The Pennsylvania State University
The Graduate School
College of Engineering

AN ASSESSMENT OF NOVICE AND EXPERT
USERS’ DECISION-MAKING STRATEGIES
DURING VISUAL TRADE SPACE EXPLORATION

A Thesis in
Mechanical Engineering
by
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ABSTRACT

Thanks to advances in computing power and speed, designers can now generate a wealth of data on demand to support engineering design and decision-making. Unfortunately, while the ability to generate and store new data continues to grow, methods and tools to support data exploration have evolved at a much slower pace. Moreover, current methods and tools are often ill-equipped at accommodating evolving knowledge sources and expert-driven data exploration that is being enabled by computational thinking. This thesis contributes to ongoing research that seeks to transform decades-old decision-making paradigms to more effectively convert data into knowledge ultimately leading to better decisions. Specifically, this thesis addresses decision-making within the area of trade space exploration by conducting human-computer interaction experiments using multi-dimensional data visualization software created at The Pennsylvania State University. In this thesis, the goals are to: (1) evaluate the current performance of novice decision-makers, (2) develop novice user training protocols by evaluating expert decision-maker problem solving methodology, (3) evaluate the ability of these training protocols to support efficient and effective trade space exploration for novice decision-makers, and (4) provide a foundation for additional training protocols for problems with varying tradeoffs and complexity. The results suggest that, without proper training, novices are ineffective at using multi-dimensional data visualization and visual steering tools to solve a design problem. The training protocols developed in this analysis were effectively able to teach the novices valuable design decision-making strategies. This was demonstrated, through
controlled experiments, to provide substantial improvement in their average performance when using trade space exploration to solve a complex engineering design problem. The training protocols also successfully encourage the novices to utilize visualization and visual steering tools that were previously misused or ignored.
# Table of Contents

ABSTRACT ................................................................................................................................. iii  
List of Figures .......................................................................................................................... vii  
List of Tables ............................................................................................................................ ix  
Preface ....................................................................................................................................... x  
Acknowledgements .................................................................................................................. xi  
CHAPTER 1 - INTRODUCTION ................................................................................................. 1  
CHAPTER 2 - REVIEW OF RELATED WORK ............................................................................. 4  
  2.1 Decision-Making during Trade Space Exploration ......................................................... 4  
  2.2 User Expertise and Decision-Making ............................................................................. 5  
CHAPTER 3 - OVERVIEW OF MULTI-DIMENSIONAL VISUALIZATION AND VISUