be utilized to identify the impact of changing preferences. The sequential decision making problem can be solved multiple times for different reward parameter values associated with an actual and known change in preference structures. These evaluations are completed using a series of simulations.

The goal of conducting simulations is to better understand the impacts of potential preference structures, both changing requirements and variable preferences throughout the reduction process. For a given simulation, a progressive preference structure for the variable preferences is assumed and the optimal policy is calculated. The initial preferences for every simulation are the same and are defined as the variable JOPs associated with the current round of negotiations. The future state preferences are based on the particular simulation's assumed preference structure, which varies by simulation. The assumed preference structure is what varies between simulations.

While any valid DM shape can be used as the assumed preference structure, a simple triangular shape is used for this work. The triangular preference shape is defined by three points: left-lower (ll), upper (u), and right-lower (rl). Each is associated with specific variable values. The preference levels of ll and rl are equal to zero and the preference level of u is equal to one. The governing constraint regarding the variable values associated with these points is provided in Equation 6.24, where lb and ub are the lower and upper bounds of the variable set-range, respectively. This constraint ensures that a valid preference curve is generated that can be inputted into the DM method. Figure 6.18 shows an example preference structure with defining points and bounds.

$$lb \leq ll \leq u \leq rl \leq ub \tag{6.24}$$

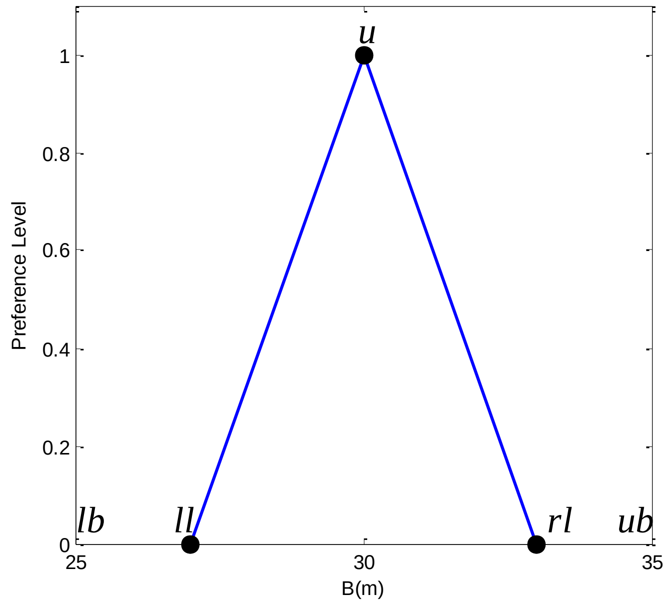


Figure 6.18: Preference Structure Defining Points

An additional input that identifies the number of preference structure combinations is required to complete the sensitivity analysis. This input, defined as the preference structure variation value, is the number of evaluations along the set-range for each defining point. This number must be greater than one. For example, if the variation value is equal to two, each defining point (*ll*, *u*, and *rl*) would have evaluation points at the lower and upper bound. All combinations of the evaluation points, subject to the constraint provided in Equation 6.24, are used as inputs into the simulations. When the variation value is equal to two, as seen in Figure 6.19, there are a total of three valid combinations. The valid combinations for each variable are determined, and then the total combinations of all the variable preference structures are calculated, which is equal to the total number of simulations conducted. For example, if there are two variables with three valid combinations each, a total of nine (3^2) simulations would be completed.

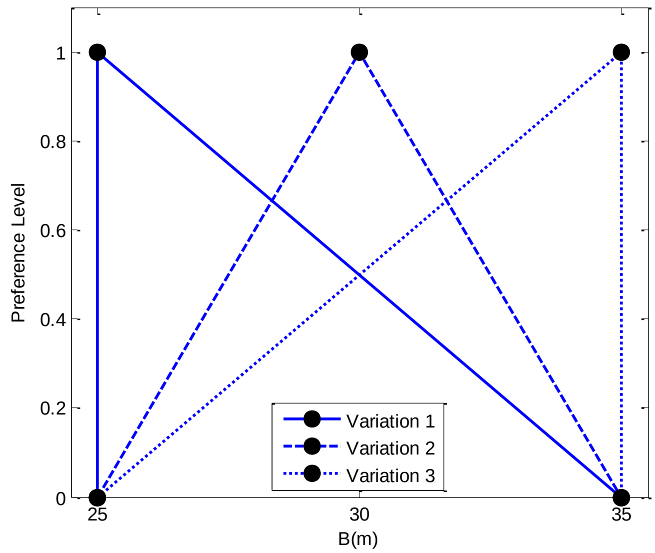


Figure 6.19: Preference Structure Variations for Variation Value Equal to Two

The preferences associated with the states after the initial state in the reduction graph are clipped versions of the assumed preferences for a given simulation. A demonstration of the clipping method is provided in Figure 6.20. The assumed preference is on the left. With two partitions, the clipped preference for the state associated with a reduction in length from 250 to 300 is shown on the right. Using this method, the preferences for all the states for a given simulation, except the initial state, are based on the same assumed preference structure. The progressive preference structure for a simulation is the compilation of the initial and clipped preferences.

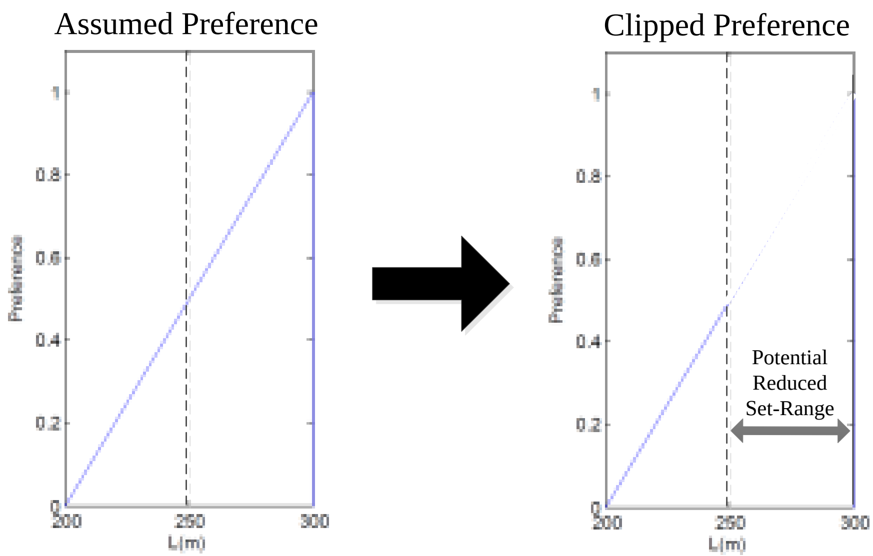


Figure 6.20: Preference Clipping Method Demonstration

For each progressive preference structure, the MDP is solved and an optimal policy and reward is calculated. By varying the progressive preference structures, optimal policies under varying conditions can be identified, including the most robust policy to change.

The outputs of the simulations include the optimal path length (or total reward) and the optimal reduction path for every preference structure combination. While the total reward accurately represents the reward level relative to other optimal paths, the value does not have any physical meaning, such as distance traveled or net present value seen in other MDP formulations. This is addressed further in the next section. An example optimal path result from a simulation is provided in Table 6.7. It can be seen for all preference structure combinations, there are only two optimal paths that result. Four simulations result in an optimal path 1-4-6-10, while five results in an optimal path 1-3-6-10. The 1-4-6-10 path is associated with a reduction in beam values between 25 and 30 first, then a reduction in length values between 250 and 300. The 1-3-6-10 path is associated with a reduction in length values between 250 and 300 first, then beam values between 25 and 30. For a single reduction scenario, the difference is which variable should be reduced first.

Table 6.7: Simulation Optimal Path Results

	Epoch			
Simulation #	**1**	**2**	**3**	**4**
1	1	4	6	10
2	1	4	6	10
3	1	4	6	10
4	1	4	6	10
5	1	3	6	10
6	1	3	6	10
7	1	3	6	10
8	1	3	6	10
9	1	3	6	10

While the results of the simulations provide some insight, larger simulation results would be too difficult to comprehend in table format, such as in Table 6.7. The key is to provide the decision maker with simple and understandable representations of the results and additional traceable information as a decision support tool. This effort is outlined in the next section.

6.4 Representation

The goal of generating representation information is to provide the chief engineer with useful information to make better informed decisions. This is step 6 in the execution strategy. The combination of DM, the LPP MDP formulation, and simulation provide information on optimal reduction paths, rewards through time, and the overall mapped preferences in the function and variable space. Being able to communicate this large amount of information to a chief engineer making set reduction decisions can be challenging. This section offers unique representations of the information provided by the framework outlined in the previous sections. The length-to-beam example problem is used to illustrate these representations. It is important to note that these are for purely illustrative purposes only. The results are not associated with a specific design effort.

6.4.1 Optimal Strategy

The first two identified research problems included time-dependent design relationships and determining the impact of reducing certain areas of the design space. This section focuses on how an optimal strategy can be determined before initial preferences are provided. This would allow the chief engineer to have a better understanding of the relationships between variables and potential reductions that can be made. Leveraging the simulation structure, the initial preference structures can be replaced with the assumed preferences associated with each simulation. The future state preferences are determined based on the clipping method introduced in the previous section. Utilizing the assumed triangular preference shape, the peak variable preference values can be linked to the optimal policy associated with that preference structure. Table 6.8 shows the optimal strategies for various combinations of variable peak preference values for the length-to-beam example problem. The problem consists of the single reduction scenario with two variable partitions. The optimal strategy in Table 6.8 is for the decisions associated with being in epoch 1, or the initial state. The numbers in the table are associated with the next state, or combination of set-ranges, that are optimal for the given epoch. These state numbers also correspond to the graph structure provided in Figure 6.3.

Table 6.8: Optimal Strategy Given Peak Preferences (Epoch 1)

		Peak Beam Preference (m)				
		25	**27.5**	**30**	**32.5**	**35**
Peak Length Preference (m)	**200**	4	4	4	3	3
	225	4	4	4	3	3
	250	4	4	3	3	3
	275	4	4	3	3	3
	300	4	4	3	3	3

The first important element of Table 6.8 is that the optimal policy for a combination of variable peak preference values can be determined. This provides the decision-maker with a better understanding of the relationships between variables and also the function of interest, because the optimal strategy is based on the rewards associated with the overall preference in the function space. A similar table can be generated for each epoch of the sequential decision making problem. For example, the optimal strategy in Epoch 2 for the same problem is provided in Table 6.9. Regardless of the peak preference values for either variable, the optimal strategy is shown to always reduce to state 6.

Table 6.9: Optimal Strategy Given Peak Preferences (Epoch 2)

		Peak Beam Preference (m)				
		25	**27.5**	**30**	**32.5**	**35**
Peak Length Preference (m)	**200**	6	6	6	6	6
	225	6	6	6	6	6
	250	6	6	6	6	6
	275	6	6	6	6	6
	300	6	6	6	6	6

The second important element that can be seen in Table 6.8 is the identification of the boundaries where the optimal strategy shifts to a different action. The two actions seen in Table 6.8 include moving to state 4 (eliminating beam values 25-30) and moving to state 3 (eliminating length values 250-300). A clear line is seen for this example, but does not always have to be true. This is helpful for a decision-maker for a number of reasons. The major takeaway is a better understanding of how the optimal strategy changes if peak preferences are different than expected or change as the design progresses. For example, if the designer believed that the peak beam value will remain around 25m but the length value is relatively uncertain, this graph can indicate that that scenario is not of major concern for the decision-maker. Regardless of the peak length value for a beam of 25m, the optimal strategy remains the same, moving to state 4. If an opposing scenario was true, however, and the peak length value stayed constant around 300m and the beam peak value was uncertain, there would be two optimal strategies to contend with.

It is a major advantage to know whether a decision a designer needs to make is affected by changing conditions. Instead of spending time and effort attempting to reduce the uncertainty associated with a variable value, this can be ignored if the outcome does not matter. The optimal strategy shown in Table 6.9 would be even more ideal for a decision-maker. This would be associated with selecting a robust reduction decision. For any combination of variable peak preference values, the optimal policy will be the same, which for this example is a reduction to length values 200-250m and beam values of 30-35m. The optimal strategy tables can provide substantial insight to designers before a design effort even begins, and should be the starting point in understanding how changing design relationships affect the decisions that need to be made. In an effort to analyze preference structures beyond single-peak shapes, such as bi-modal preferences, additional work should be completed to develop a generic metric for various types of shapes.

6.4.2 Robust Decision Paths

Identifying robust decision paths is the third research problem introduced at the beginning of this chapter. Using the MDP formulation of the LPP, potential future decisions can be incorporated into the analysis at early stages. Also, in an effort to avoid entering infeasible regions of the design space in the future, following a more robust decision path can be more beneficial than following what is considered "optimal" based only on current information. The optimal policies for all the simulations can be aggregated to identify which path(s) are optimal more than others. For example, the length-to-beam problem with four variable partitions has six unique optimal paths that occur for all of the simulations; however, only one is optimal in most. Table 6.10 provides the optimal paths identified from the simulations and the percentage of the simulations that each path was optimal, shown in descending order. To generate this table, the unique optimal paths for every simulation are first calculated. The number of unique paths that multiple simulations have in common is then calculated and converted into a percentage. For example, the first unique optimal path seen in the first row was optimal for 40% of the simulations. The reduction graph structure associated with the four partition length-to-beam problem is provided in Figure 6.21.

Table 6.10: Optimal Paths with Percentage Optimal

Optimal Paths	Epoch 1	2	3	4	5	6	7	8	Percentage Optimal
1	1	4	6	10	20	30	70	101	0.40
2	1	11	21	24	26	30	80	101	0.32
3	1	4	6	10	20	30	80	101	0.12
4	1	11	21	61	62	65	69	101	0.08
5	1	4	6	16	26	66	69	101	0.04
6	1	11	21	61	64	66	69	101	0.04

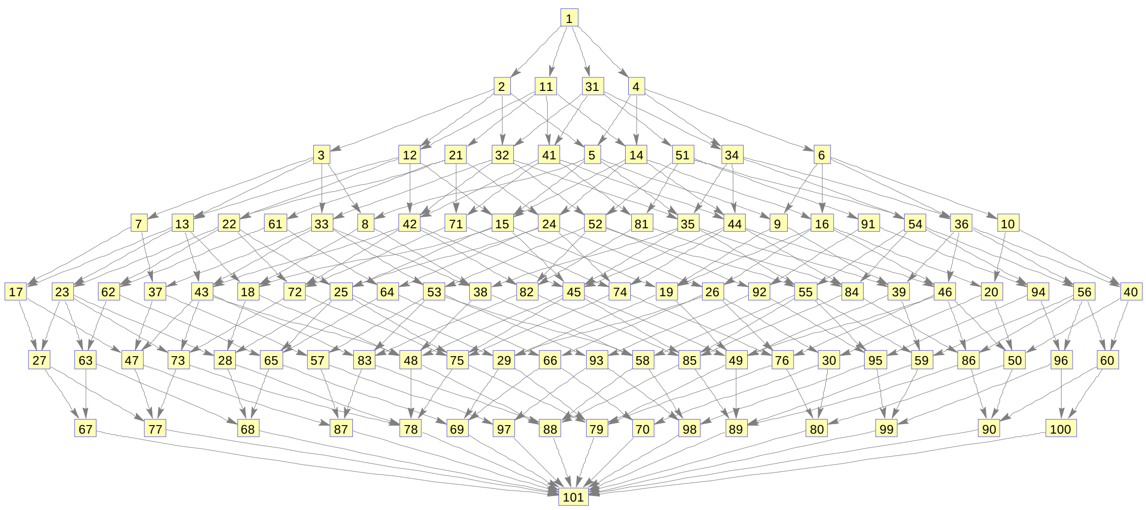


Figure 6.21: Four Partition Graph Structure for Length-to-Beam Problem

The percentage optimal is defined as the robustness metric for the given simulation scenario. The most robust path can be identified in Table 6.10 as the first path (highlighted) with a percentage optimal of 0.4, or 40%. It is important to note that the second optimal path has a high percentage as well at 32%. To gain a better understanding of the proportionality between optimal decisions in each time step, a stacked bar graph can be generated, known as a decision path output. Figure 6.22 shows the associated decision path output for the problem described above. The *x*-axis is the epoch or time step (defined as a round in this SBD research) and the *y*-axis is the percentage that the action resulting in the shown state is optimal. Epoch 1 is the starting state, which is defined a priori, and epoch 8 is the artificial terminal state, at which all paths should end.

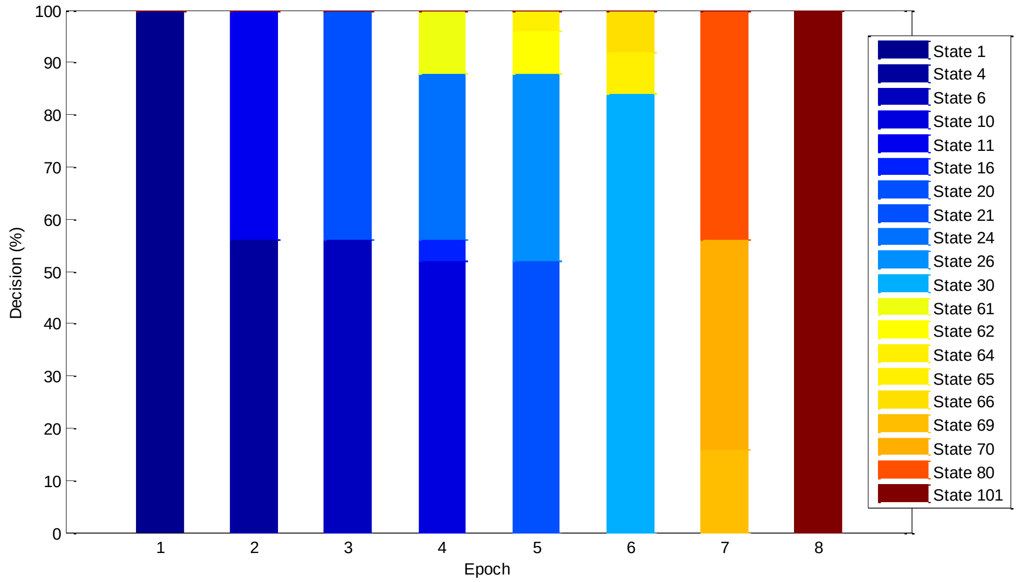


Figure 6.22: Decision Path Output

The one important element that is lacking in the decision path outputs is how the optimal action in each epoch is related to other epochs. To better understand the relationships between epochs, the top two optimal policies provided in Table 6.10 can be mapped over the decision path output in three dimensions. When visualizing the decision path in three dimensions, the stacked bar graph, seen in Figure 6.23, is taken and each stack is plotted individually. The colors of the stacks are linked to the state colors in Figure 6.22, but in three dimensions are not required to make an interpretation. The black solid lines show the top two policies. Notice that both policies include state 30 in epoch 6. This can provide the decision-maker with a better understanding of decision paths, while considering the optimal decision to make in a given epoch, or time step.

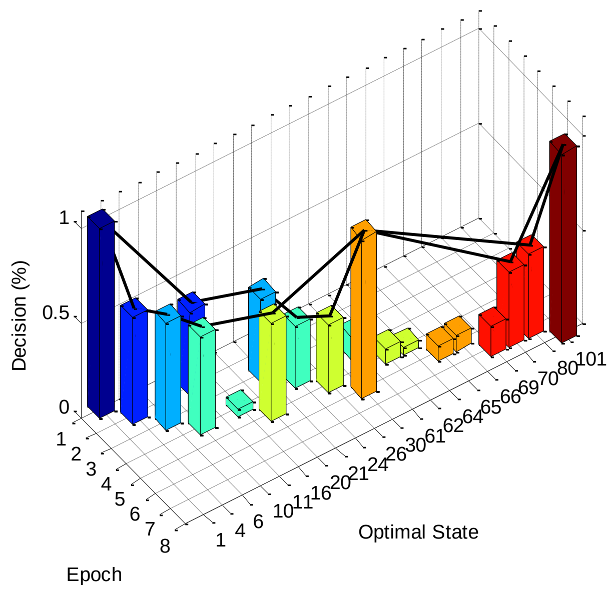


Figure 6.23: Three-Dimensional Decision Path Output with Optimal Policies

Identifying robust decision paths and the optimal decision for a given epoch, as well as connecting both together is the main goal of conducting simulations. The designer now can incorporate information about potential futures into present decisions. While no one can predict with certainty what will happen in the future, including changing design relationships or requirements, making a robust decision reduces the likelihood of failing. The decision path output with optimal policies can provide the information necessary for a designer to identify robust decision paths.

6.4.3 Alternative Paths

While the decision path output with optimal policies can be helpful, it can also be difficult to follow if there are many optimal policies or optimal states for a given epoch. A designer must always be cognizant of when a current path or decision fails. One way to determine this is by tracking the connections between a given policy and the number of alternative optimal states it can reduce to over time. The more optimal states a given policy can connect to, the greater chance of reducing without a failure. This adds a layer of flexibility to the decision making process by quantitatively evaluating the ability to change directions if need be.

Table 6.11 provides the number of optimal path connections for every optimal policy in descending order based on the number of optimal path connections. A connection is defined as an arc between states part of a particular path and other optimal states. This number does not include the connections associated with the given path. The path with the highest number of connections does not have the highest optimal percentage (highlighted in table). Also, it can be seen that the optimal path with the highest percentage optimal has one of the lowest number of connections. This could potentially identify an issue if the path becomes infeasible at some point in the reduction process.

Table 6.11: Optimal Path Connections for Optimal Policies

Optimal Path #	Percentage Optimal	Optimal Path Connections
2	0.32	5
5	0.04	5
6	0.04	5
1	0.40	3
3	0.12	3
4	0.08	3

A visual representation of all connections between optimal states, including feasible connections not seen in the optimal policies, is provided in Figure 6.24. The thin gray arrows identify connections associated with the optimal policies. The thick red arrows identify additional feasible connections not seen in any optimal policy. By identifying these additional connections, previously unknown connections can now be exploited if any optimal paths become infeasible.

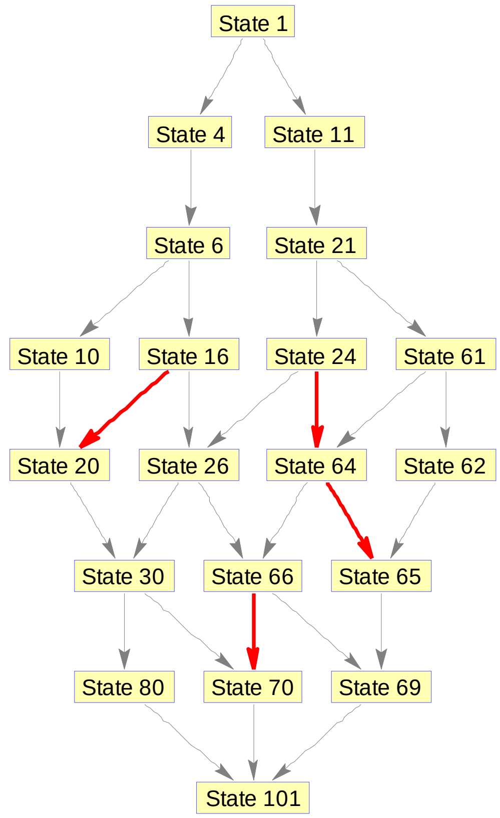


Figure 6.24: Optimal Policy Connections

The ability to identify alternative paths if the current path becomes infeasible is essential for successful reduction. The optimal policy connections metric can provide a decision-maker with relevant and easy to understand information about alternative reduction paths if one is required. Also, by selecting a policy that has both a high percentage and a large number of optimal policy connections, the policy becomes even more robust to changes.

6.4.4 Reward over Time

While the previous representations have focused solely on path dependencies, analyzing components of the optimal rewards can gain additional insight. As mentioned earlier, the rewards are defined as the combination of areas associated with a given state and specific preference structures in the variable space. Trends associated with the rewards over time can provide insight into the optimal paths identified by the simulations.

Figure 6.25 provides the mean and minimum/maximum reward over time associated with all optimal paths from the simulations. The reward at time equal to one is associated with moving from the state in epoch one to the state in epoch two. Therefore, the total number of time-steps will be one less than the total number of epochs. It is important to note that the calculated values in Figure 6.25 are *not* cumulative, but are for the reward at each time-step. This plot can identify trends in the reward values over time. For example, the reward at time-step three has a lower magnitude than at time-step two. Lower relative magnitudes can potentially signify where the path is intentionally accepting a lower reward for the possibility of obtaining much larger rewards at some future time. By understanding how the reward changes over time, a designer can identify areas that require further analysis, even for a simple plot.

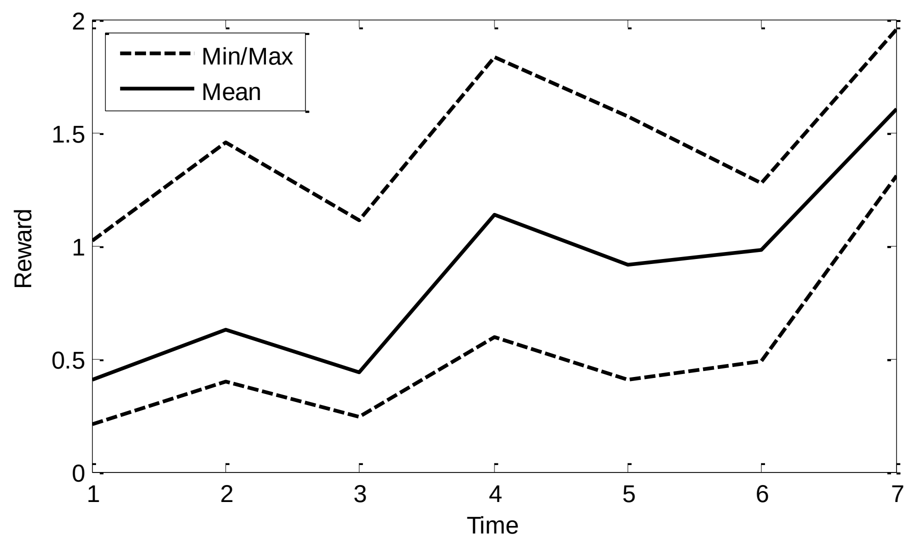


Figure 6.25: Mean and Minimum/Maximum Reward over Time

A similar type of graph that can provide additional insight is the cumulative reward over time. Figure 6.26 provides the mean and minimum/maximum cumulative reward over time associated with all optimal paths from the simulations. By identifying trends in the reward over time plot, such as a change in the reward magnitude, the cumulative reward plot can be referenced to determine the total impact of the optimal paths. For example, multiple paths can be compared and a lower magnitude reward at an earlier time-step can be justified based on a larger cumulative reward at a later time.

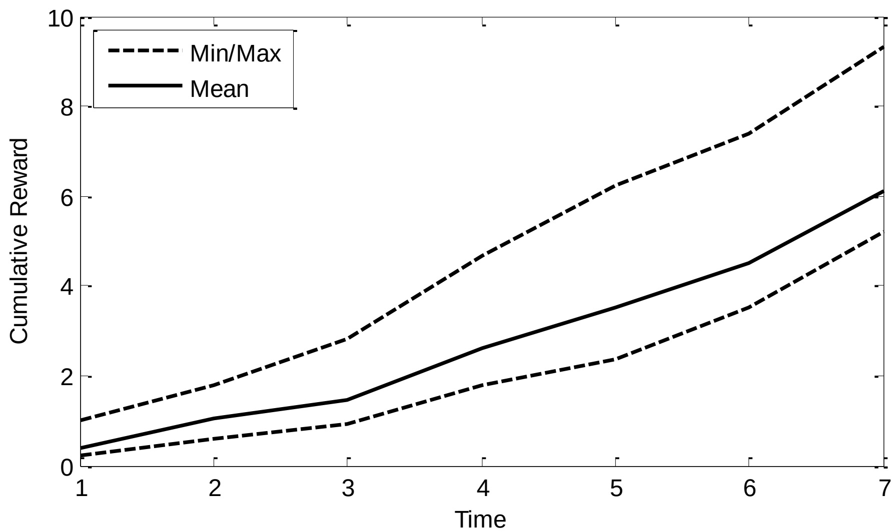


Figure 6.26: Mean and Minimum/Maximum Cumulative Reward over Time

Reward over time plots can be beneficial for a designer by identifying trends as well as comparing the rewards associated with different paths. Figure 6.27 shows a comparison between the two paths that had the highest optimal percentage. For each path, the mean of the rewards for that given path was taken and plotted through time. Figure 6.28 shows a similar comparison for the cumulative reward. Based on designer preferences, he/she might choose an optimal path with a lower optimal percentage if the reward and cumulative reward is more favorable in their eyes.

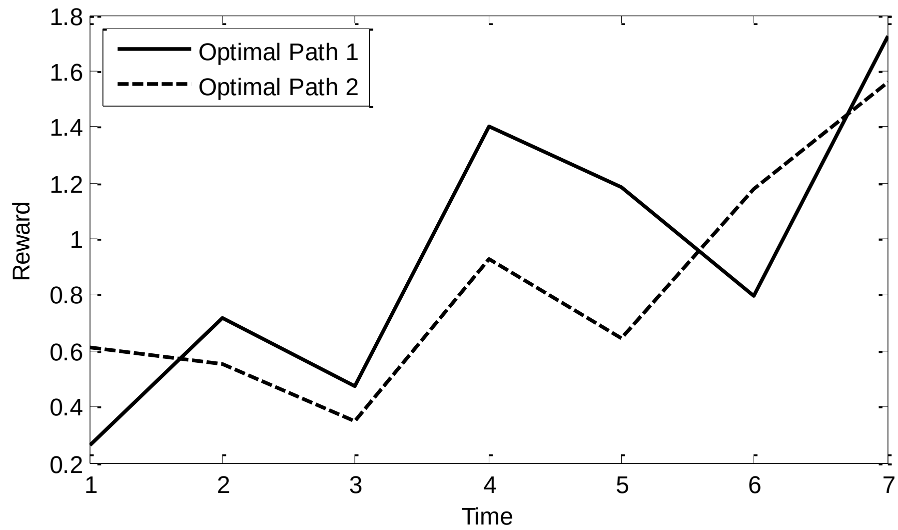


Figure 6.27: Mean Reward over Time for Top Optimal Paths

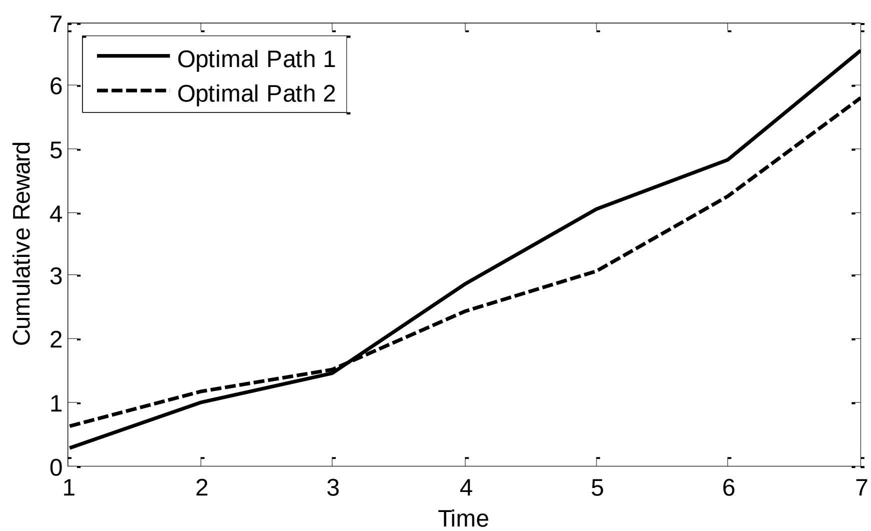


Figure 6.28: Mean Cumulative Reward over Time for Top Optimal Paths

As seen in the previous figures, reward over time plots can provide the designer with additional information to aid in the decision making process. Using this type of information, there might be various reasons why one path is chosen over another. A designer might be comfortable accepting lower rewards earlier for a larger payout later. Or a designer might prefer larger rewards earlier if the final cumulative rewards are similar. Regardless of the designer's preference, the reward over time plots provide valuable information for the decision making process.

6.4.5 Likelihood of Attainment

The final, and perhaps most important, developed representation of the simulation results is defined as the likelihood of attainment (LoA). The calculated overall preferences using DM, associated with the states of a given path, can be used to gain insight on the overlapping regions in the function and variable space. The overall preference in the function space is the overlapping region between the mapped combined variable preference and the designer-provided function preference. This curve, in a sense, describes the attainable function values given certain variable preferences. In the variable space, the overall preference describes the variable values that are associated with the overlapping region. For a single state and mapping, the overall preference can be transformed to represent a probability density function (PDF). The transformed PDF would represent the relative likelihood for the function to take a given value.

For every optimal path identified by a single simulation, the overall preference curve, both in the function and variable space, can be tracked through time. A composite curve can be generated for every optimal path from each simulation. The composite curve is calculated by determining the average preference level at each function or variable value for all states associated with an optimal path. The composite curves can be analyzed in different ways, including the generation of a single composite for all simulations or comparing composite curves associated with different unique optimal paths. The composite curves can be considered representations of various types of PDFs, but it is important to state that these combined curves are not the actual PDF for the function.

Figure 6.29 shows the 25 composite curves associated with the 25 simulations with differing preference structures, which are the average preference levels for L/B values for the states associated with the simulation's optimal path. These composites can then be combined to form a single composite curve, or the likelihood of attainment associated with all simulation optimal paths. Again, the average preference level at each L/B value for all simulation composite curves is calculated to obtain a single curve. Figure 6.30 shows the composite curve for all optimal paths from the simulations. This represents the likelihood of attaining certain function values given the potential outcomes represented by the various simulation preference structures.

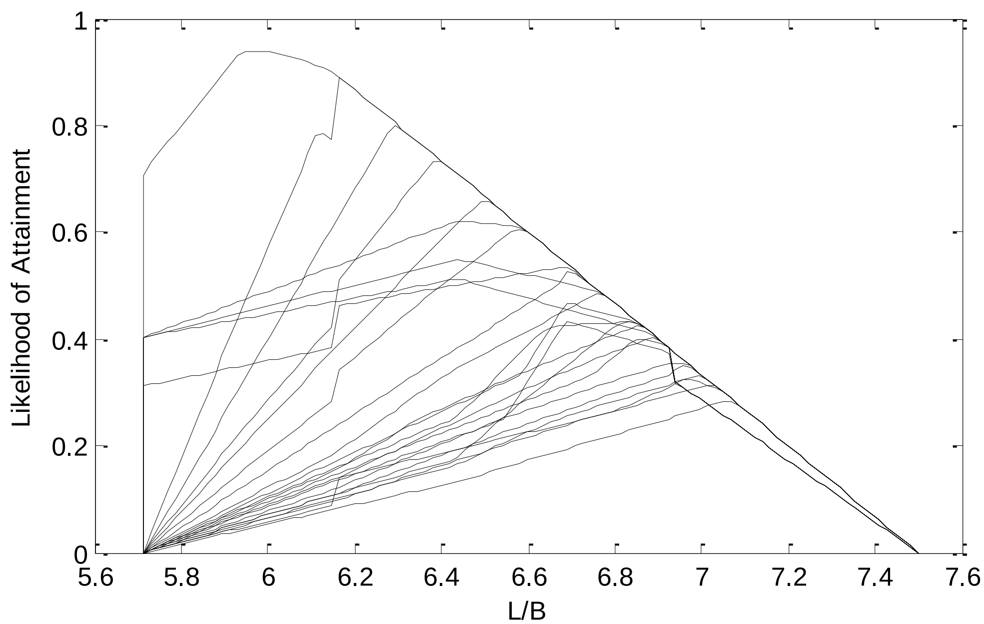


Figure 6.29: Likelihood of Attainment for Individual Optimal Paths

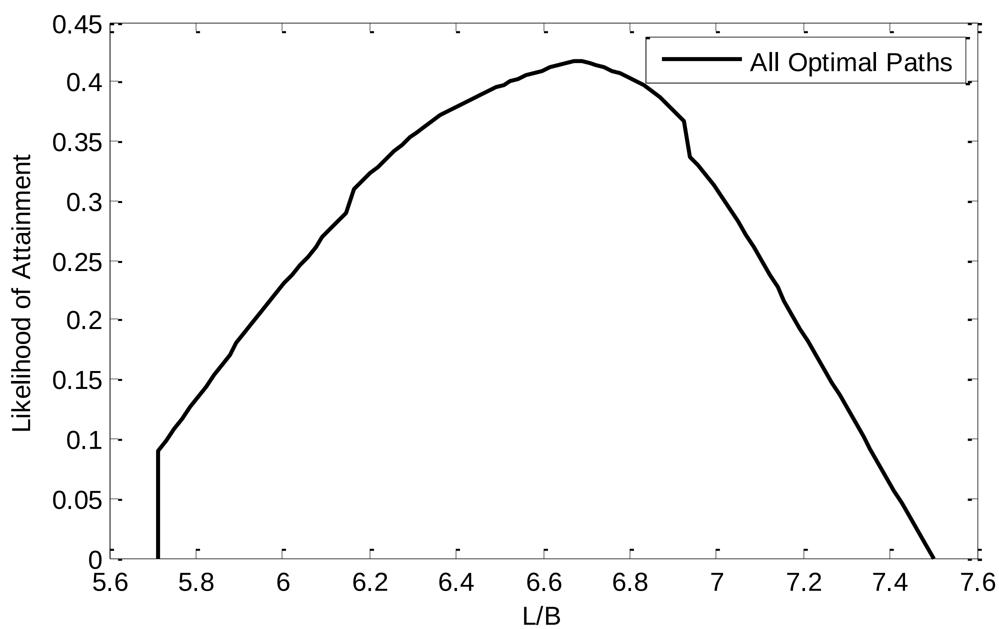


Figure 6.30: Likelihood of Attainment for All Optimal Paths in Function Space

The composite curves are defined as the likelihood of attainment. LoA curves can be calculated for both the function and its variables. The curve in the function space represents the overlap between the combined preference associated with the mapping of variable preferences to the function space and an inputted function preference (or requirement). If the combined preference completely encapsulates the function preference, then the likelihood of attainment would be equal to the function preference. More importantly, when there is no overlap between the functions, the likelihood of attainment is equal to zero for those values. These curves provide valuable information to the designer when weighing their options on how to reduce the design space based on what function values are obtainable.

Composite curves can also be generated for the unique optimal paths identified. The higher percentage paths have more curves that make up the composite. The composite curves associated with the two optimal paths with the highest percentage of occurrences in the simulations are provided in Figure 6.31. This can provide additional insight on making the decision between two paths. For example, if length-to-beam values between 7 and 7.5 are of concern, then both paths have relatively the same likelihood of attainment in that region. If values between 6 and 7 matter to the designer, then this is a different story. It might be worth investigating which technical aspects are impacting the two optimal paths and choose to go into greater detail for that aspect during the next negotiation round. Using the likelihood of attainment to compare different paths can provide the designer with additional information.

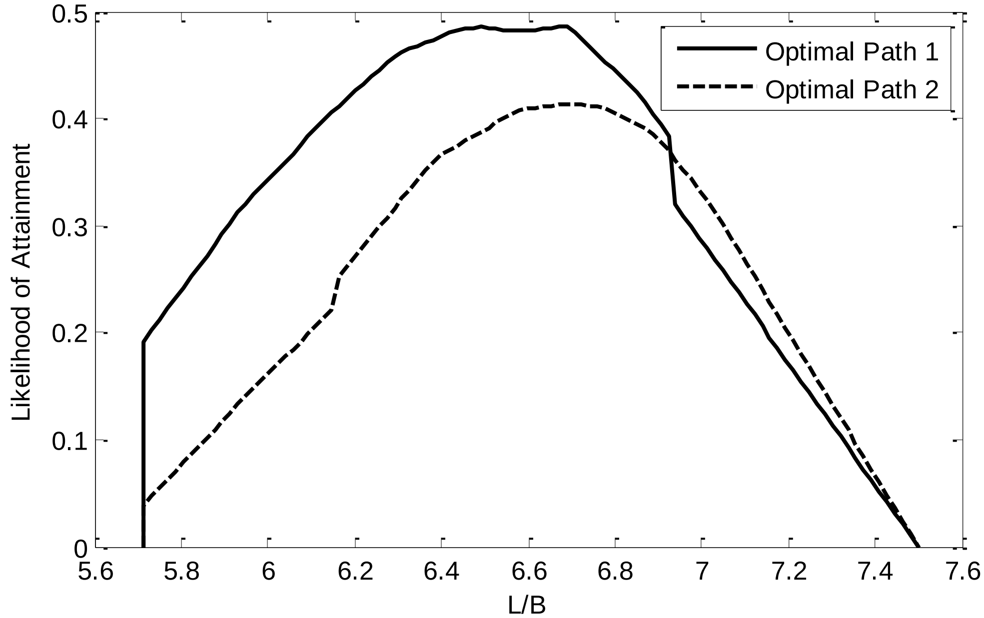


Figure 6.31: Likelihood of Attainment for Top Two Unique Optimal Paths

The significance of the likelihood of attainment curves can be far-reaching. LoA curves can be used to identify areas where unrealistic function or requirement preferences exist. The curve also provides the designer with the risk level of moving towards a certain region of the design space. For example, if it is desirable to obtain a function value with a low likelihood of attainment, these curves warn the designer that risk is high and the likelihood of attaining that value is low. Also, LoA curves can be used to determine how certain desired reduction decisions impact attainability for a specific function.

The same likelihood of attainment curve can be determined in the variable space as well. These curves for all optimal paths in the variable space are provided in Figure 6.32. The likelihood of attaining a certain variable value given the optimal paths as well as the risk associated with moving towards a certain region can be identified. Also, if you compare the likelihood of attainment curves to the optimal reduction paths, the initial decisions are either a reduction in higher length values or lower beam values. From this perspective, it would make sense that an elimination of lower likelihoods would be desired.

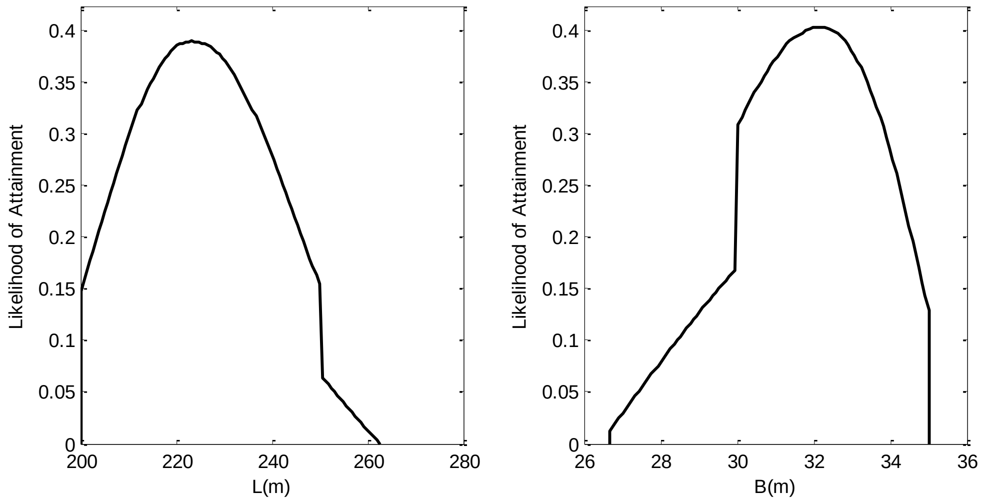


Figure 6.32: Likelihood of Attainment for All Optimal Paths in Variable Space

The likelihood of attainment curves presented in this section provides both a powerful and simple piece of information that designers can utilize to make better reduction decisions. Beyond making a better decision, these curves can be used to quantify the risk or likelihood associated with moving towards a particular area of the design space. This can be helpful when designers are defending certain solutions or attempting to argue that a solution carries too much risk. These curves are easily understood by stakeholders involved in the design, such as customers like the U.S. Navy, since the likelihood of attainment curves represent a substantial amount of analysis in an easy to understand way.

6.5 Multi-Objective Trade-Offs

This section discusses the development of a method to understand multi-objective trade-offs for set reduction decisions. When a chief engineer has more than one function to analyze using the developed set reduction framework, this method can be used to link the analyses together. A visualization technique is also introduced that allows the likelihood of attainment curves, discussed in the previous section, to be viewed from multiple function perspectives.

Decision making tradeoffs are somewhat unique compared to typical tradeoff scenarios that deal with a solution space. The tradeoffs are intentionally in the *decision* space, which emphasizes the decisions to reduce the design space. A common approach to presenting tradeoff information is through the use of Pareto optimality, which identifies a set of non-dominated solutions. For the points on the Pareto front, in order to improve one point in any of the objectives, another objective must become worse. Hence, a point on the front is not better or worse than any other without an additional selection method. Pareto fronts help to identify and understand potential tradeoffs between multiple objectives and are typically provided to human decision-makers for consideration. A Pareto front can be determined using the percentage optimal values from the robust decision path analysis for two separate functions.

For illustrative purposes only, an additional function defined as length multiplied by beam, is introduced in addition to the length-to-beam ratio. While this has little meaning for a naval architect, it is used to demonstrate the types of results that multi-objective trade-off analysis can provide. Due to the fact that both functions have the same variables, the states in their graph structure will be the same. If the functions have different numbers of variables, the link between their states must be made. This is discussed further in Chapter 8 when presenting a demonstration of the set reduction framework.

The Pareto front uses the percentage optimal values, defined as robustness, for the identified optimal paths from the simulations. First, any unique optimal paths that are in common for both functions are identified and their robustness values recorded. Non-dominated decision paths are then determined. For two partitions and the single reduction case, there are three points on the Pareto front that represent decision paths (provided in Figure 6.33). In some scenarios, there might not be any completely unique paths in common, especially for functions that do not have the same variables. An additional calculation method is introduced that focuses just on the initial decision that must be made. The robustness values associated with the same initial decisions for each function are calculated using the modified method. The Pareto front associated with this method is provided in Figure 6.34. It can be seen, when comparing Figure 6.34 to Figure 6.33, that robustness values increase in the vertical direction as there were more unique optimal paths, but most had common initial decisions. The robustness along the horizontal axis remained the same because there were only two unique optimal paths for this function.

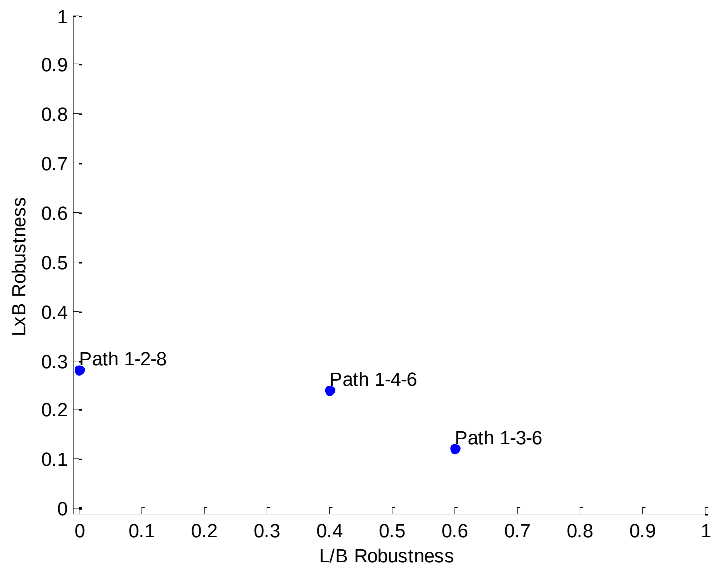


Figure 6.33: Unique Path Robustness Pareto Front for Two Partitions and Single Reduction Case

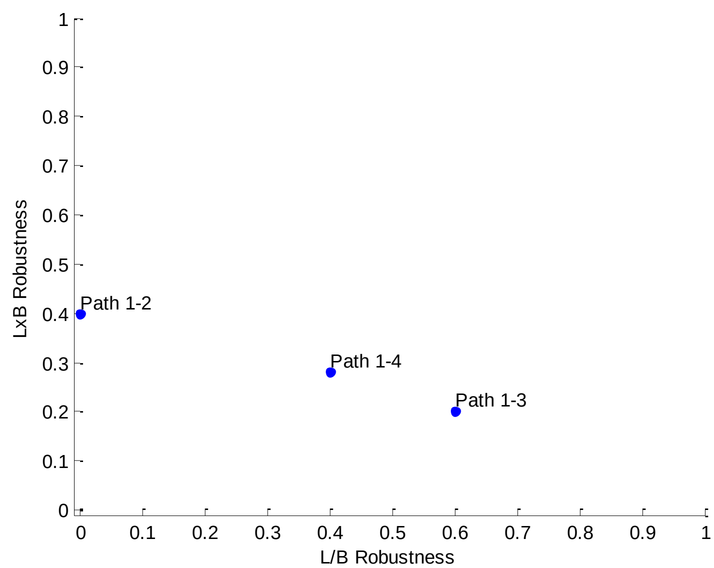


Figure 6.34: Initial Decision Robustness Pareto Front for Two Partitions and Single Reduction Case

The value of the Pareto front plots provided in Figure 6.33 and Figure 6.34 for the designer making set reduction decisions is in the ability to account for function uncertainty. For example, if the designer feels that one function has more uncertainty associated with it than another function, a path along the Pareto front that has a higher robustness value for that function would be preferred. The Pareto front plots add an even higher degree of robustness identification and the ability to identify customized decisions based on what the designer truly cares about.

Similar to the discussion in the previous section, the designer does not want to ignore the actual function values associated with given paths, which led to the development of LoA curves. This concept can be extended into the third dimension to present a likelihood of attainment curve for a combination of optimal paths associated with both functions. Two examples of the multi-objective likelihood of attainment curves are provided in Figure 6.35. The paths correspond to two of the paths in the Pareto front provided in Figure 6.33. The 1-3-6-10 path is associated with a reduction in length values between 250 and 300 first, then beam values between 25 and 30. The 1-4-6-10 path is associated with a reduction in beam values between 25 and 30 first, then a reduction in length values between 250 and 300. It can be seen that there is a drop in likelihood for Path 1-3-6 at an LB value of 7,500. A similar drop occurs for Path 1-4-6, but that drop occurs at an LB value of 6,000. A designer can use these contour plots to better understand the risk associated with attaining a requirement or function value given a reduction decision or path.

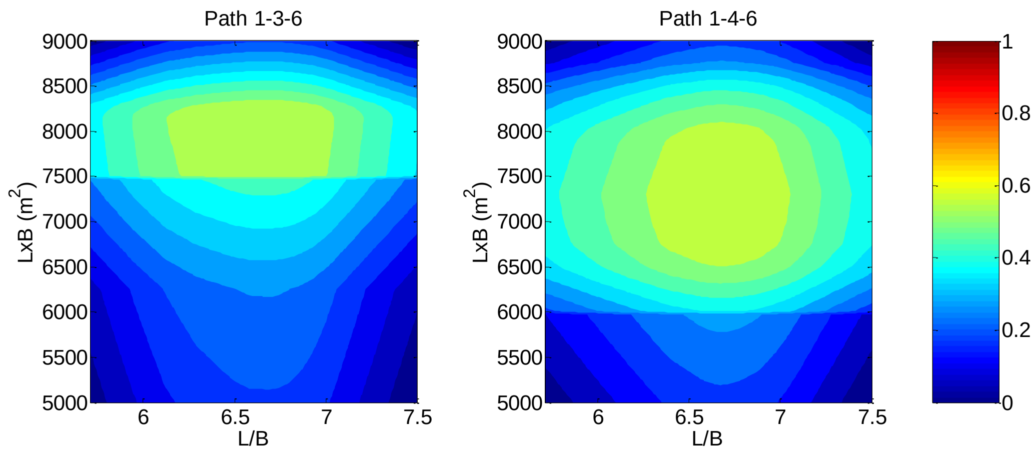


Figure 6.35: Multi-Objective Likelihood of Attainment Contour Plots for Two Unique Optimal Paths

The ability to interpret and understand set reduction decisions from multiple perspectives is critical to making the right decision, however the designer may define the right decision. Robustness Pareto fronts and the likelihood of attainment contour plots are additional pieces of information a designer can use during the design process.

6.6 Chapter Summary

This chapter initially focuses on the problem formulation associated with the proposed method presented in this dissertation. Investigation in previous work led to the formulation of three aims for research. This research focuses on developing a method with a more formal framework to aid in SBD execution for large-scale, team-based design, a better understanding of time-dependent design relationships and the potential impact of current decisions on the design process, as well as the identification of robust decision paths that avoid failure opportunities while considering reduction path and rate.

The developed method that addressed the identified problem statements includes an extension of design space mapping, the longest path problem formulated as a Markov Decision Process, and preference change simulations. Design space mapping enhances preference-based reasoning by identifying the impacts of variables on key functions of interest, such as performance objectives. The design space mapping method was extended through the development of set reduction decision making metrics. These metrics are used as inputs into the LPP MDP formulation. One of the main objectives when guiding design reduction is to maximize the reward associated with eliminating a certain area of the design space, while considering the risk associated with that decision. The MDP formulation is able to model the reduction path problem through the use of a risk-adjusted reward evaluated over the complete set reduction process. Additionally, a novel approach to automatically generate reduction graph structures is introduced. The final component of the method utilizes the MDP outputs to conduct a series of preference structure simulations. The goal of conducting simulations is to better understand the impacts of potential preference structures, both changing requirements and variable preferences throughout the reduction process.

There are a number of factors that make the set reduction problem unique from typical MDP and LPP formulations. Therefore, various representations of the framework's results that can be used by the designer to make set reduction decisions were developed. These considerations included determining the link between preference structures and optimal reduction policies, identifying robust decision paths, determining if alternative paths exist if a selected path failed to remain feasible, and determining the impact of uncertainty on meeting a specific function value or obtaining a specific variable value. Additionally, multi-objective trade-offs were considered by providing Pareto fronts that describe the robustness of common decision paths for multiple functions. The visualization of uncertainty in both objectives using contour plots was presented.

Finally, individual pieces of the developed method are combined together during a discussion on the overall execution strategy. The execution strategy can be broken down into a series of distinct steps that occur during a single round of negotiation, or time-step in the decision making process. The proposed method is designed for use at every negotiation round. The reduction structure used in this dissertation and reasoning behind its selection is then presented. While this chapter covered a wide array of topics, the execution strategy is able to consolidate all aspects into an understandable and executable strategy that is utilized in the next chapter when demonstrating the proposed method and validating its usefulness.

Chapter Citations

1. Antonsson, E.K., & Otto, K.N. (1995). Imprecision in Engineering Design. *ASME Journal of Mechanical Design*, 117(B), pp. 25-32.
2. Bellman, R. (1957). A Markovian Decision Process. *Journal of Mathematics and Mechanics*, 6.
3. Bertsekas, D. P., & Tsitsiklis, J. N. (1991, August). An Analysis of Stochastic Shortest Path Problems. *Mathematics of Operations Research*, 16(3), pp. 580-595.
4. Briggs, A. J., Detweiler, C., Scharstein, D., & Vandenberg-Rodes, A. (2002, December). *Expected Shortest Paths for Landmark-Based Robot Navigation*. Paper presented at the Fifth International Workshop on Algorithmic Foundations of Robotics, Nice, France.
5. Briggs, A.J., Detweiler, C., & Scharstein, D. (2004). Expected Shortest Paths for Landmark-Based Robot Navigation. *International Journal of Robotics Research*, 23(7-8), pp. 717-728.
6. Hopp, W. (1988). Sensitivity analysis in discrete dynamic programming. *Journal of Optimization Theory Applications*, 56, pp. 257-269.
7. Huang, B. & Fery, P. (2005). Aiding route decisions for hazardous material transportation. *Transportation Research Board*.
8. Law, W.S., & Antonsson, E.K. (1994). Implementing the Method of Imprecision: An Engineering Design Example. *Proceedings of the Third IEE International Conference on Fuzzy Systems*, 1, pp. 358-363.
9. Miller-Hooks, E. & Mahmassani, H. S. (1998). Optimal Routing of Hazardous Materials in Stochastic, Time-Varying Transportation Networks. *Transportation Research Record*, Vol. 1645, pp. 143-151.
10. Niese, N. D. (2012). *Life Cycle Evaluation under Uncertain Environmental Policies Using a Ship-Centric Markov Decision Process Framework*. (Doctoral dissertation). University of Michigan, Ann Arbor, MI.
11. Nikolova, E., & Karger, D. R. (2008, July). *Route Planning under Uncertainty: The Canadian Traveller Problem*. Paper presented at the Twenty-Third Conference on Artificial Intelligence, Chicago, IL.
12. Papadimitriou, C. H., & Yannakakis, M. (1991). Shortest paths without a map. *Theoretical Computer Science*, 84, pp. 127-150.
13. Polychronopoulos, G. H., & Tsitsiklis, J. N. (1996). Stochastic Shortest Path Problems with Recourse. *Networks*, 27, pp. 133-143.
14. Puterman, M. L. (1994). *Markov Decision Processes: Discrete Stochastic Dynamic Programming*. Hoboken: John Wiley & Sons.
15. Russel, S., & Norvig, P. (2003). *Artificial Intelligence: A Modern Approach*. 2nd ed. New York: Prentice Hall.
16. Tan, C., & Hartman, C. (2011). Sensitivity analysis in Markov Decision Processes with uncertain reward parameters. *Journal of Applied Probability*, 48, pp. 954-967.
17. Wallace, S. (2000). Decision-making under uncertainty: Is sensitivity analysis of any use? *Operations Research*, 48, pp. 20-25.
18. Wang, X. (2003). *Set Mapping in the Method of Imprecision*. (Doctoral dissertation). California Institute of Technology, Pasadena, CA.
19. White, C., & El-Deib, H. (1986). Parameter imprecision in finite state, finite action dynamic programs. *Operations Research*, 34, pp. 120-129.

20. Wood, K.L., Otto, K.N., & Antonsson, E.K. (1992). Engineering Design Calculations with Fuzzy Parameters. *Fuzzy Sets and Systems*, 51(1), pp. 1-20.
21. Zadeh, L.A. (1965). Fuzzy Sets. *Information and Control 8*, pp. 338-353.
22. Bellman, R. (1957). *Dynamic programming.* Princeton: Princeton University Press.

Chapter 7: Evaluation and Comparison Studies

The developed framework presented in the previous chapter provides a designer within a SBD environment an understanding of time-dependent relationships through design space mapping, the impact of reducing areas of the design space using the MDP framework, and identifies robust decision paths from preference change simulations. While both design space mapping and MDPs have proved to be effective for certain applications individually, the combination of the two has yet to be studied.

In order to establish the link between mapping outputs and the rewards associated with the MDP framework, the reduction metrics presented in the previous chapter are evaluated to determine their combined effectiveness. After an initial evaluation of all combinations between the reward and risk metrics, two were selected to be analyzed in more detail. After a more detailed evaluation including how the two selected metrics represent design changes, a single metric is selected as the most compatible for the SBD reduction problem.

This chapter also presents a series of studies conducted to determine the value associated with using the MDP formulation with the developed metrics over reduction methods based solely on current in-state knowledge. While mapping information can be useful, there is still no consideration of future scenarios. Design requirements and relationships are constantly changing through time, especially for organizations such as the U.S. Navy. By having the ability to understand potential outcomes and identifying paths more robust to changing conditions through preference change simulations, the designer has additional and valuable information to make sound decisions.

Novel contributions presented in this chapter include:

- An evaluation of the developed metrics within the MDP formulation and the identification of a single metric best suited for the set reduction problem
- A demonstration of the advantage of considering future state prediction versus the use of in-state knowledge

7.1 Metrics Evaluation

As described in the previous chapter, reduction metrics are used to make the link between the DM method and the MDP formulation. The risk and reward metrics selected are multiplied together to form the risk-adjusted rewards used in the MDP. In order to better understand the implications of using different combinations of the risk and reward metrics, a series of studies were conducted using the LPP MDP SBD formulation. Based on the emphasis of each metric, it was determined that certain combinations of risk and reward metrics made more intuitive sense and produced more reasonable results when used within the MDP formulation. This section first discusses an initial evaluation of the potential combinations used to identify the most promising reward and risk combinations. From this evaluation, two combinations were analyzed in further detail to identify their strengths and weaknesses. This comparative evaluation uses likelihood of attainment curves in both the function and variable space to compare the two combined metrics.

7.1.1 Initial Evaluation

An initial evaluation of the risk and reward metric combinations was completed using the length-to-beam problem. The purpose of this evaluation was to identify metric combinations that complemented each other and produced reasonable and intuitive results for a simple problem. The length-to-beam problem with two variable partitions each and a single-reduction graph structure were used. The graph structure is provided in Figure 7.1 for reference, which is a duplicate of the one provided in the previous chapter.

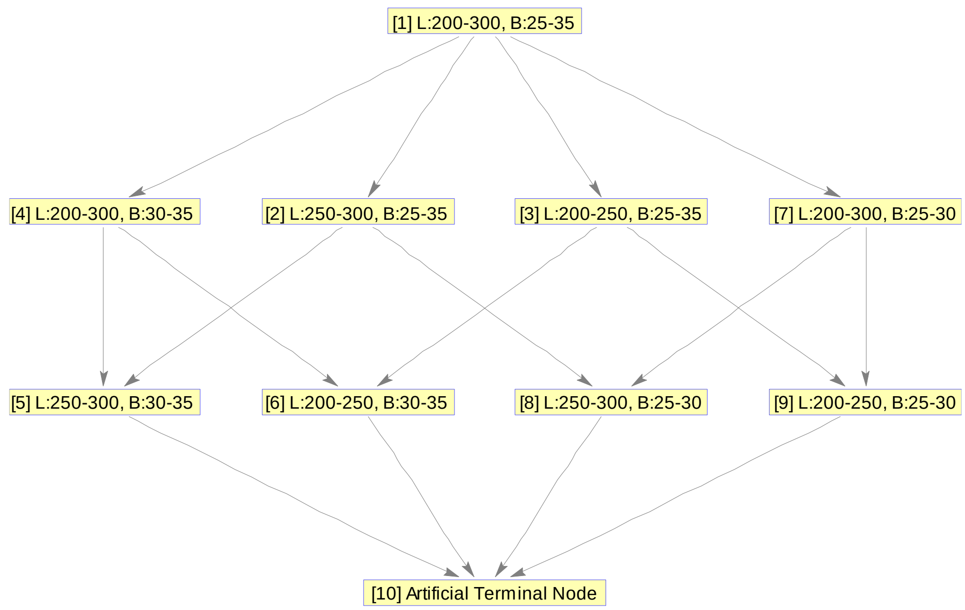


Figure 7.1: Length-to-Beam Single Reduction Graph (Two Partitions)

The initial variable preferences used for the evaluation were triangular with peaks at the middle of the set-ranges and endpoints at the set-range limits. The initial state (State 1) mapping of these preferences with an assumed function preference is provided in Figure 7.2. The overall preferences with the initial variable preferences are provided in Figure 7.3. The risk-adjusted rewards associated with State 1 used in the MDP framework are calculated using a combination of risk and reward metrics, which are based on the areas associated with these figures. For the function risk metric, additional function space mappings are required, which are not shown here.

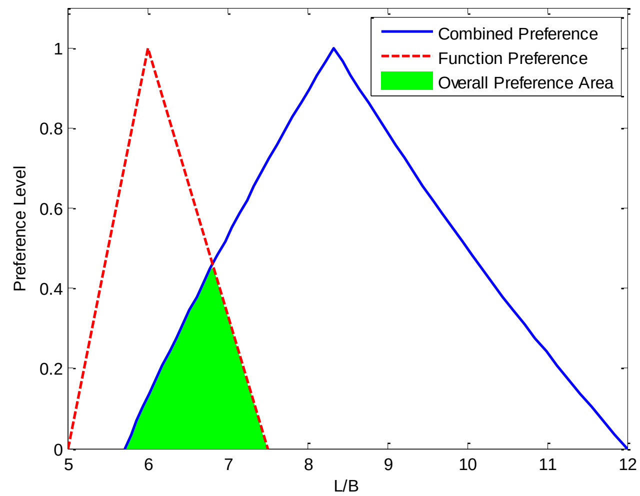


Figure 7.2: Combined and Function Preferences in Function Space (State 1)

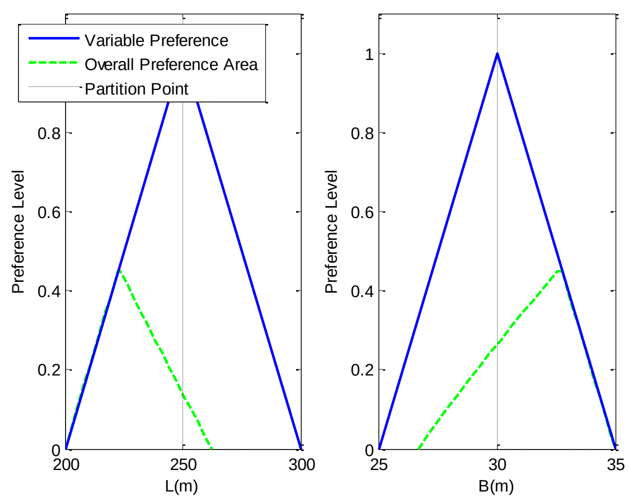


Figure 7.3: Variable and Overall Preferences in Variable Space (State 1)

As discussed in the previous chapter, the adjusted reward used in the MDP framework is the multiplication of the associated reward and risk metric. Table 7.1 outlines the four risk/reward combinations evaluated. The same problem introduced above was evaluated using each combination. A total of nine simulations varying the preference structures for future time steps were completed. The percent chance that a given decision is optimal out of all the simulations completed is also shown in Table 7.1. While there are four potential reduction decisions, only two were part of the optimal paths identified by the simulations. The decision to reduce to State 3 is associated with reducing length values between 250 and 300. The decision to reduce to State 4 is associated with reducing beam values from 25 to 30. These two options are logical when considering all of the variable preferences in Figure 7.3.

Table 7.1: Risk/Reward Combinations Evaluated

Combination	**Reward**	**Risk**	**Robust Decision (% Opt)**	
			3	**4**
1	Satisfaction	Variable	0.67	0.33
2	Satisfaction	Function	1	0
3	Reduction	Variable	Infeasible	
4	Reduction	Function	0.44	0.56

The most significant result, seen in Table 7.1, is the reduction reward with variable risk combination. In this case, there is little emphasis placed on meeting the desired function preference. This led to reduction decisions that were infeasible (no overlap in function space), and did not have an overlap with the function preference. When using this metric combination, certain regions with a little or no overall preference ranked high. This produced false results that signified a favorable region, that in reality, was infeasible. Another combination with notable results is the satisfaction reward with function risk, where State 3 was 100% optimal. Both satisfaction reward and function risk describe the similar aspect of meeting the desired function preference, except for the fact that one is in the function space and the other is in the variable space. Results of the analysis show little conflict between these two metrics, which caused State 3 to be optimal for all simulations. These two metrics were eliminated from consideration for use in the MDP framework due to their inconsistences and singular focus.

The satisfaction reward and variable risk metrics complement each other well by identifying unpreferred regions while at the same time balancing the desire to remain in an unconstrained area of the design space. Results favor State 3 approximately two-thirds of the time. A similar conclusion regarding the reduction reward and function risk combination can be seen, however in this case the results favor State 4. The reduction reward emphasizes the gap between desired and obtainable variable values, while function risk ensures overlap. It cannot be determined from this initial analysis whether one combined metric is better than the other, however, as identified in Chapter 5, the reduction path taken does have an impact on the ability to handle changing conditions. In order to better understand the implications of the two combined metrics remaining, further analysis is required. For notational purposes, from this point forward, the satisfaction reward scenario refers to the combination with variable risk, and the reduction reward scenario refers to the combination with function risk.

7.1.2 Reward Type Comparison

After identifying the two combinations that were the most compatible, further analysis was completed to better understand the implications of using each type. The two combinations analyzed were the satisfaction reward with variable risk and reduction reward with function risk. Initially, a series of baseline reductions using each reward type was completed using the length-to-beam function with different initial preference structures. A triangular function preference is assumed with a range of $L/B = [5,7.5]$ and peak at $L/B = 6$. In an effort to move away from the simplicity associated with using only two partitions for each variable, four partitions were used. Assuming the single reduction scenario, a total of three reductions for each variable is required to reduce to the final partition ranges. This is associated with a total of 8 epochs, including the initial and terminal states. A total of nine different initial preference structures were used as part of the analysis. For each initial preference structure, a series of simulations were completed that solved the LPP MDP problem using different future preference structures. The initial preference structures were triangular and fully spanned the initial set-ranges. The peak of the triangle was either at the left (L), center (C), or right (R) of the set-range. A list of the cases analyzed and their initial preference structures are provided in Table 7.2. The *L/B* value associated with the peak preferences is also provided for reference.

Table 7.2: Initial Preference Structures and Peak Function Values

Case #	Length	Beam	Peak L/B
1	L	C	6.67
2	L	R	5.71
3	L	L	8
4	C	C	8.33
5	C	R	7.14
6	C	L	10
7	R	C	10
8	R	R	8.57
9	R	L	12

To simplify the interpretation of the results, only the robust decision paths and the number of alternative paths were used to make reduction decisions. Specifically, the percentage that a state was optimal for epoch 1 was used along with the average number of alternative paths for a given state. The number of alternative paths is averaged for the simulations that resulted in the state being optimal in epoch 2. There were certain situations where the optimal percentage was the same for multiple states. In these situations, the most robust reduction decision was considered the state containing a higher average number of alternative paths. The results of the initial analysis for the satisfaction and reduction rewards are provided in Table 7.3 and Table 7.4, respectively.

Table 7.3: Satisfaction Reward Initial Results

Case #	Robust Decision (% Opt.)			Alternative Paths (Avg. #)		
	4	**11**	**31**	**4**	**11**	**31**
1	0.67	0.33	0	3.67	3	0
2	0.67	0.33	0	3.67	3	0
3	0.67	0.33	0	3.67	3	0
4	0.67	0.33	0	3.67	3	0
5	0.67	0.33	0	3.67	3	0
6	0.67	0.33	0	3.67	3	0
7	0.67	0.33	0	3.67	3	0
8	0.56	0.44	0	3.67	4	0
9	0.67	0.33	0	3.67	3	0

Table 7.4: Reduction Reward Initial Results

Case #	Robust Decision (%)				Alternative Paths (Avg. #)			
	2	**4**	**11**	**31**	**2**	**4**	**11**	**31**
1	0.11	0.89	0	0	1	7.83	0	0
2	0	0.67	0.33	0	0	6.20	6	0
3	0.11	0.89	0	0	1	7.83	0	0
4	0	0.78	0	0.22	0	6.5	0	2
5	0	0.56	0.22	0.22	0	7.5	7	3
6	0	0.78	0	0.22	0	6.5	0	2
7	0	0.11	0.56	0.33	0	6	8.5	5
8	0	0.00	0.67	0.33	0	0	8.4	4
9	0	0.33	0.33	0.33	0	8	9	5

The states with the highest optimal percentage for each initial preference structure are shaded in the tables above. One note is that for preference structure 9, three states resulted in the same percentage; the state with the largest number of average alternative paths is shaded. When comparing the results of the two metrics, preference structures 1-6 have the highest optimal percentage at State 4. These results differ for preference structures 7-9. The satisfaction reward shows State 4 being more robust, while the reduction reward shows State 11. State 4 is associated with a reduction in length from 275-300 and State 11 is associated with a reduction in beam from 25 to 27.5. Similar to the analysis conducted in the previous section, the two metrics suggest different paths be taken for three initial preference structures. These three preference structures are associated with a length preference peak to the right. Also, referring to Table 7.2, these three preference structures are also associated with large peak length-to-beam ratios outside the range of the function preference. This means that it is difficult to obtain variables that both overlap with the desired function preference and high variable preference values.

To better understand the implications of the different paths identified by the two metrics, a complete reduction analysis was completed for each preference structure. The values presented in Table 7.3 and Table 7.4 only show the results associated with analyzing potential outcomes from the perspective of being in epoch 1. Similar to how the method would be used at each negotiation round with updated preferences, a simulation is completed at each epoch for this problem. The reduction decision at each epoch is based on the optimal percentage and alternative path information, while the updated preferences are clipped versions of the initial preference structure. As set reduction occurs, the preference structures for the states at previous epochs are set based on the initial preference structure and future epoch preferences that are defined based on the simulations. In the end, a robust reduction path is identified for each initial preference structure and reward type. The best way to compare the two metrics is using the composite likelihood of attainment curves in both the function and variable space associated with the robust set reduction path. These curves can identify the impact of taking one reduction path over another.

7.1.2.1 Unconstrained Scenario

Before looking at the scenarios where the two reward types identified different robust paths, a study of a preference structure that had similar robust paths for both metrics was completed. An unconstrained scenario is when the combined preference in the function space, which is based on initial preferences, has a large amount of overlap with the function preference. Preference structure 2 is associated with a left length peak preference and right beam peak preference. The peak L/B is equal to 5.71, closest to the function preference peak of 6. The reduction plots for preference structure 2 are provided in Figure 7.4. It can be seen that the reduction paths are similar for the early rounds, but differ in reduction order later. Also, while the final set-range for length was the same, the final beam set-range was shifted lower for reduction reward.

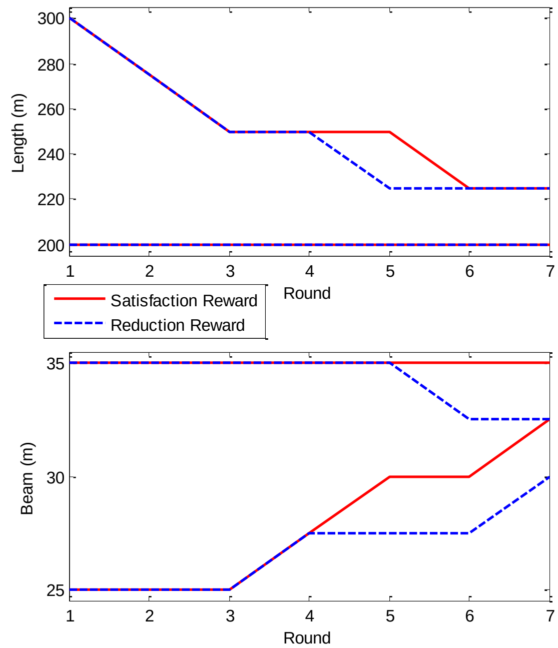


Figure 7.4: Reduction Plots for Initial Preference Structure 2

The composite likelihood of attainment curves for all the states associated with the robust paths can be calculated and compared in order to identify the impacts of the different reduction paths. Figure 7.5 and Figure 7.6 provide the likelihood of attainment curves for preference structure 2 in the function and variable space, respectively. Results show that the two reward types produce similar results when the likelihood of attainment is relatively high. Also, the attainment curves are similar to the function and variable preferences, which are the solid black lines in the figures. This is associated with a high likelihood of meeting the desired function preference, or requirement.

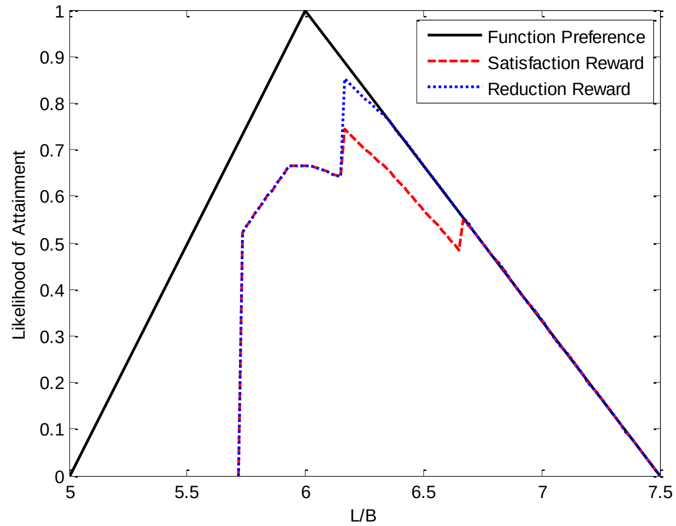


Figure 7.5: Function Space Robust Path Likelihood of Attainment Curves (Preference Structure 2)

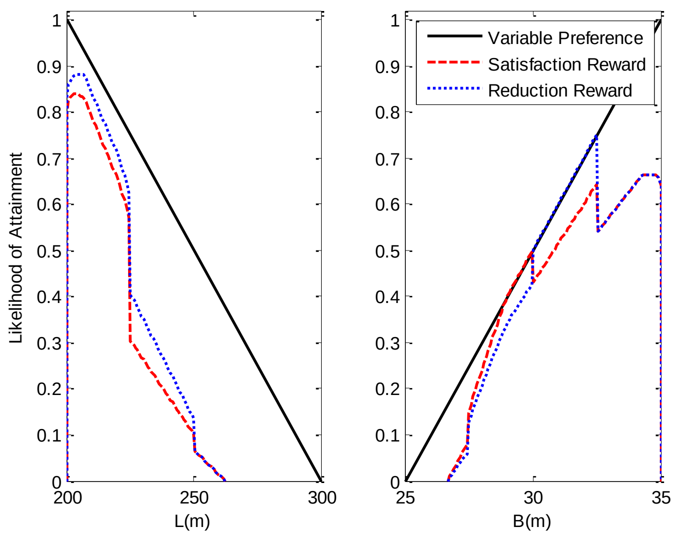


Figure 7.6: Variable Space Robust Path Likelihood of Attainment Curves (Preference Structure 2)

For the relatively unconstrained problem associated with preference structure 2, additional preference change studies were completed to better understand how each reward type manages changing conditions. These studies are similar to the detailed design experiments presented in Chapter 5. When making a preference change within the developed structure, the preferences for the prior epochs are set to clipped versions of the initial preference structure. During the round when a change occurs, the preferences change to the new preference structure. To evaluate the actual impact of the change, the new preference structure is used for the future state mappings. This is associated with the preferences staying at the new preference structure for the remainder of the reduction. If all simulations are considered, the result would be the robust decision path moving forward after the change occurs. Identifying this robust decision path is important, but for a more direct comparison, the preferences are fixed for the remainder of the reduction process.

The first change study completed for preference structure 2 was a change in the length peak from the left to the right during round or epoch 5. Figure 7.7 and Figure 7.8 provide the likelihood of attainment curves for preference structure 2 with the length change. The black solid lines show the new preference structures after the change was implemented. Notice the shift in the length preference. The most obvious difference from the unchanged scenario is the dramatic decrease in likelihood of attainment. This confirms that the problem was further constrained by the change in preference. Again, in this scenario, the likelihood of attainment curves are similar. One important observation is in the length variable space where the change occurred. The black solid line shows the changed preference structure where the satisfaction reward is able to attain higher likelihoods for larger length values. When this change occurs, the set-ranges are identical for both reward types. This means that the reduction path identified by satisfaction reward after the change was more successful at attaining higher likelihood values.

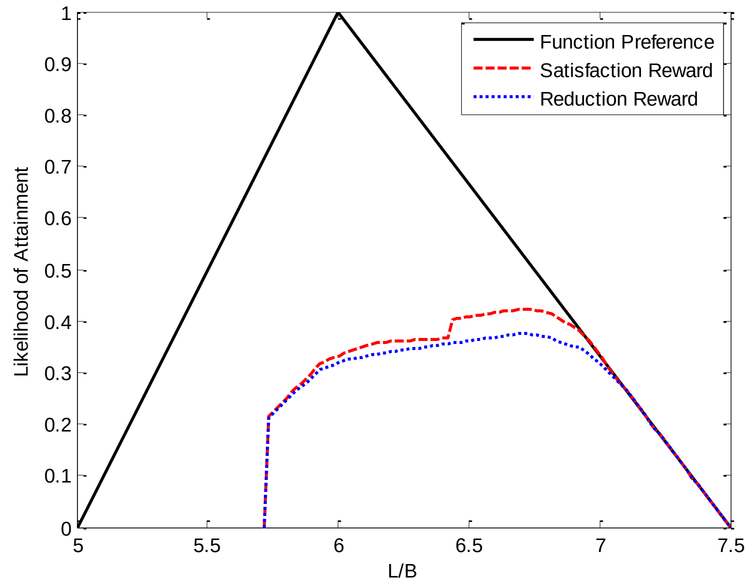


Figure 7.7: Function Space Likelihood of Attainment Curves (Preference Structure 2 with Length Change)

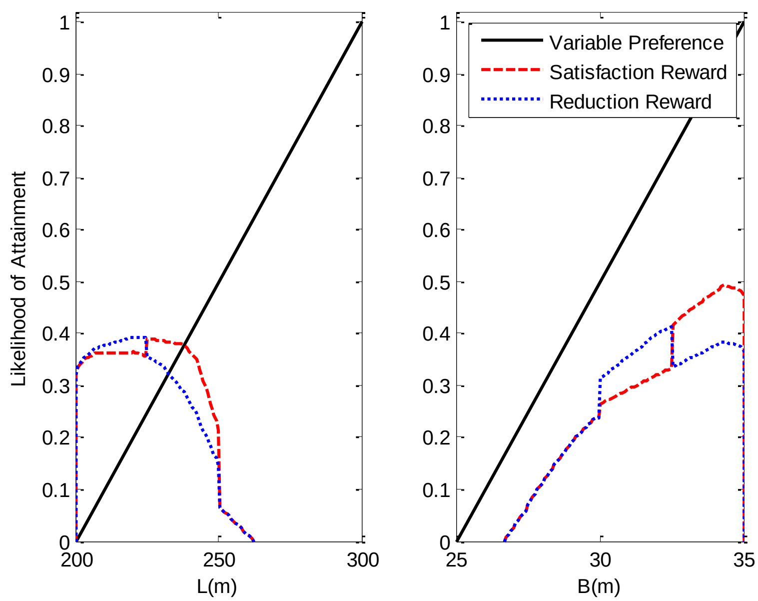


Figure 7.8: Variable Space Likelihood of Attainment Curves (Preference Structure 2 with Length Change)

The second change study completed for preference structure 2 was a variance in the beam peak from the right to the left during round 5. Figure 7.9 provides the likelihood of attainment curves for preference structure 2 in the variable space with the beam change. In the function space, the likelihood of attainment curves were similar and the level of attainment was comparable to that of the length change. In Figure 7.9, the curves are almost identical for both variables. Unlike the length change, the paths identified by each reward type produced similar results. This shows that in certain scenarios (but not all), satisfaction reward can potentially attain higher likelihood values in preferred regions after a change occurs.

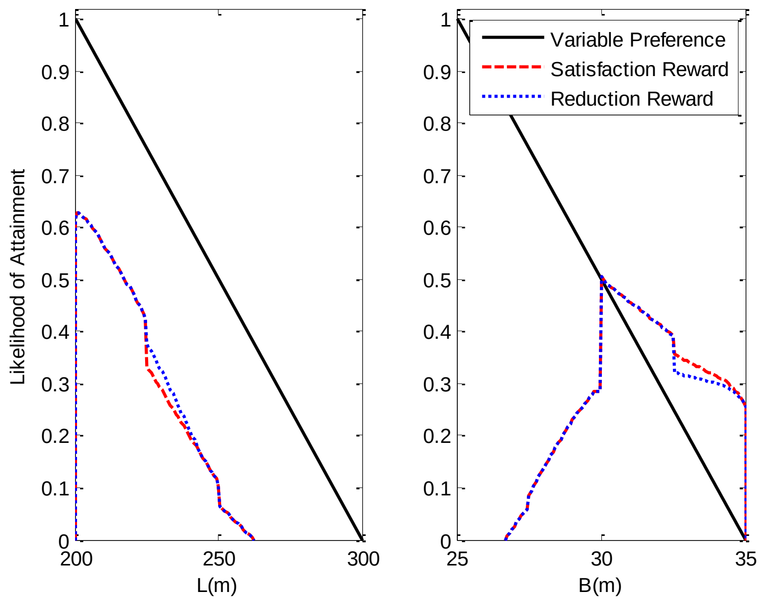


Figure 7.9: Variable Space Robust Path Likelihood of Attainment Curves (Preference Structure 2 with Beam Change)

7.1.2.2 Constrained Scenarios

With an understanding of unconstrained situations where both reward types have the same solution, the scenarios where the reward types produced different results can be analyzed. It is important to first determine how the reduction paths differ from the preference structures with a peak length preference to the right. Table 7.5 provides the reduction paths for preference structures 7, 8, and 9 for both reward types. Each number is associated with a state. State 1 is associated with the initial set-ranges and state 101 is associated with the artificial terminal node. The reduction paths for preference structures 7 and 8 within each reward type are exactly the same. Preference structure 9 has a different robust path, but does not differ substantially. The differences are associated with the order in which a set-range is reduced. The reduction plots associated with preference structure 7 for both reward types are provided in Figure 7.10. In this case, the satisfaction reward path reduces length initially, while the reduction reward path reduces the beam completely. The reduction plots associated with preference structure 9 for both reward types are provided in Figure 7.11. The states associated with a specific case's robust path, seen in Table 7.5, correspond to variable set-ranges in the reduction plots provided in Figure 7.10 and Figure 7.11. The trends in these figures are similar when comparing the 7 and 8 paths to the 9 path with minor changes in the order of the reduction and shifts in the end set-ranges for satisfaction reward. The key distinction between the paths for the two reward types is which variable is reduced in the early rounds.

Table 7.5: Robust Reduction Paths for Initial Preference Structures 7, 8, and 9

Epoch	Satisfaction Reward			Reduction Reward		
	Case 7	**Case 8**	**Case 9**	**Case 7**	**Case 8**	**Case 9**
1	1	1	1	1	1	1
2	4	4	4	11	11	11
3	6	6	6	21	21	21
4	16	16	10	61	61	24
5	26	26	40	64	64	26
6	66	66	50	66	66	30
7	69	69	80	70	70	70
8	101	101	101	101	101	101

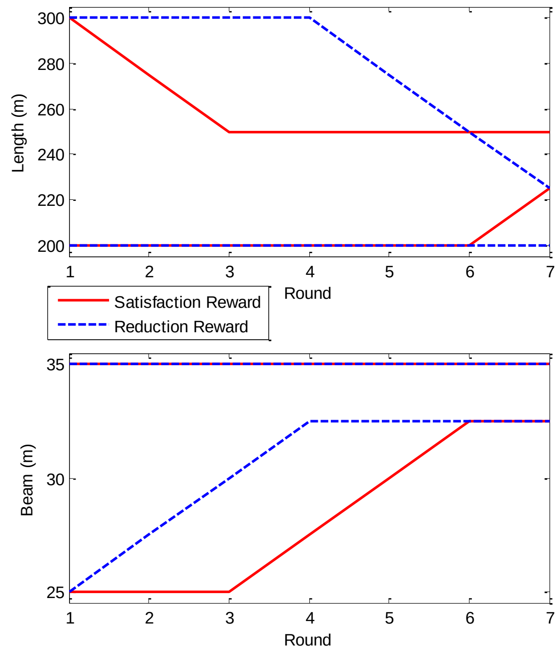


Figure 7.10: Reduction Plot for Initial Preference Structure 7

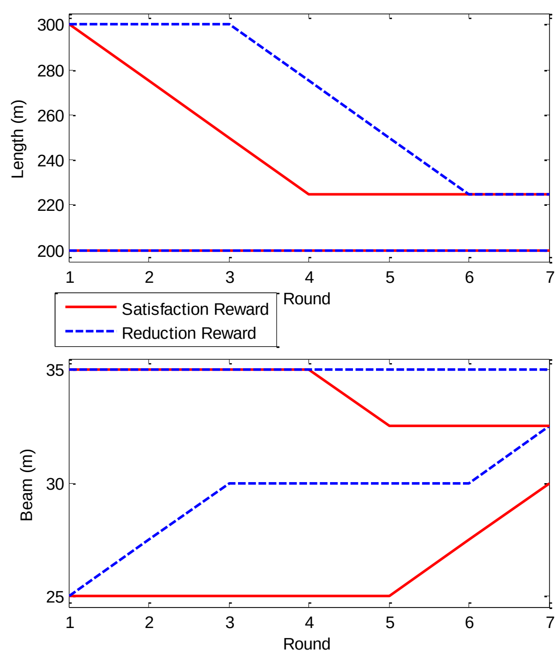


Figure 7.11: Reduction Plot for Initial Preference Structure 9

After understanding how the reduction paths differ, a comparison using likelihood of attainment curves can be completed. Figure 7.12 and Figure 7.13 provide the likelihood of attainment curves for preference structure 9, in the function and variable space, respectively. It can be seen that the likelihood of attainment in the function space is similar for both reward types; however, in the variable space there are some key differences. Reduction reward is able to attain slightly higher length likelihoods, but less beam likelihoods for the lower beam values that are preferred. This is due to the emphasis of the reduction reward on a single variable set-range at a time. While reduction reward can attain more values for one variable, the other variable is more negatively affected. Also, the initial reduction of beam values for the reduction reward led to low attainment in lower beam values. From this analysis, the satisfaction reward is able to select the path that impacts the attainment the least. Similar results were found for preference structures 8 and 9 as well. The results show that for situations where the peak combined preference is distant from the preferred function preference, reduction reward can potentially cause a decrease in attainment for certain values.

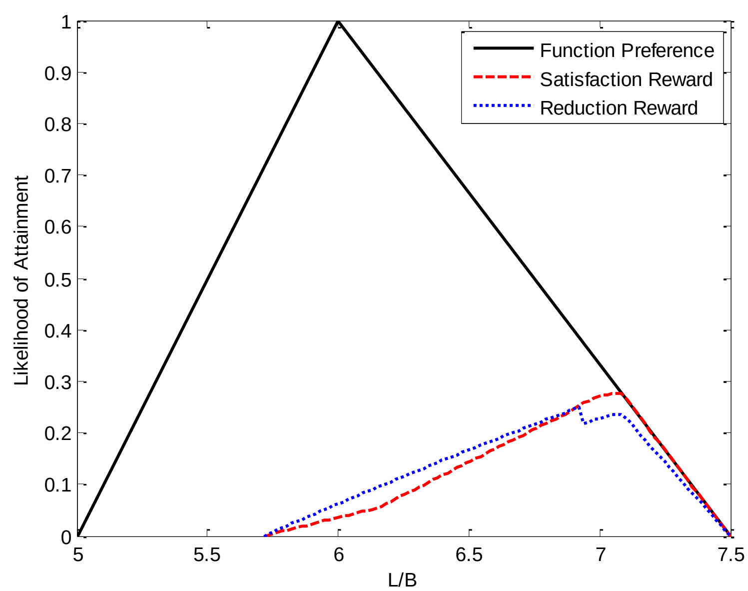


Figure 7.12: Function Space Robust Path Likelihood of Attainment Curves (Preference Structure 9)

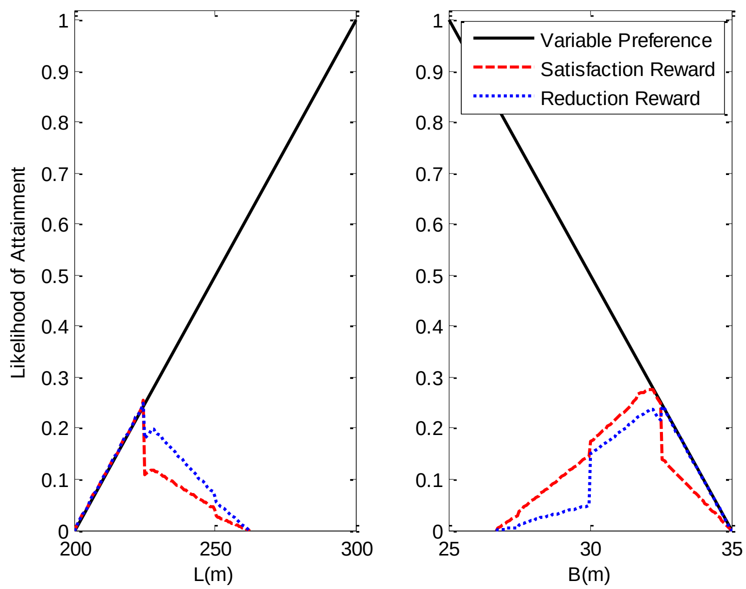


Figure 7.13: Variable Space Robust Path Likelihood of Attainment Curves (Preference Structure 9)

Another study using preference structure 9 was also conducted, which has the opposite structure of 2. The preference changes instituted included a peak length change from right to left, and a peak beam change from left to right. Similar to the previous studies, the likelihood of attainment curves in the function space were close and showed the same trends. Figure 7.14 provides the likelihood of attainment curves in the variable space for the length change instituted in round 4. Similar to the robust path results for preference structures 7, 8, and 9, reduction reward attainment is higher in one variable, while at the same time satisfaction reward attainment is higher in the other, where higher preferences exist. These differences are circled in Figure 7.14. Figure 7.15 provides the likelihood of attainment curves in the variable space for the beam change instituted in round 4. When the change occurs within the non-reduced variable in the reduction reward path, its attainment is higher in both variable regions where higher preferences exist. The areas where reduction reward has higher attainment, also where the higher variable preferences are after the change, are circled in Figure 7.15. This illustrates the situation where the one-sided leaning emphasis reduction reward places lines up with a change scenario that is benefitted.

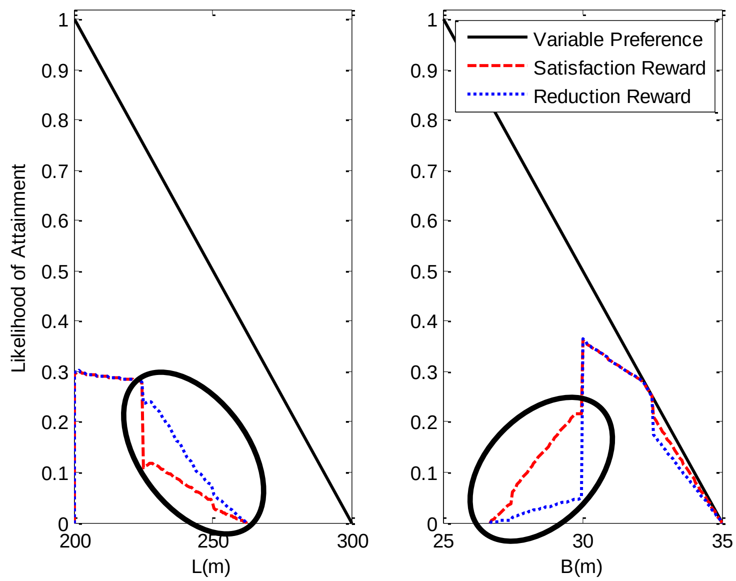


Figure 7.14: Variable Space Likelihood of Attainment Curves (Preference Structure 2 with Length Change)

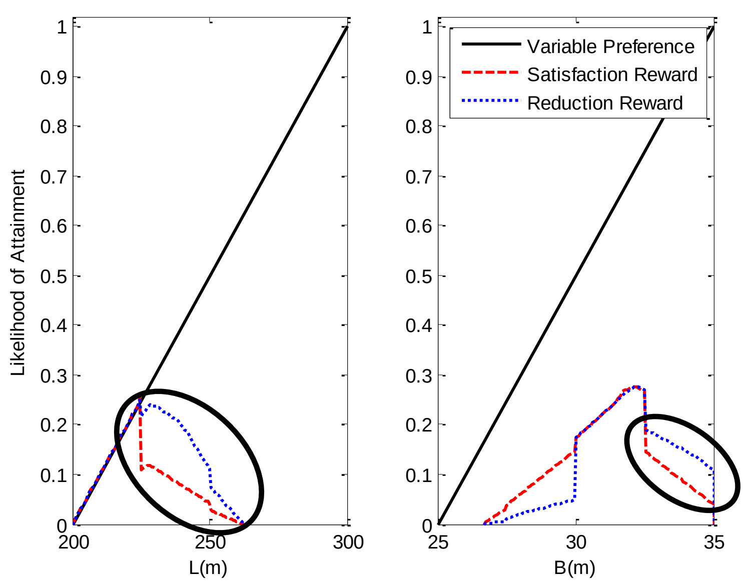


Figure 7.15: Variable Space Likelihood of Attainment Curves (Preference Structure 2 with Beam Change)

When examining the results of the studies from a top-level perspective, there are a number of key observations that can be drawn. Both reward types identified valid reduction paths that resulted in feasible final set-ranges. Also, typical reduction relationships were confirmed using the metrics, including the impact of a change that constrains the design space. The usefulness of using the reward metrics, even though results differ between them, can be seen, particularly in the case of a designer that currently uses a heuristic or clipping reduction method.

More detailed observations include the difference in results between the two reward metrics. First, when the problem is unconstrained, meaning the peak variable preferences align with the preferred function values, both reward metrics produce similar results. If the problem is unconstrained and a constraining change is instituted, the satisfaction reward that considers all variable spaces is either the same or better at attaining higher likelihoods.

For the constrained problems, where the peak variable preferences did not match the function peak preference, the reward metrics identify initial reductions of different variables. The results show that the reward types have higher attainment for opposite variables. However, the lower attainment values associated with reduction reward in beam were relatively smaller when compared to the same satisfaction reward values in length. It is not clear if this would be the case for other functions. Finally, when an unconstrained problem became less constrained by a preference change, the scenario that occurred in the constrained case also occurs for the length change. For the beam change, reduction reward had higher attainment values in both variables, where higher preferences existed. These observations indicate that, in general, for situations where the potential changes are unknown, satisfaction reward is a better choice. Even though reduction reward can be better under specific circumstances, the potential change will never be certain. Therefore, the risk associated with using this metric would be higher. The benefits of using satisfaction reward over reduction reward stems from the fact that information from all variables is being incorporated into the reward calculation.

The results of the studies presented in this section highlight the value of using the DM method in conjunction with the developed metrics. Designers can identify potential reductions associated with meeting specific function values to gain a better understanding of variable/function interactions that would normally have to be done in a designer's head. The studies also observed that the satisfaction reward is able to identify reduction paths that are able to better handle changing conditions associated with the types of design problems considered. The next step in the evaluation process involves a better understanding of the implications associated with using the metrics in combination with the MDP framework.

7.2 Future State Prediction versus In-State Knowledge

The major advantage associated with the use of a SBD MDP framework is the consideration of potential future outcomes. While using the mapping metrics provides additional information to a designer over heuristic or clipping reduction methods, utilizing the combination of the mapping metrics and the MDP framework provides even more insight into the reduction process. In an effort to evaluate the effectiveness of the combined method, a series of studies were completed that compares it against making a decision based solely on the mapping information associated with the current state and epoch. Utilizing the knowledge obtained from the previous section, both unconstrained and constrained initial preference structure problems were evaluated and compared for the two reduction approaches. For this study, the satisfaction reward metric is solely used. The MDP output using the satisfaction reward metric is called the robust path for the analysis presented in this section. These paths were previously calculated when comparing the two reward metrics. The paths based solely on in-state knowledge are defined as current paths for the analysis presented in this section. These paths are determined by calculating the maximum risk-adjusted reward for the current state, which is generated from the mapping results using the initial preference structure of interest.

7.2.1 Unconstrained Scenario

The first initial preference structure considered was the unconstrained case, preference structure 2 defined in the previous section, where lower length values and higher beam values are preferred. Reduction plots for both the robust path and current path for preference structure 2 are provided in Figure 7.16. As seen below, the only major difference occurs in the earlier rounds.

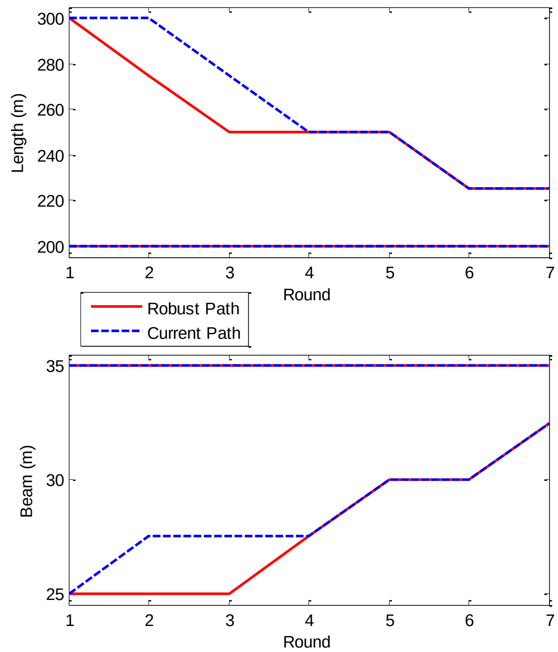


Figure 7.16: Reduction Plots for Initial Preference Structure 2

To better understand the implications of the paths shown in Figure 7.16 for the unconstrained case, the likelihood of attainment curves must be analyzed. Figure 7.17 shows the likelihood of attainment curves for preference structure 2 in the function space. In the function space, the current path has higher attainment values than the robust path. This shows the cost associated with using a robust path over what is believed to be the "best" for the current preference structure. For example, if the variable preferences did not change throughout the entire reduction process, the path identified using current mapping information for the unconstrained problem would produce better results. These results indicate that for an unconstrained problem with no changes, taking a robust reduction path is, in most cases, not required. However, this scenario is rarely the case in real-world design efforts. The results for the unconstrained case also show that different reduction paths, although similar, can produce feasible designs that meet requirements. These results are seen in the detailed experiments discussed in Chapter 5 as well. While a change study can be completed for the unconstrained case, the results under more constrained scenarios are of particular interest.

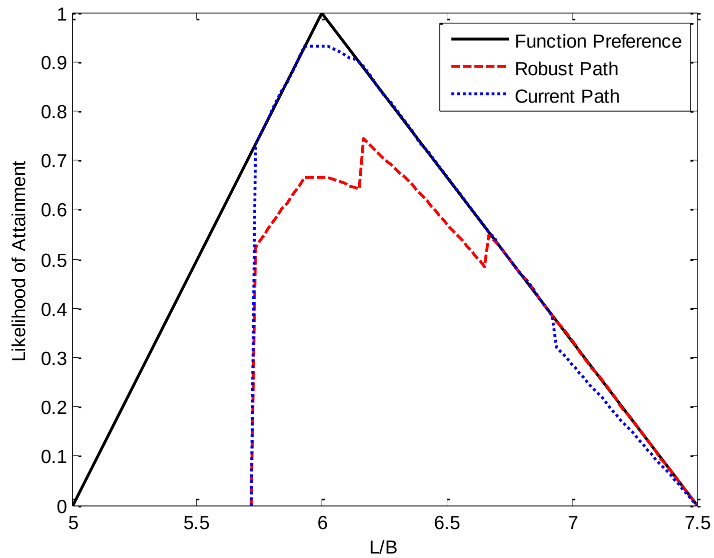


Figure 7.17: Function Space Likelihood of Attainment Curves (Preference Structure 2)

7.2.2 Constrained Scenarios

The next initial preference structure studied was a moderately constrained case, 8, with both variable peaks at the right of the set-ranges. The robust and current reduction paths, provided in Figure 7.18, indicate a larger difference than in the unconstrained case discussed above. Again, both paths conclude in the same regions for both variables, but take significantly different paths to get there.

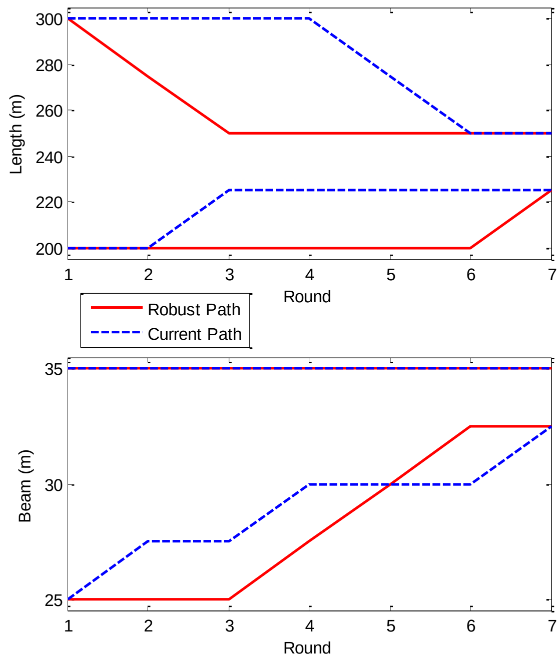


Figure 7.18: Reduction Plots for Initial Preference Structure 8

The likelihood of attainment curves in the function space for preference structure 8 are provided in Figure 7.19. In this case, the current path curve is lower for the highly preferred function values. This indicates that for constrained problems, path dependence does have an impact. Also, the identified robust path was able to handle a more constrained problem than the path based only on current time step information. In contrast to the findings of the detailed experiments, when the problem was more constrained (change in requirement occurred), certain paths were able to handle the situations better than others. Unfortunately, at that time, there was no way to identify which path was better until after the change occurred.

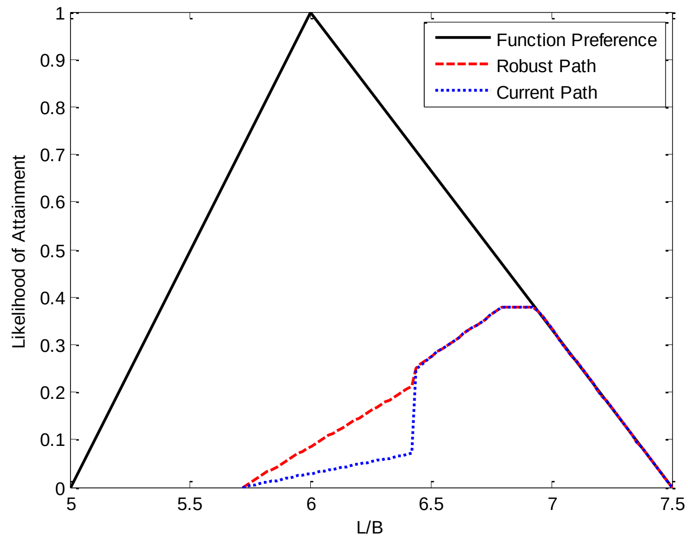


Figure 7.19: Function Space Likelihood of Attainment Curves (Preference Structure 8)

An additional study for preference structure 8 was conducted to identify the impact of a further constraining design change on the attainable function and variable values. During round 5, the beam peak preference was changed from the right to the left of the set-range. Figure 7.25 and Figure 7.26 provide the likelihood of attainment curves for preference structure 8 with a beam change in the function and variable space, respectively. In this case, the attainment values are lower than when a change does not occur. Also, the current path attainment curve is lower than the robust path for most of the function range. In the variable space, the beam attainment values are most affected by taking the current path. This study identifies that the identified robust path is able to handle changes better than the current path.

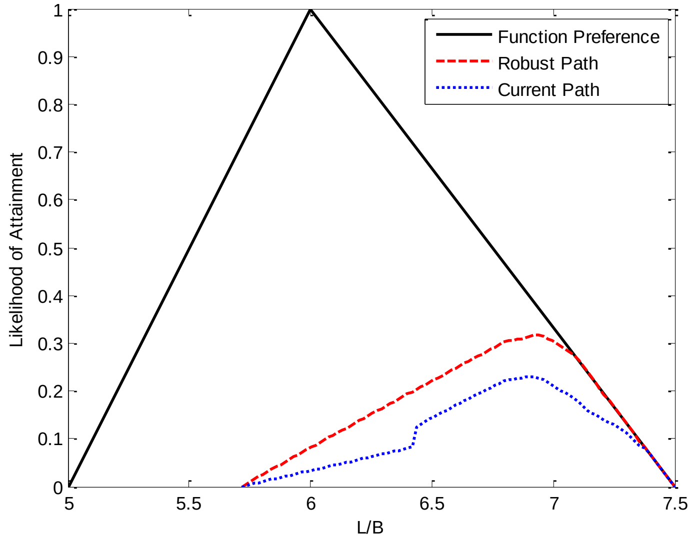


Figure 7.20: Function Space Likelihood of Attainment Curves (Preference Structure 8 with Beam Change)

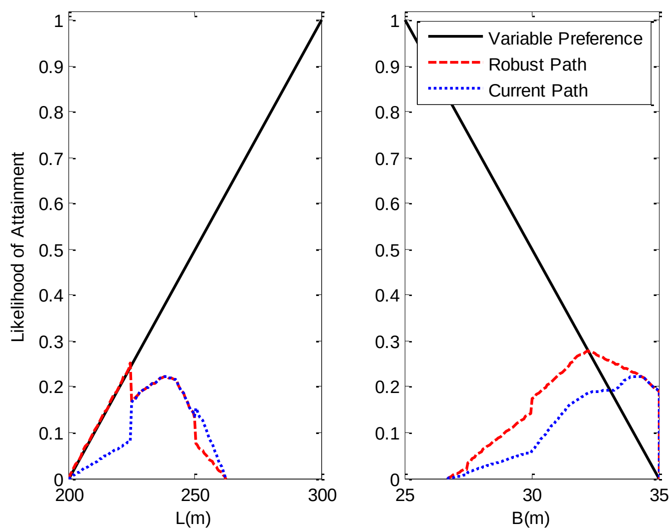


Figure 7.21: Variable Space Likelihood of Attainment Curves (Preference Structure 8 with Beam Change)

The most constrained initial preference structure, 9, with right length peak and left beam peak was evaluated next. For this preference structure, the current path led to an infeasible region in round 6. This means that the combined preference did not overlap with the function preference. In an actual design effort, this would be associated with all currently considered solutions being infeasible. Figure 7.22 provides the reduction paths for this preference structure. The cause of the failure is quite obvious and can be seen in the length reduction plots. The current path continued to reduce lower length values, which are critical for feasibility. With no information about potential futures or the impact of reducing higher length values, the current information continued to lead the design down dead design directions. This can potentially indicate variables that are drivers of function space overlap.

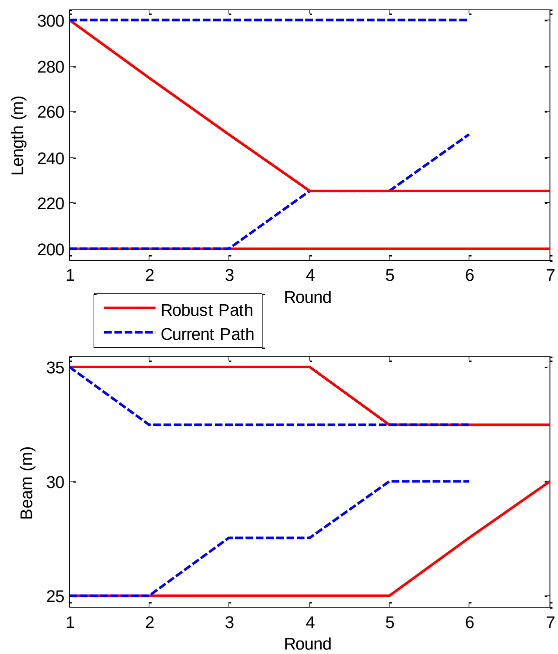


Figure 7.22: Reduction Plots for Initial Preference Structure 9

A comparison of the likelihood of attainment curves up to the point of failure is provided in Figure 7.23. In this scenario, the current path has even lower attainment values for a wider range than preference structure 8. This study shows the importance of accounting for future scenarios when dealing with constrained problems. The likelihood of failure greatly increases when only current information is considered.

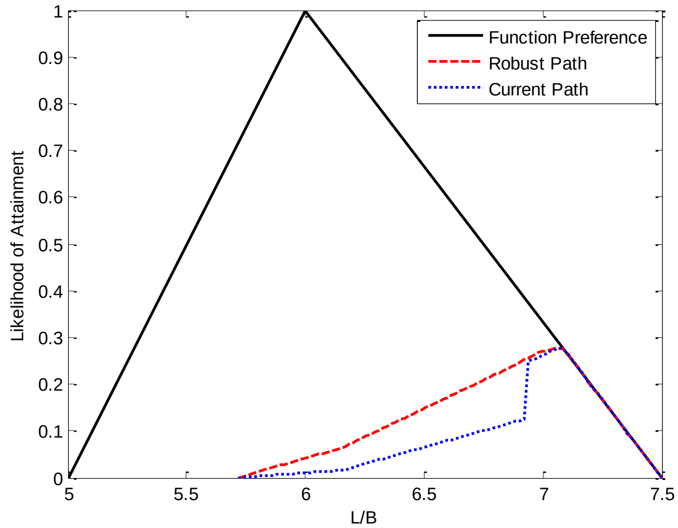


Figure 7.23: Function Space Likelihood of Attainment Curves up to Round 6 (Preference Structure 9)

The results of the studies presented in this section highlight similar observations seen during the detailed experiments presented in Chapter 5. Two observations of note from both sets of experiments is that multiple reduction paths can be successfully taken when the problem is unconstrained, and reduction paths become more important as the problem becomes more constrained. These similarities suggest that the developed metrics, in combination with the MDP framework, properly demonstrate the issues that arise during various types of reduction processes. The detailed experiments also revealed that certain paths are more robust to changes than others. Using the developed metrics with the developed MDP method, the robust paths can now be identified prior to set reduction, as opposed to finding out only after a change is implemented. Gray (2011) provided an alternative approach to dealing with more constrained situations by introducing type-2 fuzzy logic uncertainty modeling, which was discussed in Chapter 4. A natural extension of this work would be combining the work completed by Gray (2011) with identifying a robust reduction path.

7.3 Chapter Summary

Multiple combinations of the developed reduction metrics were evaluated, and two were selected for further analysis. Both metrics identified valid reduction paths that resulted in feasible final set-ranges, and their value was apparent when handling more constrained problems. The satisfaction reward metric was able to manage more situations than the reduction reward, mainly due to the fact that information from all variables is incorporated into the reward calculation. The results of the studies presented in this section highlight the value of using the DM method in conjunction with the developed metrics. Designers can identify potential reductions associated with meeting specific function values to gain a better understanding of variable-function interactions that would normally have to be done in a designer's head. The developed decision support framework is utilized at each negotiation round of a SBD execution so the updated variable preferences, or JOPs, can be included in the analysis.

The other major conclusion drawn from the series of studies is that the developed framework is able to identify robust reduction paths that can handle constrained problems and changing preferences. When compared to a method that only uses current in-state knowledge, the developed framework was able to attain a wider range of both function and variable values. The results of the studies also highlight similar observations from the detailed experiments presented in Chapter 5. These similarities suggest that the developed metrics, in combination with the MDP formulation, properly demonstrate the issues that arise during various types of reduction processes. Additionally, instead of using lag indicators, such as set reduction failures to identify poor reduction paths, the developed framework can be used as a lead indicator to provide the designer with information regarding future outcomes before reduction decisions need to be made.

Chapter Citations

1. McKenney, T. A., Gray, A. W., Madrid, C., & Singer, D.J. (2012, October-December). The Use of a Fuzzy Logic Set-Based Design Tool to Evaluate Varying Complexities of Late-Stage Design Changes. *Transactions of the Royal Institution of Naval Architects Part A: International Journal of Maritime Engineering*, 154(A4), pp. 179-189.
2. Gray, A.W., & Singer, D. J. (2011, October 25-27). *Applied Set-Based Communications and Negotiation System*. Paper presented at ASNE Human Systems Integration Symposium, Vienna, VA.
3. Singer, D. J. (2003). *A Hybrid Agent Approach for Set-Based Conceptual Ship Design Through the Use of a Fuzzy Logic Agent to Facilitate Communications and Negotiation*. (Doctoral dissertation). University of Michigan, Ann Arbor.

Chapter 8: Reduction Demonstration

The developed decision support framework aids a designer in making reduction decisions within a SBD environment. This framework was specifically developed for chief engineers or design managers to understand the implications associated with variable preferences (JOPs) provided by functional design groups. During each SBD negotiation round, variable preferences, which are based on analysis completed by the functional design groups, are provided to the chief engineer. The chief engineer then uses the developed framework to gain a better understanding of reduction decisions associated with the current design effort. Using its results, the chief engineer makes a reduction decision. The updated variable set-ranges are then communicated to the functional design groups and the process begins again using the reduced set-ranges.

When utilizing the developed framework, the chief engineer must select one or more functions of interest. The specific functions and the reasoning for their selection can vary widely. So far in this dissertation, the length-to-beam ratio has been used to illustrate the developed methods and conduct comparative studies. To demonstrate the use of the decision support framework with more complicated functions, this chapter presents a ship design case study. More than one function is also considered to describe the multi-function interpretation process. The case study focuses on a basic container ship design. Details of the case study formulation and the selected functions are first discussed, followed by a complete reduction demonstration using the developed decision support framework.

8.1 Container Ship Design Case Study

This section presents the formulation of the container ship design case study. First, the functions of interest are selected. Next, the required inputs, outlined by the execution strategy presented in Chapter6, are provided for the case study.

8.1.1 Functions of Interest

The first step was selecting functions of interest. One type of function that a chief engineer would be interested in is one that has not been calculated by any of the functional design groups during their analyses. This would allow the chief engineer to gain additional insight about the design that is not captured by the functional design groups in their provided preferences. For the SSC SBD execution, these types of functions were called craft level impact equations, and included functions such as cost. For the case study, a function was developed based on regression analysis using historical container ship data. Analysis using the developed framework would indicate to the chief engineer if the design solutions are similar to those of previous efforts. The database used for the regression analysis included data for 82 ships and was obtained as a part of the NA 470 Ship Design course materials at the University of Michigan. Table 8.1 shows the minimum and maximum values of the provided ship characteristics, which included deadweight (DWT), length between perpendiculars (LBP), beam (B), depth (D), and speed (V_k). Based on the table values, it can be seen that this database included mainly smaller ships, compared to the more modern container ships currently being built. The database entries are provided in the Appendix.

Table 8.1: Minimum and Maximum Design Values in Container Ship Database

	DWT (T)	LBP (m)	B (m)	D (m)	Speed (kt)
Minimum	2,800	84.7	13.2	5.6	12.5
Maximum	83,826	302.3	42.8	24.4	26.3

Based on the available data and typical considerations made during a container ship design, speed was selected as the first function of interest for the chief engineer. A ship's speed is based on many aspects of the design, but can be correlated with basic ship characteristics, such as the ones provided in the database. An equation for speed as a function of *DWT*, *LBP*, *B*, and *D* (defined variables) was calculated based on regression analysis of the container ship data. The most rigorous method to obtain a regression equation for speed as a function of the defined variables would be to develop a multiple regression model. For this case study, a simplified approach is taken, as focus is on the development of a more complicated function, not the most accurate regression model for the given data.

The simplified approach uses a combination of single regression equations to approximate the speed for given variable values. This approach has been used in situations where raw data is not available, but the associated regression equations are. A polynomial curve with degree two was fit to the data points associated with the function and each variable. For example, one curve fit was calculated for the relationship between speed and length. A total of four polynomial curves and associated equations were calculated: one for each relationship between a function and variable. To link these four relationships together, an average of all four individual calculations for the function was taken. A single equation for the speed function was then determined as a function of the four variables. Equation 8.1 is the developed speed regression function.

$$V_k = -0.000175B^2 + 0.11515B + 0.0006D^2 + 0.13495D - \frac{LBP^2}{50{,}000} + 0.0201LBP - \frac{DWT^2}{2{,}000{,}000{,}000} + 0.000075DWT + 9.89023 \tag{8.1}$$

After the function is defined, ensuring that function inverses can be calculated is the next step. The inverses are used for the backward calculation of the overall preference in the function space to the individual variable spaces using the DM method. While direct inverses of the equation above can be found, the inverse cannot be calculated for every value and execution times are relatively longer compared to the forward calculation. An alternative approach for this problem is to develop an approximation method for the inverse calculations using additional regression analysis. Instead of calculating polynomial fit equations for the function, equations can be determined by solving for each variable and its relationships with the other variables and the function. An equation representing the average these regressions for each variable is determined. These equations are provided in the Appendix. While this method does not provided an exact inverse of the function equations provided earlier, the equations provide close estimates and substantially faster execution time.

In addition to the speed function, three other functions were selected: LBP/B, B/D, and LBP/D. Each ratio is used by designers at the early stages of design to gain some initial insight on a different design issue. There are also general guidelines for what these ratios should be, which can be used to develop the function preference. Typically, these ratios are considered constraints in engineering analysis completed by functional design groups. Using these three functions, a chief engineer can validate that these constraints. Validation can be completed by checking if the variable preferences, when combined for a particular constraint function, produce the desired results. A better understanding of the risks associated with the constraint can also be determined.

The length-to-beam ratio (LBP/B) affects both the powering and directional stability. Directional stability is equivalent to maneuvering or the ability to turn. Smaller ratio values increase the required powering and directional stability. In an effort to reduce cost, the ratio can be made smaller by increasing the beam. For container ships, larger beams are also able to hold more cargo. In order to ensure proper inflow to the propeller with the larger beams, Watson and Gilfillan (1977) recommend the ratio be between 5 and 7 for the types of ships considered in the case study. Typical values for container ships are around 6.25 (Watson, 1998).

The beam-to-depth ratio (B/D) mainly affects stability. Transverse stability is a function of both the buoyancy, which beam has an impact on, and the vertical center of gravity, which depth has an impact on. Similar to the beam-to-draft ratio, smaller ratio values result in less stability. Container ships typically have ratios around 1.7. It is not recommended to go below a ratio of 1.55 (Watson, 1998).

The length-to-depth ratio (LBP/D) is a primary factor in determining longitudinal strength. The higher the value, the longer and more slender the structure is. This means that higher ratios are associated with more required longitudinal strength. Container ships typically have a ratio around 10.6. Special consideration by classification societies is generally required for ratios greater than 15 (Watson, 1998).

8.1.2 Problem Formulation

After identifying the four functions and their associated variables, the remaining inputs to the decision support framework are required. Referring back to Figure 6.2, which presents the execution strategy of the framework, these inputs can be identified for the container ship case study. The required inputs include:

- Variables and associated set-ranges,
- Number of set-range partitions for each variable,
- Function,
- Function preferences,
- Variable preferences,
- Simulation variation strategy (how preference structures vary), and
- Type of reward.

Initial set-ranges for the variables must also be determined. The selected functions have a total of four variables in common (*DWT*, *LBP*, *B*, and *D*). Table 8.2 provides the variable set-range values used for the case study. The variable set-ranges were selected based on their associated ranges in the database.

Table 8.2: Variable Set-Range Values

	DWT (T)	**LBP (m)**	**B (m)**	**D (m)**
Min	10,000	100	15	10
Max	80,000	300	40	20

The next required value is the number of partitions for each variable. It is assumed that all variables start with two partitions. This effectively sets the goal of the reduction process to reduce half of each variable's initial set-range. Due to the use of the single reduction scenario, the developed framework aids in selecting the order that the variables are reduced. The number of partitions for a variable that is reduced lowers by one. This approach is assumed to keep the partition set-ranges the same throughout the reduction process.

Next, the function preferences can be defined. For this case study, the function preferences remain the same throughout the reduction process. For speed, the function preference can describe the desired speed values, or speed requirement expressed as a preference function. Figure 8.1 shows the assumed speed function preference used in the case study. The preferred speed range is at the higher end of the ship data values provided in the database.

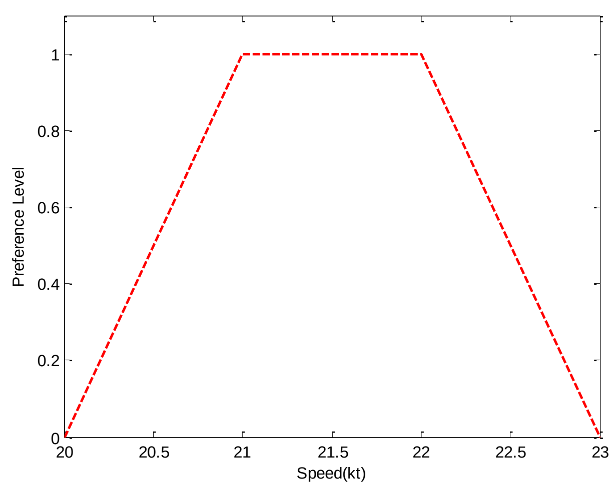


Figure 8.1: Speed Function Preference

The function preference for the three ratio functions can be developed based on the guidelines provided in the previous section. Function preferences for the length-to-beam, beam-to-depth, and length-to-depth ratios are provided in Figure 8.2, Figure 8.3, and Figure 8.4, respectively.

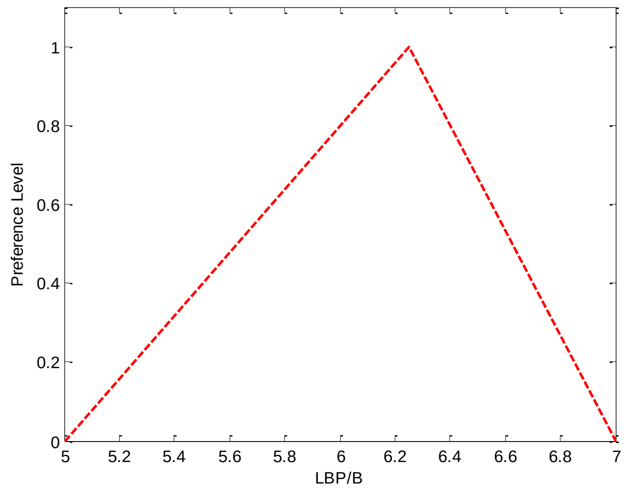


Figure 8.2: Length-to-Beam Function Preference

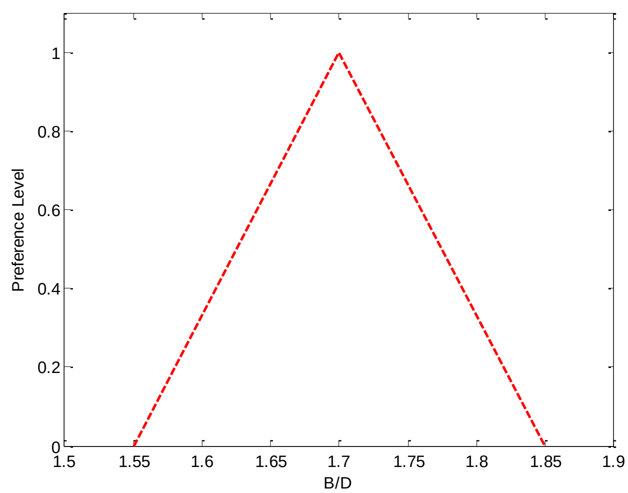


Figure 8.3: Beam-to-Depth Function Preference

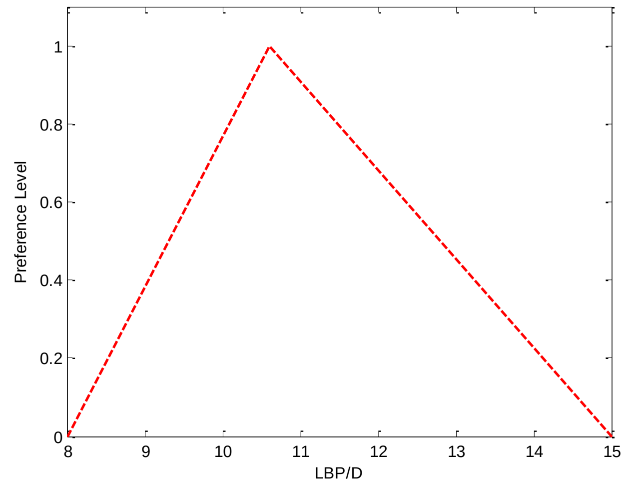


Figure 8.4: Length-to-Depth Function Preference

The generation of variable preferences for the case study can be discussed as well. One of the assumptions associated with the work presented in this dissertation is that JOPs for the negotiated variables have already been determined for a given negotiation round. While assumed initial preferences can be used to conduct studies such as the ones presented in the previous chapter, realistic preferences for case studies are preferred. The variable preferences for the container ship case study are based on trends identified through engineering analysis completed for a single functional design component. This analysis is used to simulate the work completed to develop JOPs. The design component considered is powering, which calculates the resistance using speed, variable values, and approximated or assumed parameters. The main goal of the powering component is to minimize the resistance while meeting the desired speed values.

The method used for the powering calculations was developed by Hollenbach (1999) for single screw vessels. The draft for the calculations was approximated as $0.65D$, and the block coefficient was calculated using the deadweight and principal dimensions. The ranges of the three ratios introduced earlier were also used as guidelines when generating the variable preferences. For example, a variable value that did not meet the ratio ranges for any combination of the other variables was assigned a preference level of zero. Using the Hollenbach method, various combinations of variable values were used to calculate the resistance. Under the triangular preference function assumption, the preferences are mainly able to describe identified trends. Also, the preferences are modified downward for areas where the ratio constraints were active. The variable preferences associated with the negotiation rounds are provided in Section 8.3.

While most aspects of the case study are representative of how a typical SBD reduction effort is conducted, there is an important difference that should be made clear. As mentioned in Chapter 2, the increase in the fidelity of analysis as set-ranges are reduced is crucial to the success of a SBD effort. The dynamics associated with fidelity increases are simulated by the changing variable preferences as reduction decisions are made during the demonstration.

Finally, the simulation variation strategy, including the number of preference variation combinations, are defined. For the case study, a total of three variations for each variable is considered (peak at the lower bound, middle, and upper bound). This variation strategy dictates a total of 81 simulations. This total number of simulations is calculated by taking the number of variations (3) to the power of the number of variables (4) to equal 3^4=81. Also, the satisfaction reward metric is used to calculate the risk-adjusted rewards.

8.2 Initial Understanding

Before initial variable preferences are provided, the decision support framework provides a chief engineer with certain pre-reduction indicators. As described in Chapter 6, optimal strategies given potential initial preferences are determined before the set reduction effort begins. The initial preference structures are varied to identify their impact on the optimal policy. All future state preferences are based on the assumed initial preference structure for a given simulation. Utilizing a triangular preference shape for variable preferences associated with the speed function, the peak variable preference values can be linked to the optimal policy associated with that preference structure. Unlike the length-to-beam example problem presented in the previous chapter, there are four variables. This means that when two variables are being compared, there are multiple combinations of the other variable values for the given two variables of interest. To simplify the results, the optimal strategies for all combinations are calculated and the one with the most occurrences is plotted on the table. Due to there being four variables, a total of six optimal strategy tables are generated. The optimal strategy tables for the speed function during epoch 1 are provided in Table 8.3.

Table 8.3: Optimal Strategy Given Peak Preferences for Speed (Epoch 1)

		Peak LBP Preference (m)		
		100	200	300
Peak DWT Preference (T)	10,000	3	3	28
	45,000	3	3	3
	80,000	3	3	3

		Peak B Preference (m)		
		15	27.5	40
Peak LBP Preference (m)	100	3	3	3
	200	3	3	3
	300	3	3	3

		Peak B Preference (m)		
		15	27.5	40
Peak DWT Preference (T)	10,000	3	3	3
	45,000	3	3	3
	80,000	3	3	3

		Peak D Preference (m)		
		10	15	20
Peak LBP Preference (m)	100	3	3	3
	200	3	3	3
	300	28	3	3

		Peak D Preference (m)		
		10	15	20
Peak DWT Preference (T)	10,000	3	3	3
	45,000	28	3	3
	80,000	3	3	3

		Peak D Preference (m)		
		10	15	20
Peak B Preference (m)	15	3	3	3
	27.5	3	3	3
	40	3	3	3

It can be seen in Table 8.3 that for most combinations of variable peak values, the optimal action is to reduce to State 3 in epoch 1. State 3 is associated with a reduction of DWT values from 45,000 to 80,000. For certain combinations, the optimal action is to move to State 28. State 28 is associated with a reduction of D values from 10 to 15. It is important to note, however, that some of these peak combinations are not realistic from a ship design perspective. For example, when the peaks are at $DWT = 10{,}000$ and $LBP = 300$ or at $LBP = 300$ and $D = 10$. When the variable preferences are provided and other functions considered, these combinations would be eliminated from consideration.

The optimal strategy tables can also be generated for the three ratios introduced in the previous section. Table 8.4 provides the tables for all three ratios. It is important to note that the state numbers in the tables are *not* the same between tables. This is also true when comparing these tables to the speed optimal strategy table. For example, State 3 for the length-to-beam ratio is a reduction of length values from 200 to300. State 3 for the beam-to-depth ratio is a reduction of beam values from 27.5 to 40. The ratio optimal strategy tables can identify where certain variable peak preferences are associated with a single path or various paths. It can be seen that high beam and depth preferences lead to different strategies with respect to length. The same is true for depth with respect to beam.

Table 8.4: Optimal Strategy Given Peak Preferences for Ratios (Epoch 1)

LBP/B		**Peak B Preference (m)**		
		15	**27.5**	**40**
Peak LBP Preference (m)	**100**	3	3	2
	200	3	3	4
	300	3	3	4

B/D		**Peak D Preference (m)**		
		10	**15**	**20**
Peak B Preference (m)	**15**	3	7	2
	28	3	3	2
	40	3	3	4

LBP/D		**Peak D Preference (m)**		
		10	**15**	**20**
Peak LBP Preference (m)	**100**	3	7	3
	200	3	3	4
	300	3	3	4

The optimal strategy tables provide the chief engineer with a better understanding of the relationships between variables for a particular function. This is valuable during the pre-reduction stage of design to gain initial insight into the relationship between potential variable preference peaks and reduction decisions.

8.3 Reduction Demonstration

While the identified optimal strategies can provide an initial and basic understanding of the problem, it does not provide direct guidance on set-reduction decisions for design efforts with variable preferences provided. This section provides a demonstration of the reduction process for the container ship case study, using updated variable preferences at each negotiation round. First, the structure of the reduction process for the given functions is presented. The method used to generate variable preferences at each negotiation round is then discussed. Next, each negotiation round is reviewed individually, including the rationale for the selected reduction decision. An evaluation of the final reduction path is also provided using likelihood of attainment curves.

8.3.1 Reduction Graph Structures

Before the reduction process can be initiated, the function graph structures are generated to identify the acceptable decision paths. The graph structures associated with functions are different depending on the number of variables and partitions. As presented earlier, two partitions for each variable are used for all functions. This mean that for the speed function, there are more potential reduction decisions, therefore, more nodes in the graph structure. The initial graph structures are automatically generated using the developed method outlined in the Chapter 6. The graph structure for the speed function is provided in Figure 8.5. The graph structure for the ratio functions is provided in Figure 8.6. The speed graph structure has a total of 82 nodes, including the artificial terminal node. It can be seen that there are eight potential actions that can be made in the first epoch. Each is associated with a reduced region of a particular variable set-range. The ratio graph structures have a total of 10 nodes, including the artificial terminal node. The variable set-ranges associated with the state numbers in the figures below, as well as all future graph structures, are provided in the Appendix.

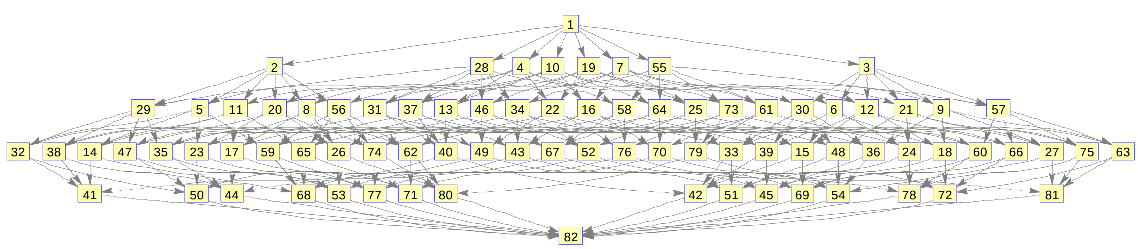


Figure 8.5: Initial Speed Graph Structure

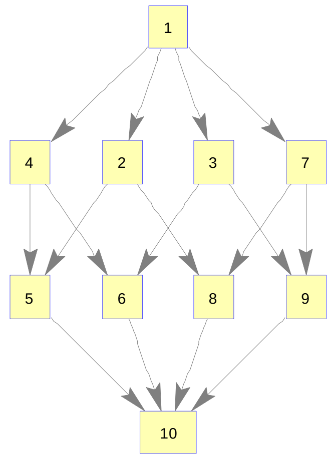


Figure 8.6: Initial Ratio Graph Structure

A total of four negotiation rounds are required to reduce the variables. After four rounds, all four variable set-ranges will be reduced in half. Which halves of the set-ranges that are reduced are based on the analysis completed using the developed method. After each negotiation round when a reduction decision has been made, a branch of certain graph structures is followed and a modified graph structure is created. The graph structure for a particular function does not necessarily have to change every negotiation round, however. This is because not every function has all the variables in them. For example, if a reduction in beam is selected, the graph structure for the length-to-depth ratio remains unchanged. This situation highlights the importance of understanding the relationships between states of different graph structures, which is discussed during the reduction process described in the next section.

8.3.2 Reduction Round Analysis and Decisions

This section discusses each negotiation round individually and provides the justification for making the selected reduction decision.

8.3.2.1 Negotiation Round One

Using the variable set-ranges from Table 8.2 and the initial variable preferences generated from the powering analysis, the developed method can be used to complete reduction analysis for the identified functions. Round one variable preferences are provided in Figure 8.7. The trends do make intuitive sense from a naval architecture viewpoint. For example, larger deadweight, beam, and depth values increase resistance. Larger length values are preferred because they reduce resistance. It can be seen that the preferences for length and beam are both cut off at certain values. These points are associated with values that do not meet the specified ratio ranges for any variable combination. These being active constraints, a penalty is place on being at these ends, even though these values are more preferred based on the identified trends.

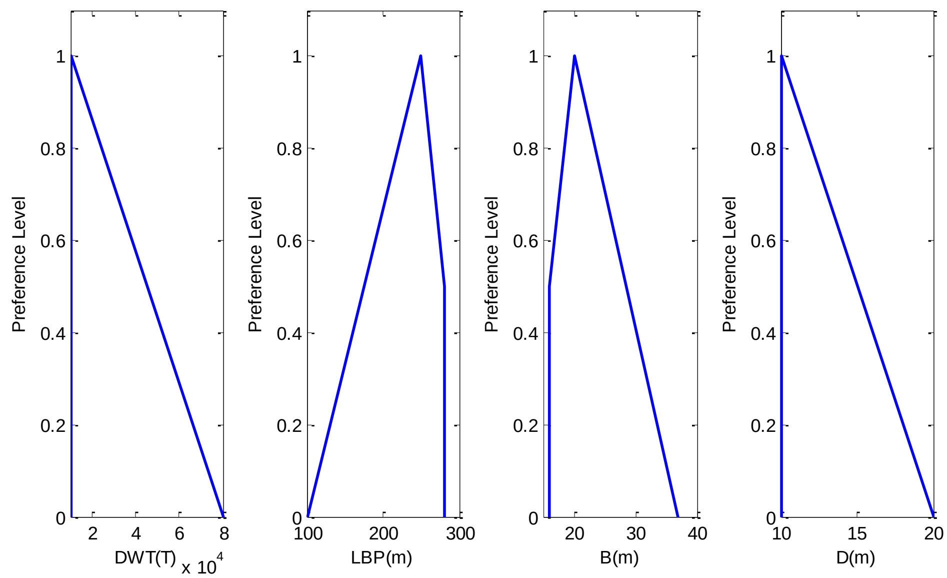


Figure 8.7: Round One Variable Preferences

The developed method was used to analyze each of the four functions individually to identify robust reduction decisions from each perspective. In an effort to more easily compare reduction decisions between functions, a new notation scheme was instituted. An example of the scheme for a reduction of deadweight between 10,000 and 45,000 (the lower region of the set-range) would be DWT/L. The letter before the forward slash describes the variable being reduced and the letter after describes the region being reduced. For this two partition problem, L is used to describe the lower region of a set-range, and U is used to describe the upper region of a set-range.

The key piece of information that should be analyzed first when dealing with multiple functions is the percentage optimal values from the simulations. As described in Chapter

6, the optimal percentages, or robustness values, are the percentages that a given path or reduction decision is optimal for the simulations. A percentage of 1 would mean that the given reduction decision, or path, was optimal for all simulations, or variations of the initial variable preference structures. The results can be summarized and presented in a table, provided in Table 8.5 for the first negotiation round. The reductions are presented using the scheme described above. The first line describes the optimality of reducing the upper region of the deadweight variable for all functions. For the speed function, this reduction decision was optimal 93% of the simulations, but is 0% for all the other functions because deadweight is not a variable in those functions. Table 8.5 provides the designer with a limited number of reduction decisions deemed the best, based on the developed method and a description of the robustness associated with each decision.

Table 8.5: Round One Robust Reduction Decisions

Reduction	**Speed**	**L/B**	**B/D**	**L/D**
DWT/U	0.93	0	0	0
L/L	0	0.11	0	0.11
L/U	0.01	0.44	0	0.33
B/L	0.02	0.11	0	0
B/U	0	0.33	0.67	0
D/L	0.04	0	0	0
D/U	0.01	0	0.33	0.56

The value in Table 8.5 that stands out is the percentage associated with the DWT/U decision for the speed function. This is a relatively high value that identifies this reduction as a safe decision. Also, the deadweight variable is only in the speed function; therefore, a reduction in deadweight would not affect any of the other functions. The three-dimensional decision path output with the top two optimal policies can be used to gain further insight into the speed function decision paths. This graph is provided in Figure 8.8. Again, the black lines are associated with the top two optimal paths. It can be seen that these two paths are similar, except for the final states before the artificial terminal node. This further demonstrates the robustness associated with the DWT/U reduction decision.

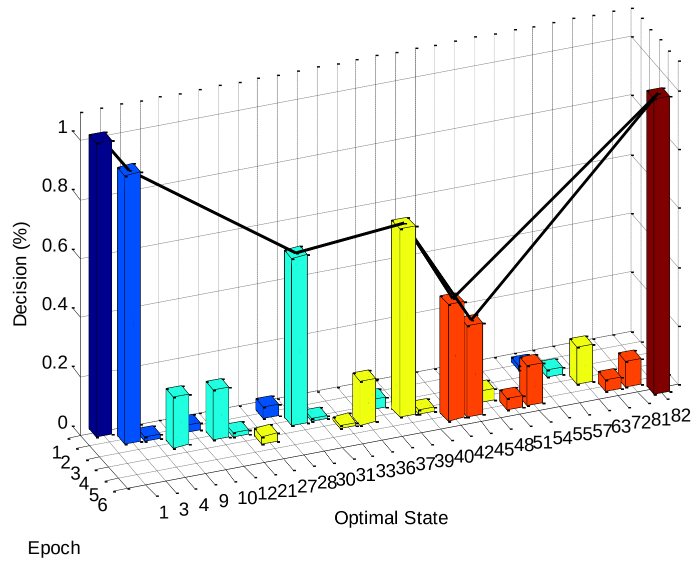


Figure 8.8: Three-Dimensional Decision Path Output of Speed Function in Round One

For the first round of negotiation, the decision to reduce deadweight values between 45,000 and 80,000 was made. This decision was based on the optimal percentage information in Table 8.5, as well as further investigation of the speed function using decision path outputs.

8.3.2.2 Negotiation Round Two

Variable preferences did not change much compared to round one, mainly because of deadweight only being part of the speed function. Also, the same trends were identified through additional powering calculations for the updated set-ranges. Figure 8.9 provides the variable preferences for negotiation round two.

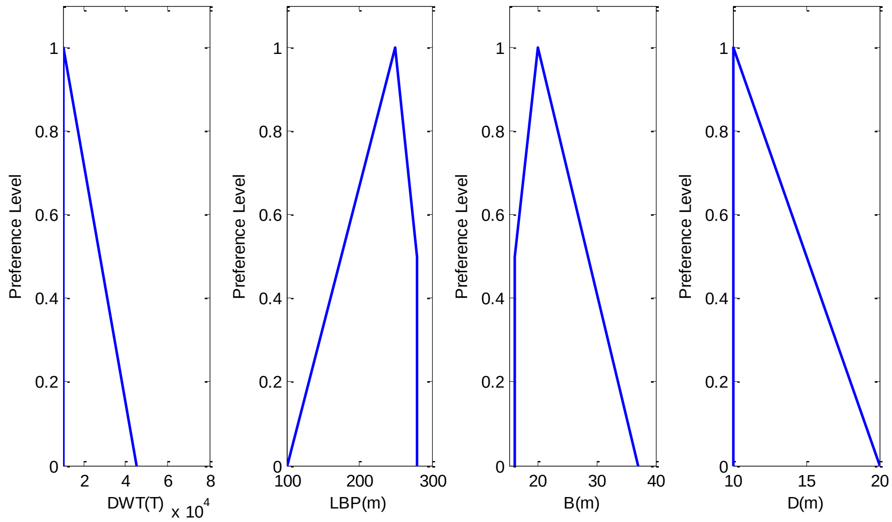


Figure 8.9: Round Two Variable Preferences

The updated graph structure associated with the speed function is provided in Figure 8.10. The graph structures for the ratio functions remain unchanged. Also, the results from round one for the ratio functions can be reused, because none of their variables were reduced. In a more realistic SBD environment, the preferences for the variables not reduced could change between rounds, even if their set-ranges are not reduced. This could be due to a fidelity of analysis increase, or a design relationship with the reduced variable that changes functional design group's perspectives.

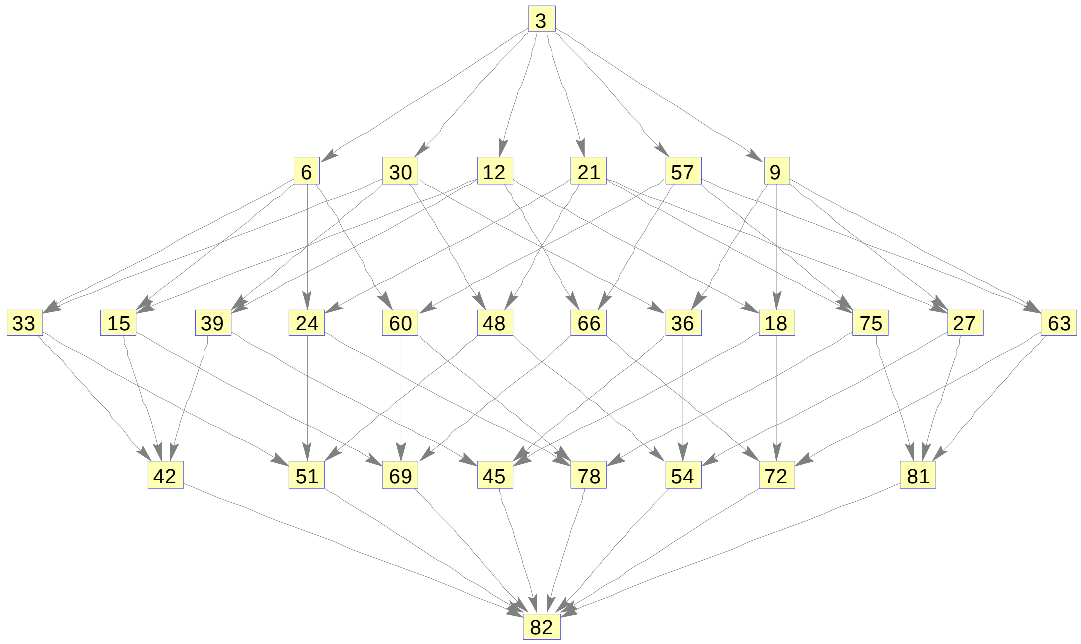


Figure 8.10: Speed Round Two Graph Structure

The developed method was used to analyze the updated speed function problem to identify new potential robust reduction decisions. A robust reduction decision summary table similar to round one can be generated, which is provided in Table 8.6. It can be seen that the columns for the ratios have remained the same. The optimal percentages for the speed function have changed, however, and the results are not as easy to interpret as in round one. For this type of situation, the multi-objective representations, presented in Chapter 6, can be helpful.

Table 8.6: Round Two Robust Reduction Decisions

Reduction	**Speed**	**L/B**	**B/D**	**L/D**
L/L	0.19	0.11	0	0.11
L/U	0.16	0.44	0	0.33
B/L	0.09	0.11	0	0
B/U	0.11	0.33	0.67	0
D/L	0.30	0	0	0
D/U	0.16	0	0.33	0.56

The robustness results provided in Table 8.6 can be graphically shown by comparing reduction decision robustness values for two functions at a time. A Pareto front of reduction decisions can then be identified for the given two functions. Figure 8.11 provides the reduction decision robustness values for the speed and L/B functions, Figure 8.12 provides the robustness values for the speed and B/D functions, and Figure 8.13 provides the robustness values for speed and L/D For speed and L/B, the Pareto front consists of the D/L, L/L, and L/U reductions. For speed and B/D, the Pareto front consists of D/L, D/U, and B/U. Finally, the Pareto front for speed and L/D consists of D/L, L/L, and D/U. Through the identification of the Pareto front points, it can be seen that there are conflicting reduction decisions for the depth and length variables. This means that from certain perspectives, the lower region of a variable is along the Pareto front, while from another perspective, the upper region is along the Pareto front. However, the beam variable only has a single reduction decision, which is reduce the upper beam region. Also, referring back to Table 8.6, it can be seen that the B/U reduction has consistently high robustness values for most of the functions.

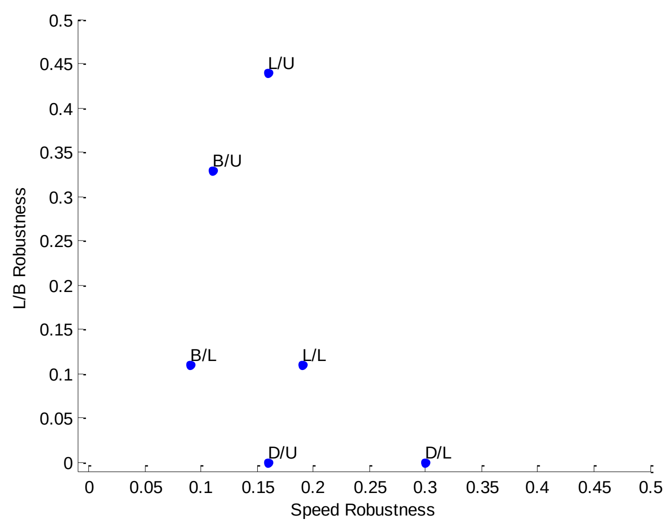


Figure 8.11: Reduction Decision Robustness for Speed and L/B

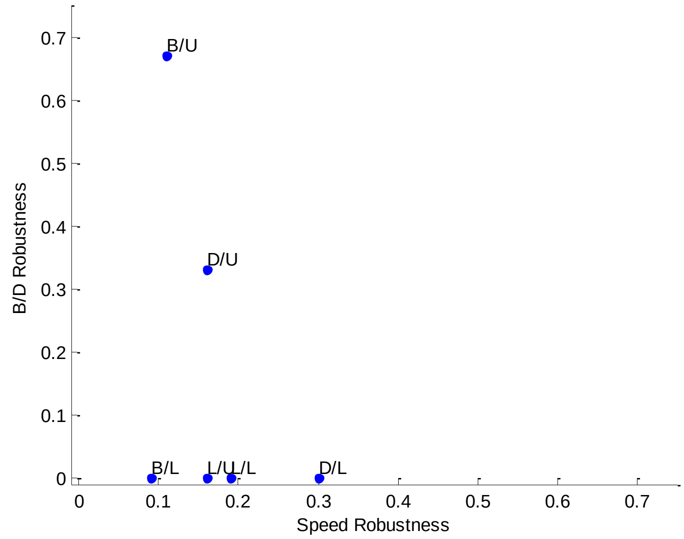


Figure 8.12: Reduction Decision Robustness for Speed and B/D

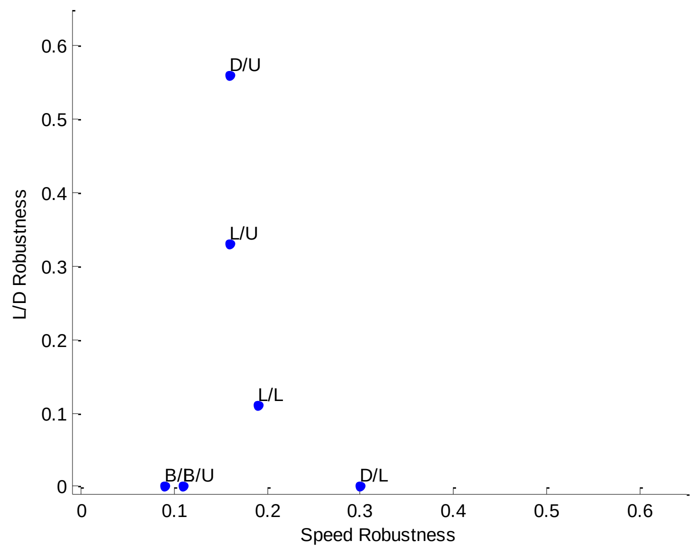


Figure 8.13: Reduction Decision Robustness for Speed and L/D

To further explore the beam reduction decisions, multi-objective likelihood of attainment contour plots can be generated and compared. Two reduction decisions, B/U and B/L, are compared from the speed and L/B perspective. The optimal path with the highest reward associated with each reduction decision was selected to plot. Figure 8.14 provides the multi-objective contour plot for these two reduction decisions. It can be seen that the shapes of the contour plots are similar, but the B/U reduction decision has higher attainment values for most of the plot. A significant increase in preference for the B/U reduction decision occurs around 22.5 knots, which is where the improvement in robustness can be attributed to.

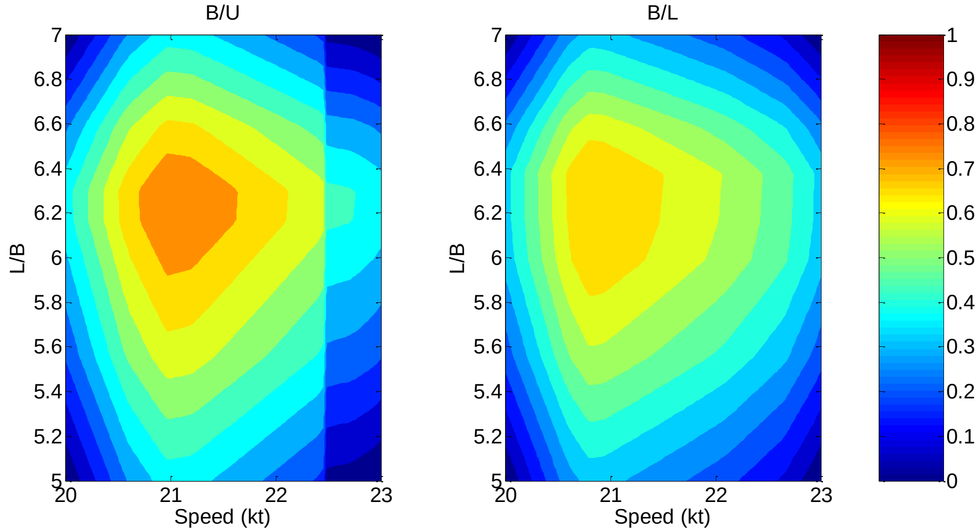


Figure 8.14: Speed and L/B Likelihood of Attainment Contour Plots for B/U and B/L

For the second round of negotiation, the decision to reduce beam values between 27.5 and 40 was made. This decision was based on the relatively low risk associated with the decision. While other reductions had higher robustness values from certain perspectives, the B/U reduction decision had moderate robustness for three of the functions, and no conflicts with the B/L reduction decision, unlike the other two remaining variables. While the B/U decision had high robustness values for the B/D and L/B ratios, it was relatively low for the speed function. It is important to note, however, that the reduction decision with highest robustness for the speed function had zero robustness in all the other ratios. When dealing with multiple functions, there are tradeoffs that a designer must understand and interpret. The final reduction decision is placed in the hands of the designer, with the aid of the results provided by the developed method.

8.3.2.3 Negotiation Round Three

After the beam reduction made during round two, powering analysis revealed that to remain within the ratio ranges, particularly L/B, the length values had to remain below 192. There was also a restriction on higher depth values. The variable preferences for round three are provided in Figure 8.15.

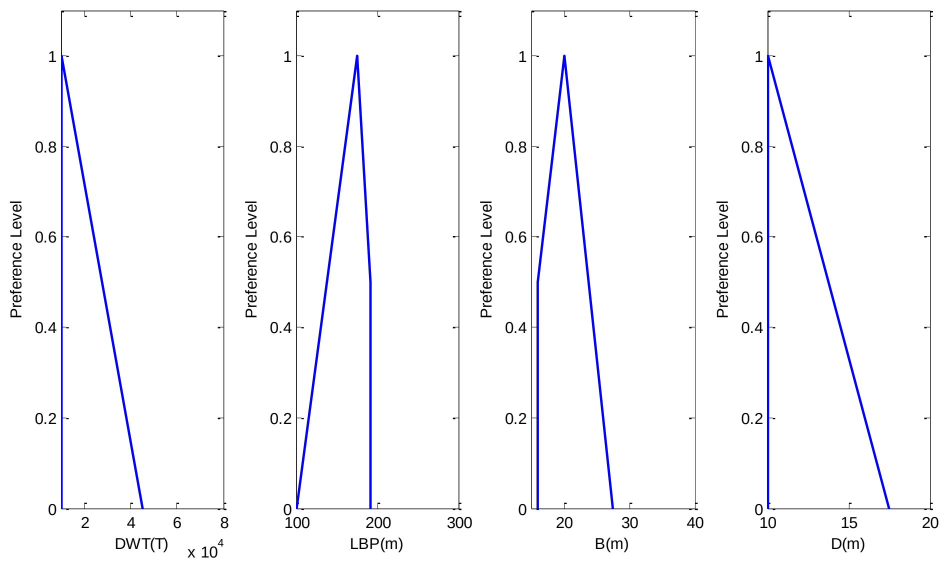


Figure 8.15: Round Three Variable Preferences

The graph structures for the speed, L/B, and B/D functions were also updated, while the L/D graph structure remained the same. Figure 8.16 provides the updated speed graph structure and Figure 8.17 provides the graph structure associated with the L/B function.

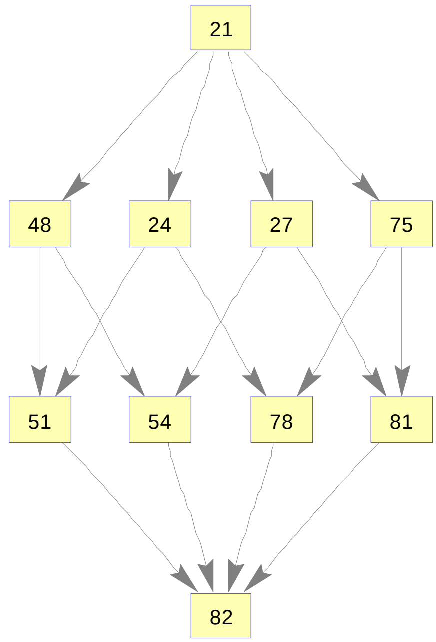


Figure 8.16: Speed Round Three Graph Structure

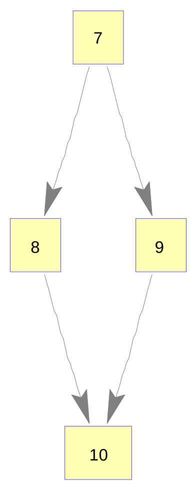


Figure 8.17: L/B Round Three Graph Structure

Similar to the previous two rounds, the robustness values associated with the remaining reduction decisions can be determined, which are provided in Table 8.7. It can be seen that the L/U reduction decision has the highest robustness values for the functions, with length as a variable. Also, there are no conflicting decisions associated with length, as seen for depth. Without conducting further analysis, the decision to reduce the upper region of the length set-range can be made. This reduction decision is associated with reducing length values between 200 and 300.

Table 8.7: Round Three Robust Reduction Decisions

Reduction	**Speed**	**L/B**	**B/D**	**L/D**
L/U	0.84	1	0	0.78
D/L	0.04	0	0	0
D/U	0.12	0	1	0.22

8.3.2.4 Negotiation Round Four

The final round of negotiation deals with the final variable reduction, which based on the previous reduction decisions is the depth variable. The updated variable preferences for round four are provided in Figure 8.18. Most variable preferences remained the same. The major difference is a change in the depth preference back to larger values. This was caused by the length reduction made in the previous round. The L/D ratio no longer is restricting the higher depth values.

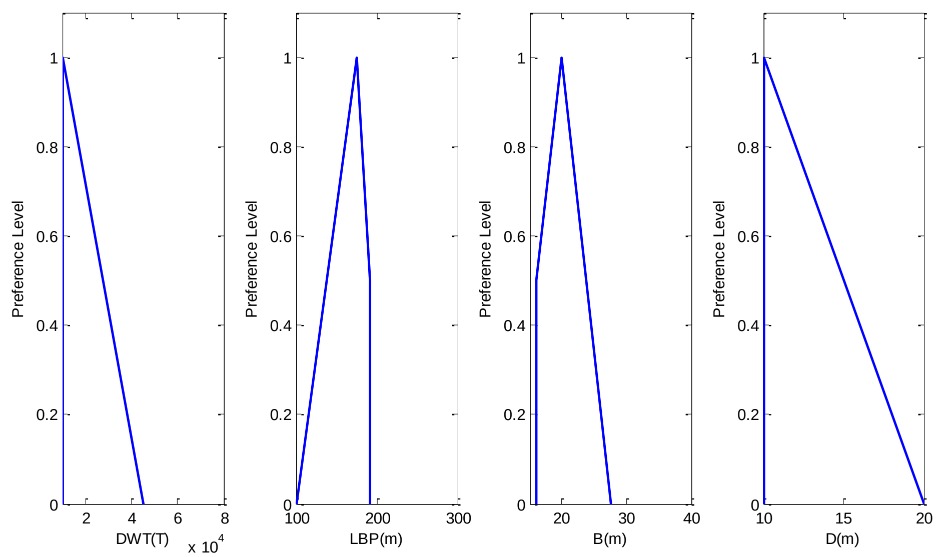


Figure 8.18: Round Four Variable Preferences

The reduction decision in this round is also relatively straight forward. Table 8.8 provides the robust reduction decisions for round four. It can be seen that the D/U reduction decision is the most robust, compared to the D/L decision. The simulations for the final reduction using the developed method vary the preferences associated with the final reduced regions, which would be associated with a final analysis of the reduced regions. For round four, the decision to reduce the upper region of depth, associated with depth values between 15 and 20, was made.

Table 8.8: Round Four Robust Reduction Decisions

Reduction	Speed	L/B	B/D	L/D
D/L	0.01	0	0	0
D/U	0.99	0	1	1

8.3.3 Final Reduction Path

Likelihood of attainment curves can be used to understand the implications of the reduction path taken, using robustness as a guide. Figures 8.19-8.22 provide the function likelihood of attainment curves associated with the selected reduction path. It can be seen that lower speed values can be attained easier than higher values, based on the regression model. This makes sense, as the upper regions of all the variables were reduced, limiting the final regions to smaller values.

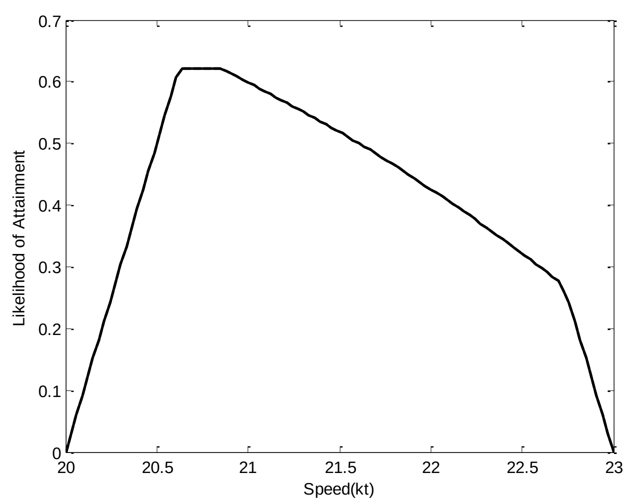


Figure 8.19: Speed Likelihood of Attainment

The L/B attainment curve was relatively flat for all values, suggesting that the reduction path did not have a direct impact on certain L/B values. Again, both upper regions of length and beam set-ranges were reduced, which kept the ratios similar. If an upper region of one and a lower region of the other were reduced, the L/B attainment curve would likely not be as flat.

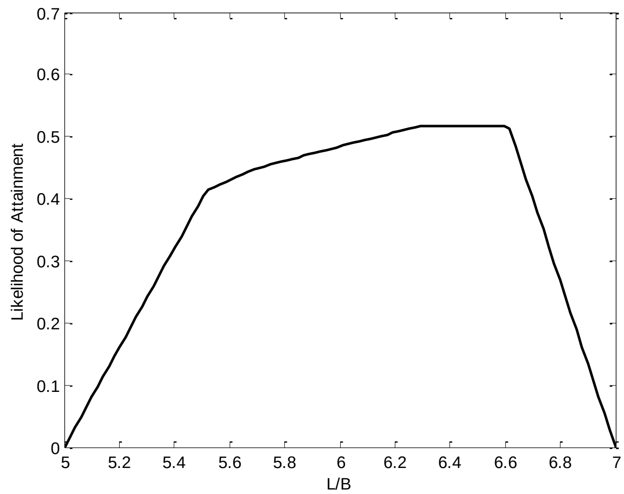


Figure 8.20: L/B Likelihood of Attainment

The B/D function did not factor much in the reduction decisions, as it did not cause the beam or depth values to be restricted. This can be seen in the likelihood of attainment curve, as the shape closely follows the initial function preference.

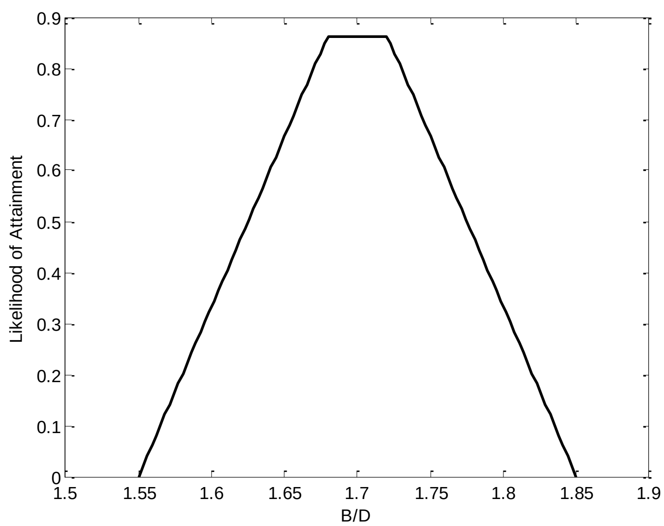


Figure 8.21: B/D Likelihood of Attainment

The likelihood of attainment curve for the L/D ratio showed a favor towards higher values. This can be attributed to the round three reduction in the upper length region. Smaller length values, in combination with the entire depth set-range, led to higher L/D ratio values for the final negotiation round.

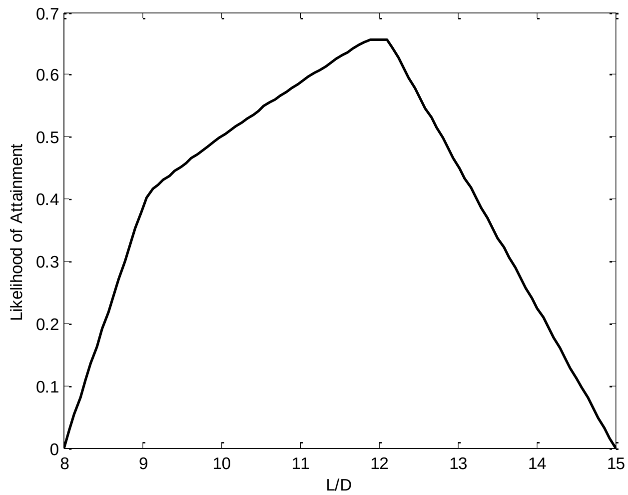


Figure 8.22: L/D Likelihood of Attainment

The reduction demonstration provides a better understanding of the intricacies associated with using the developed method. Also, potential uses of the method by designers are outlined, and the ability to analyze multiple functions at the same time is confirmed. The value associated with the representation methods presented in Chapter 6 is shown through the ability to aid a designer in making reduction decisions. Finally, likelihood of attainment curves associated with a given path can be used to easily understand the implications associated with certain reduction decisions, and the ability to achieve function or requirement values.

8.4 Chapter Summary

Through the use of a case study, this chapter presents a demonstration of the developed decision support framework in a SBD environment. The extensibility of the framework to both more complicated and multiple functions was confirmed. The case study also demonstrated the use of the developed framework throughout the reduction process during each negotiation round. Additionally, it was shown that functions can be analyzed together in a unified framework based on a common reduction decision notation scheme. Reduction decisions from different function analyses can be related and compared using the multi-objective tradeoff methods presented in Chapter 6. Both robustness Pareto fronts and multi-objective likelihood of attainment contour plots were used to gain insight on potential reduction decisions.

Chapter Citations

1. Hollenbach, U. (1998). Estimating Resistance and Propulsion for Single-Screw and Twin-Screw Ships. *Ship Technology Research*, (45)2, pp. 72-76.
2. Watson, D. G. M. (1998). *Practical Ship Design*. Oxford, UK: Elsevier Science.
3. Watson, D. G. M., & Gilfillan, A. W. (1977). Some Ship Design Methods. *Transactions of the Royal Institution of Naval Architects*.

Chapter 9: Conclusion

It is not the most intellectual of the species that survives; it is not the strongest that survives; but the species that survives is the one that is able best to adapt and adjust to the changing environment in which it finds itself.

–Leon C. Megginson (1963)

Megginson's paraphrase of Darwin's Theory of Evolution highlights an observation seen in nature. The meaning, however, can be extended to other environments, such as design. Throughout a design effort, decisions are made regarding the solutions being considered. Design solutions are selected based on being the "best" in a particular attribute, such as cost, or eliminated based on dominance or infeasibility. SBD intentionally avoids defining the "best" solution and in the process becomes robust to changing conditions. As Darwin points out, it is not the best in one particular attribute that survives, but the one most responsive to change. If the "best" solution changes after the decision to select it has already been made, the solution becomes infeasible, which is the equivalent of not surviving in nature. The developed decision support framework aids designers in understanding reduction decisions within a SBD environment to ensure the design process is as adaptable to the changing environment as possible.

This final chapter is divided into four sections. The first relates the research contributions back to the original problem statements, and summarizes how the presented solutions address these concerns. Novel contributions of the research presented in this dissertation are then presented. The third provides direction for future work and more advanced formulations of the set reduction problem. Finally, potential alternative applications of the developed framework for similar problems from different perspectives are presented.

9.1 Problem Statement Review

The three major research problems, originally presented in Chapter 1, and then seen with their proposed solutions in Chapter 6, are revisited to summarize how each problem was specifically addressed. Table 9.1 provides the original problem statements and proposed solutions, which combined, constitute the developed framework.

Table 9.1: Research Problem Statements and Proposed Solutions Revisited

Problem	Research Question	Developed Solution
Time-dependent design relationships	How can a designer understand changing dependencies as the design progresses?	Extension of Design Space Mapping
Determining impact of reducing certain areas of the design space	How can a designer organize reduction decisions to account for total design process impacts?	Longest Path Problem (LPP) formulated as a Markov Decision Process
Identifying robust decision paths	What decision paths are flexible to changing design conditions?	Preference Change Simulations

The remainder of this section discusses each research problem individually and outlines how the problem was specifically addressed using the developed framework.

9.1.1 Time-Dependent Design Relationships

The first research problem is the issue of time-dependent design relationships and how to handle changing dependencies as the design process progresses. During the initial SBD research conducted, the design change case study revealed the difficulty associated with both preference generation and understanding changing design relationships. In an effort to mitigate these difficulties, the design facilitation tool was developed. While the method was able to aid designers in set-based thinking and the generation of preferences, it lacked the ability to be extended to larger-scale problems. For simple problems, the design relationship analysis was able to provide a good understanding of the impact of variables on functions and the feasibility of solutions. However, in order to link the analysis of different functions together and determine the same design relationships for larger-scale problems, an increased level of synthesis and decreased level of fidelity of analysis would be required. As one of the major goals of the research presented in this dissertation was to develop a structure that supported concurrent engineering, this research direction was not extensible. Both increasing the level of synthesis and decreasing the level of fidelity are counter to the original goal of supporting a CE approach.

After identifying the limitations of the design facilitation tool for understanding large-scale design relationships for team-based design, the explicit goal of identifying relationships through the use of preferences, not synthesis, was defined. Design space mapping (DM) was identified as a more applicable method based on this research's newly defined goal. DM methods are consistent with and a natural extension of previous work on preference facilitation. DM is used to determine relationships between the various design spaces, including variable, constraint, and objective spaces. These mapping techniques also facilitate human designer preferences for variable and function values. Using the preferences provided at each SBD negotiation round, a series of mappings are completed to determine the influence of variables for different set-ranges. Preferences are updated as the design process continues and the mappings are repeated to gain an updated view of design relationships.

9.1.2 Impact of Reduction Decisions

The second research problem deals with the difficulty of determining when and where to make design reduction decisions. While DM methods provide information on design relationships for changing preferences and set-range values, there still needs to be a framework to use the DM information to understand reduction decisions. As part of the initial SBD research, the design change case study revealed that using SBD, there is the ability to handle changing conditions and understand the impact of a change using designer provided preferences. However, there was no direct understanding of how reduction decisions were related to the ability to handle changes. The detailed design experiment, presented in this dissertation, was completed to gain a better understanding of the types of relationships and important considerations made during a set reduction process. Results showed that reduction rate and path were strongly related to the success or failure of a reduction effort. This both validated the importance of design decisions, and identified the importance of understanding design relationships through time.

In an effort to turn the lag indicators seen in the detailed experiment into lead indicators to avoid making poor reduction decisions, a framework that models and analyzes the set reduction problem was developed. The longest path problem (LPP) was used to model the set reduction problem, where instead of traveling along a physical path such as a road, the path was related to the variable set-ranges through time. In order to analyze this structure to identify the impacts of reduction decisions, the LPP was formulated as a Markov Decision Process (MDP). This method is able to balance the risk and reward of reducing certain areas of the design space and used to determine the impact of these decisions on the overall design process. Using information provided by the design space mappings, the MDP is used every round of the SBD effort to identify optimal decision paths, while incorporating future reduction decisions. The MDP results provide the chief engineer, or design manager, with valuable guidance on how to reduce the design space from the perspective of the identified function. This process is completed for multiple functions of interest to provide a clearer design reduction strategy for the overall design effort.

9.1.3 Identification of Robust Decision Paths

The third research problem focuses on the identification of robust decision paths. It was identified during the detailed design experiments that certain paths were able to handle changes better than others. The goal is to avoid failure opportunities and potential situations where the current set-ranges cannot handle a changing design relationship. Identifying potential decision paths that are more robust to changing design conditions would be preferred. As a type of sensitivity analysis, preference change simulations are used to identify these robust decision paths. The LPP MDP problem is solved using various design preference structures representing potential future changes in preferences. Additionally, the likelihood of a certain path being able to handle varying magnitudes of changing conditions, including preference changes, is determined.

As the developed LPP MDP formulation has never been used to analyze set reduction problems, a series of metrics and representations using the MDP and simulation results were developed. Optimal strategy tables are used prior to variable preferences being provided to gain an initial understanding of the potential reduction strategies given various preference structures. The robust decision paths are identified by determining the reduction decisions that occur most frequently in the simulation results for various preference structures. A decision path output is also generated to determine optimal reduction decisions for a given epoch, or time-step. An alternative path analysis is completed to identify the number of optimal secondary connections if the primary path fails. The reward over time is used to establish trends, or compare the rewards associated with different paths. Also, likelihood of attainment curves for both the variable and function space are generated to gain an understanding of the risks associated with meeting certain variable or function values. These simple and easy to understand curves are used to visually describe how certain areas of the design space are constrained. The developed metrics and representations provide various types of information desirable to a designer under different circumstances. The designer has the freedom and power to pick and choose the pieces of information most useful for the problem at hand.

9.1.4 Unified Framework

While each research question was addressed by an aspect of the developed framework, a substantial amount of effort went into the unification of these three different components. The first important linkage was between the DM method and the MDP framework. Reduction metrics based on DM results for the various set-range combinations were developed and evaluated using the MDP framework. The two reduction metrics that adequately represented reduction considerations were further considered and a single metric was identified as being able to better describe the conditions that deal with changing conditions. Using the identified reduction metric, in combination with the MDP formulation, a series of simulation studies were completed to determine the value of accounting for potential future scenarios. By adding the sensitivity analysis generated through the preference change simulations to the MDP formulation, all three components were combined. It was shown through a series of studies that the framework is able to better handle situations with changing conditions, as well as better accommodate more constrained problems compared to a method based solely on current in-state knowledge. This observation solidifies the advantages associated with the unified framework, and its potential advantages in more complicated reduction efforts.

Another important aspect is utilizing the unified framework for multiple functions. Additional representations are introduced, including robustness Pareto fronts and multi-objective likelihood of attainment contour plots. As part of the reduction demonstration, presented in Chapter 8, the development of a reduction notation scheme was used to link states between multiple functions with different variables. The ability to analyze multiple functions at the same time is critical for a designer, as there is never just one perspective to consider. The ability of the framework to be used for multiple functions further extends its applicability and increases its value to a designer during a set reduction effort.

9.2 Novel Contributions

The primary contribution of this dissertation is the development of a set reduction decision support framework within a SBD environment that accounts for future changing conditions. The framework provides the designer with valuable and easy to understand information that is used to make better informed reduction decisions within a SBD environment. The specific contributions demonstrated through the successful development of a framework that addresses the posed research problems are as follows:

1. Aided in the development of a rigor standard that can be used to evaluate a design activity and determine the degree of adherence to five major SBD elements. Standards enable proper and repeatable execution of SBD principles.

2. Developed a design facilitation tool that aids in understanding design relationships at the functional design level, thereby, improving the preference generation process for designers.
3. Conducted a series of experiments with human designers that validated the ability of the SBD method to handle changes, and identified two elements, reduction path and reduction rate, as key factors in successful reduction efforts.
4. Developed a novel approach to generate automatically set reduction graph structures. This approach avoids the need to manually generate a graph for every problem.
5. Developed an MDP formulation of the longest path problem for SBD reduction decision making, providing both a structure for the problem and a method for analysis.
6. Created novel visual representations of the support framework results in simple and understandable formats so that SBD reduction decisions are presented to the designer.
7. Developed a series of DM reduction metrics utilized within the support framework to describe quantitatively the impact of reducing certain regions of the design space.
8. Through simulation, demonstrated the advantage of considering potential future outcomes versus the use of current in-state knowledge.

Although the developed framework was applied to the field of early-stage ship design, application to other fields that involve complex design processes and systems can be easily accomplished. Additionally, the principles and insights gained from the framework's development can be utilized for any type of design effort.

9.3 Future Work

Within the reduction decision making component of SBD execution, there are three major areas where further research can be completed. First, the developed method's applicability can be extended to more reduction scenarios. Second, additional value can be introduced through the incorporation of separate MDP reward and probability values.

Third, the simulation structure can be tuned to more accurately represent the likelihoods of certain design aspects changing. This section discusses each area in more detail and proposed approaches to accomplishing the research.

9.3.1 Reduction Scenarios

As discussed in Chapter 6, only the single reduction scenario was considered for the research presented in this dissertation. Two other potential scenarios can provide additional options and insight to the designer. The first is the multiple reduction scenario, which allows the designer to reduce multiple variables and variable set-ranges at each epoch. The second is the potential reopening scenario, which allows a designer to reopen set-ranges already reduced if a reduction path becomes infeasible, an error occurs, or an improved reduction path is identified.

The multiple reductions scenario is a natural progression from the single reduction scenario. Instead of being restricted to only reducing one variable and set-range at a time, any combination of variable and set-range reductions can occur, in addition to the decision to remain at the current set-ranges. This presents the classic problem of exploration versus exploitation, "in which one must decide whether to exploit the (possibly suboptimal) information acquired so far, or invest further cost in exploration in the hope of acquiring better information" (Nikolova & Karger, 2008). For the set-reduction application, this problem presents itself to the chief engineer making the design decision. The chief engineer must decide whether to reduce multiple set-ranges using current preferences, or pay the cost to ask for a new round of negotiations from designers.

When comparing these two scenarios, the multiple reductions graph structure is different from the single reduction case. With the ability to move to any current or future state at every epoch, the graph structure technically goes on for an infinite amount of epochs. This is because a decision can be made to remain at the current set-ranges at every epoch. A multiple reductions graph structure for the length-to-beam function with two partitions and four epochs is provided in Figure 9.1. It can be seen that after the second epoch, there is an artificial terminal node at every epoch. This means that the designer can choose to finish the reduction process with only one decision. The automatic graph generation can be completed for the multiple reductions scenario, similar to the single reduction case, but with different logical arguments to the ones provided in Equation 6.16 for single reduction.

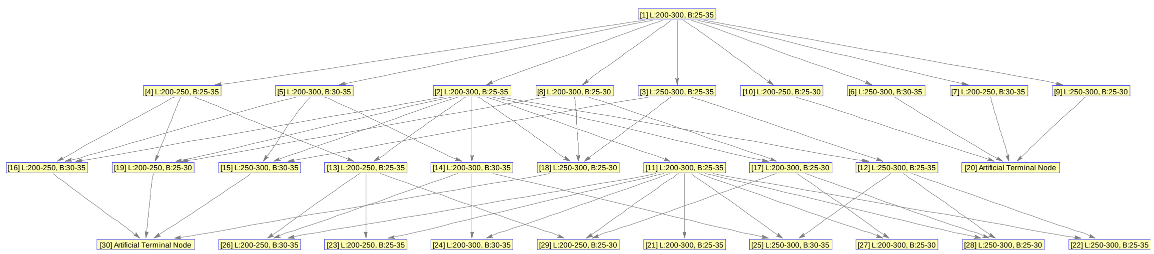


Figure 9.1: Multiple Reductions Graph Structure

The MDP formulation is required to be slightly different for the multiple reductions scenario due to its infinite nature. There are two ways to ensure that the problem is solved in a finite amount of time. The first way is to formulate the problem using a finite horizon. This means that there is a fixed time after which nothing matters (Russell & Norvig, 2003). The second way is to use a discount factor, which describes the preference for current or future rewards. With discounted rewards, the infinite sequence's utility becomes finite (Russel & Norvig, 2003). While the formulation is not challenging, tuning the factors to properly address the exploration versus exploitation problem can be challenging for guiding set reduction.

The second scenario, potential reopening, describes the situation that this dissertation's developed method attempts to avoid. In certain instances, however, the reopening of a set might be required. Valid reasons for set-range reopening include design errors and innovative or new ideas. Also, the set-ranges can be reopened if a high risk/reward technology pans out. Initially, the high risk would have resulted in a low variable preference and possibly result in a set reduction. Once the risk of the new technology is significantly reduced, one could see a different preference curve for multiple variables. The graph structure for this scenario would include the use of undirected arcs, allowing movement back and forth between states. This formulation does make the problem difficult to solve using popular dynamic programming algorithms. Within the MDP framework, the ability to revisit states and update rewards can potentially mitigate some difficulties present in other algorithms. An additional challenge, which future research should address, is how to properly determine edge weights and probabilities when describing the reduction process via an undirected graph.

9.3.2 MDP Formulation

As described in Chapter 6, the rewards for the MDP formulation are risk-adjusted rewards, and the probabilities are either zero or one depending on if two states are connected by an arc. To improve the formulation for the set reduction problem, a separate probability matrix can be calculated that describes the likelihood a set-range contains feasible solutions. This type of problem can be considered an expected longest path problem formulated as an MDP. A similar type of formulation is used for landmark-based robot navigation (Briggs, Detweiler, Scharstein, & Vandenberg-Rodes, 2002). In the robot navigation case, the edge weights (or rewards) are distance traveled or time and the probabilities are likelihoods that edges are passable. For the set reduction problem, the rewards would remain the same, and the probabilities would represent the likelihood that a solution exists at a given set-range.

9.3.3 Simulation Tuning

The simulation structure presented in this dissertation takes multiple combinations of potential preference changes. In an effort to improve the simulation results to make them more realistic, additional information can be provided to make the predictions of potential future outcomes more accurate. For example, historical data of design changes, and the likelihood of certain changes occurring, can be added to the simulation structure to more adequately reflect real-world scenarios. Additionally, a feedback mechanism can be put in place to determine if the predictions of future preference structures are valid. A better understanding of the impact of a set reduction on design relationships can be recorded and factored into the simulation structure as well. With the simulation structure more representative of the specific problem at hand, improved results and consideration of potential future outcomes can be obtained.

9.4 Alternative Applications

It is worth mentioning, briefly, the alternative applications of the developed framework for similar types of problems. The first is related to the distinction between design variable set-ranges and design alternatives or solutions. For the framework presented in this dissertation, the variable preferences describe the preference for design solutions within a given range. However, the same method can be used with specific design solutions. The major difference would be instead of providing preferences for a variable set-range, a different metric would have to be used by functional design groups to describe their preferences.

Another application of the developed framework is its use as a post design evaluation of set reduction decision making. For design activities that have already been conducted, the method can be used to compare the actual reduction path to the robust path identified by the method. The comparison analysis can be used to improve future design efforts or to tune the MDP formulation to properly reflect what are considered valid reduction decisions.

Chapter Citations

1. Briggs, A. J., Detweiler, C., Scharstein, D., & Vandenberg-Rodes, A. (2002, December). *Expected Shortest Paths for Landmark-Based Robot Navigation*. Paper presented at the Fifth International Workshop on Algorithmic Foundations of Robotics, Nice, France.
2. Nikolova, E., & Karger, D. R. (2008, July). *Route Planning under Uncertainty: The Canadian Traveller Problem*. Paper presented at the Twenty-Third Conference on Artificial Intelligence, Chicago, IL.
3. Russel, S., & Norvig, P. (2003). *Artificial Intelligence: A Modern Approach*. 2nd ed. New York: Prentice Hall.

Appendix

Container Ship Database

Identification	DWT(T)	LBP(m)	B(m)	D(m)	V_k(kt)
Bermuda Islander	2800	84.7	13.75	5.55	13.5
Batavier VI	3480	85.0	15.85	6.18	15.0
Pacheco	4200	98.0	15.90	8.50	14.7
A.B. Bilbao	4210	85.0	13.17	7.15	12.5
Leknes	4226	84.8	13.80	7.15	12.5
Cari Sea	4766	93.0	16.50	7.50	14.0
Ute Johanna	4855	91.5	16.90	7.55	15.3
Clipper Confidence	5264	95.0	20.40	11.10	16.5
Sloman Challenger	5665	94.7	17.80	8.20	14.5
Flinterzee	5820	105.3	14.50	8.25	14.5
Celtic Monarch	6250	94.3	17.00	8.20	19.8
Sietas 1	6650	103.4	19.00	8.50	15.6
Duro-Felg	7000	94.5	16.50	9.70	13.3
Singapore	7800	112.6	18.40	9.00	15.0
Hanjin Bangkok	8075	114.0	20.00	8.80	14.0
Secil Angola	8371	115.5	20.80	10.80	15.0
Sea Arctica	8500	118.5	24.00	15.10	17.0
Germania	8790	117.0	19.00	13.50	16.0
Markborg	8950	127.2	16.50	9.80	15.6
Cape Bonavista	10410	126.4	22.70	10.80	16.6
Carmen Dolores H	11004	125.7	20.50	10.50	18.8
Jork	11870	147.0	23.50	12.80	19.9
Kairo	12580	140.1	22.30	11.10	18.5
Cape Hatteras	12855	134.0	23.50	11.50	18.1
CMBT Endurance	13100	145.0	24.00	13.90	18.7
Sea Nordica	13248	135.9	23.28	11.70	19.0
Frotasantos	13270	158.3	27.80	13.50	18.4
Oren & K	13800	142.8	22.80	11.10	16.4
Ganta Bhum	15027	141.2	25.00	13.60	19.0
San Lorenzo	17205	156.0	27.40	13.20	19.5
Uni-Crown	17446	141.0	25.60	12.70	16.0
Westerdeich	17600	156.0	26.70	14.40	20.0
Cecilie Maersk	19530	180.2	27.80	15.23	19.0
Kota Wijaya	20755	174.0	27.60	14.00	19.1
Bunga Kenari	21571	165.0	27.30	13.90	18.0
Taixing	22271	162.5	27.50	13.80	16.2
Nordlake	22450	167.3	25.30	13.50	19.0
Contship Pacific	23276	153.7	27.50	14.30	19.4
Nedlloyd Amazonas	23793	172.7	29.80	15.60	20.0
Muscat Bay	23805	172.0	28.40	15.60	18.7

Identification	DWT(T)	LBP(m)	B(m)	D(m)	V_k(kt)
CGM Provence	26288	167.0	27.50	14.30	18.6
Marwan	27200	156.7	25.00	13.40	18.6
Sea-Land Argentina	27290	196.0	29.80	16.40	21.0
Patricia Rickmers	28274	185.5	30.20	16.60	20.5
Hanjin Zenoa	29800	190.0	32.25	19.00	22.0
Cap Polonio	33205	188.2	32.20	18.80	18.5
OOCL Canada	33640	203.8	32.20	19.00	20.0
Canmar Fortune	33800	204.0	32.20	19.00	19.9
Tokyo Senator	35734	206.2	32.20	19.40	20.5
Nuevo Leon	36887	191.0	32.20	19.40	20.0
Villa De Vela	37128	225.2	32.20	19.00	22.5
Chesapeake Bay	37500	232.0	32.20	18.80	23.5
Zim Hong Kong	37865	224.5	32.20	18.80	21.0
Vladivostok	40250	225.3	32.20	18.80	22.0
Trade Sol	41700	190.8	30.60	16.00	19.5
Zhonghe	44037	264.2	32.20	21.50	24
NYK Procyon	47300	283.0	37.10	21.80	23.5
APL Korea	49350	262.0	40.00	24.30	24.6
Hanjin London	49390	265.0	40.30	24.10	26.3
OOCL California	50037	262.0	40.00	24.30	24.6
Sea-Land Mistral	51900	230.0	32.20	19.00	24.0
Neptune Sardonyx	53320	281.6	32.25	21.40	24.5
Pusan Senator	55543	283.2	32.20	21.80	23.7
Luhe	55988	267.0	39.80	23.60	24.5
Ever Racer	56100	281.0	32.22	21.25	22.7
NYK Antares	72097	283.8	40.00	23.90	23.0
P&O Nedlloyd Southhampton	83826	283.8	42.80	24.40	24.5
Arktis Fighter	5212	93.6	18.80	9.30	15.7
Acadian Faith	5273	96.7	16.40	8.30	16.0
Bunga Mas Satu	10400	124.6	20.80	10.50	17.0
Haneburg	11187	125.2	21.00	11.50	17.0
Mukaddes Kalkavan	12292	136.8	22.70	11.30	19.3
Nadir	18000	164.2	28.20	16.80	21.0
Cathrin Oldendorff	18242	145.8	23.60	13.50	16.7
Nedlloyd River Platt	19762	158.0	27.20	13.80	19.4
Pegasus	21400	180.2	28.20	16.80	21.0
Clipper Fantasy	28000	172.0	26.00	14.40	14.0
Sea Excellence	30554	197.1	32.20	19.40	23.0
MSC Alexa	36606	230.0	32.25	21.50	23.0
Hyundai Independence	51120	263.0	40.00	24.20	25.8
Hannover Express	55590	281.6	32.25	21.40	23.8
Regina Maersk	65610	302.3	42.80	24.10	25.0

Speed Function Inverse Equations

$$DWT = 100\big(750 - (-35B^2 + 23030B + 120D^2 + 26990D - 4LBP^2 + 4020LBP - 200000V_k + 2540546)^{1/2}\big)$$

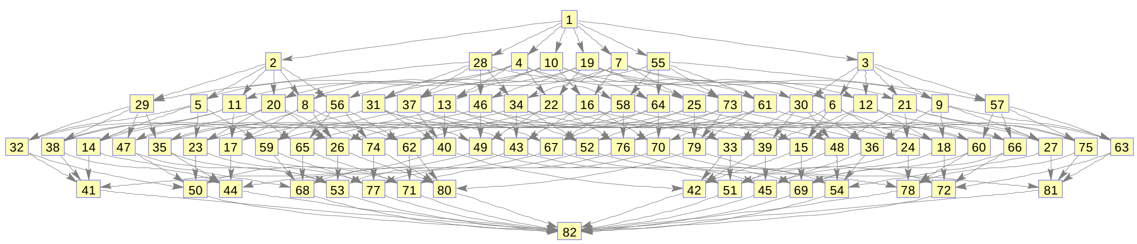
$$LBP = \frac{1}{200}\big(100500 - (-350000B^2 + 230300000B + 1200000D^2 + 269900000D - 2000000000V_k - DWT^2 + 150000DWT + 29880710000)^{1/2}\big)$$

$$B = \frac{1}{3500}\big(1151500 - \sqrt{35}(1200000D^2 + 269900000D - 40000L^2 + 40200000LBP - 2000000000V_k - DWT^2 + 150000DWT + 57664810000)^{1/2}\big)$$

$$D = \frac{1}{6000}\big(\sqrt{10}(1050000B^2 - 690900000B + 120000LBP^2 - 120600000LBP + 6000000000V_k + 3DWT^2 - 450000DWT - 13812623750)^{1/2} - 674750\big)$$

Associated Graph Structure Set-Ranges

Speed Function



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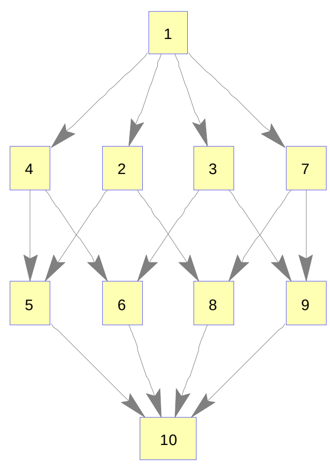
'[38] DWT:45000-80000, LBP:100-300, B:27.5-40, D:15-20'
'[39] DWT:10000-45000, LBP:100-300, B:27.5-40, D:15-20'
'[40] DWT:10000-80000, LBP:200-300, B:27.5-40, D:15-20'
'[41] DWT:45000-80000, LBP:200-300, B:27.5-40, D:15-20'
'[42] DWT:10000-45000, LBP:200-300, B:27.5-40, D:15-20'
'[43] DWT:10000-80000, LBP:100-200, B:27.5-40, D:15-20'
'[44] DWT:45000-80000, LBP:100-200, B:27.5-40, D:15-20'
'[45] DWT:10000-45000, LBP:100-200, B:27.5-40, D:15-20'
'[46] DWT:10000-80000, LBP:100-300, B:15-27.5, D:15-20'
'[47] DWT:45000-80000, LBP:100-300, B:15-27.5, D:15-20'
'[48] DWT:10000-45000, LBP:100-300, B:15-27.5, D:15-20'
'[49] DWT:10000-80000, LBP:200-300, B:15-27.5, D:15-20'
'[50] DWT:45000-80000, LBP:200-300, B:15-27.5, D:15-20'
'[51] DWT:10000-45000, LBP:200-300, B:15-27.5, D:15-20'
'[52] DWT:10000-80000, LBP:100-200, B:15-27.5, D:15-20'
'[53] DWT:45000-80000, LBP:100-200, B:15-27.5, D:15-20'
'[54] DWT:10000-45000, LBP:100-200, B:15-27.5, D:15-20'
'[55] DWT:10000-80000, LBP:100-300, B:15-40, D:10-15'
'[56] DWT:45000-80000, LBP:100-300, B:15-40, D:10-15'
'[57] DWT:10000-45000, LBP:100-300, B:15-40, D:10-15'
'[58] DWT:10000-80000, LBP:200-300, B:15-40, D:10-15'
'[59] DWT:45000-80000, LBP:200-300, B:15-40, D:10-15'
'[60] DWT:10000-45000, LBP:200-300, B:15-40, D:10-15'
'[61] DWT:10000-80000, LBP:100-200, B:15-40, D:10-15'
'[62] DWT:45000-80000, LBP:100-200, B:15-40, D:10-15'
'[63] DWT:10000-45000, LBP:100-200, B:15-40, D:10-15'
'[64] DWT:10000-80000, LBP:100-300, B:27.5-40, D:10-15'

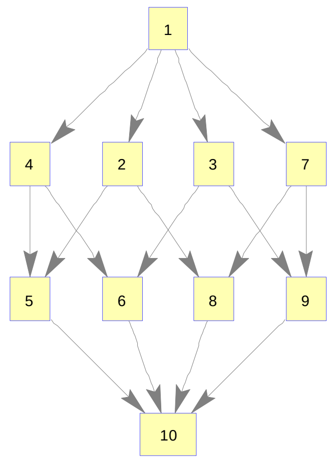
'[65] DWT:45000-80000, LBP:100-300, B:27.5-40, D:10-15'
'[66] DWT:10000-45000, LBP:100-300, B:27.5-40, D:10-15'
'[67] DWT:10000-80000, LBP:200-300, B:27.5-40, D:10-15'
'[68] DWT:45000-80000, LBP:200-300, B:27.5-40, D:10-15'
'[69] DWT:10000-45000, LBP:200-300, B:27.5-40, D:10-15'
'[70] DWT:10000-80000, LBP:100-200, B:27.5-40, D:10-15'
'[71] DWT:45000-80000, LBP:100-200, B:27.5-40, D:10-15'
'[72] DWT:10000-45000, LBP:100-200, B:27.5-40, D:10-15'
'[73] DWT:10000-80000, LBP:100-300, B:15-27.5, D:10-15'
'[74] DWT:45000-80000, LBP:100-300, B:15-27.5, D:10-15'
'[75] DWT:10000-45000, LBP:100-300, B:15-27.5, D:10-15'
'[76] DWT:10000-80000, LBP:200-300, B:15-27.5, D:10-15'
'[77] DWT:45000-80000, LBP:200-300, B:15-27.5, D:10-15'
'[78] DWT:10000-45000, LBP:200-300, B:15-27.5, D:10-15'
'[79] DWT:10000-80000, LBP:100-200, B:15-27.5, D:10-15'
'[80] DWT:45000-80000, LBP:100-200, B:15-27.5, D:10-15'
'[81] DWT:10000-45000, LBP:100-200, B:15-27.5, D:10-15'
'[82] Artificial Terminal Node'

L/B Ratio Function



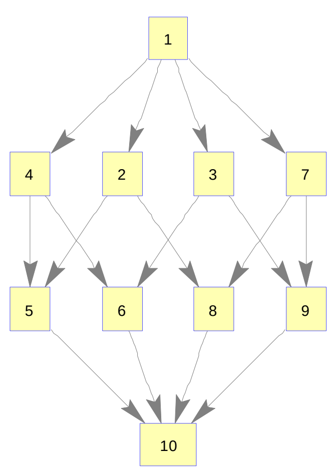
'[1] LBP:100-300, B:15-40'
'[2] LBP:200-300, B:15-40'
'[3] LBP:100-200, B:15-40'
'[4] LBP:100-300, B:27.5-40'
'[5] LBP:200-300, B:27.5-40'
'[6] LBP:100-200, B:27.5-40'
'[7] LBP:100-300, B:15-27.5'
'[8] LBP:200-300, B:15-27.5'
'[9] LBP:100-200, B:15-27.5'
'[10] Artificial Terminal Node'

B/D Ratio Function



'[1] B:15-40, D:10-20'
'[2] B:27.5-40, D:10-20'
'[3] B:15-27.5, D:10-20'
'[4] B:15-40, D:15-20'
'[5] B:27.5-40, D:15-20'
'[6] B:15-27.5, D:15-20'
'[7] B:15-40, D:10-15'
'[8] B:27.5-40, D:10-15'
'[9] B:15-27.5, D:10-15'
'[10] Artificial Terminal Node'

L/D Ratio Function



'[1] LBP:100-300, D:10-20'
'[2] LBP:200-300, D:10-20'
'[3] LBP:100-200, D:10-20'
'[4] LBP:100-300, D:15-20'

'[5] LBP:200-300, D:15-20'
'[6] LBP:100-200, D:15-20'
'[7] LBP:100-300, D:10-15'
'[8] LBP:200-300, D:10-15'
'[9] LBP:100-200, D:10-15'
'[10] Artificial Terminal Node'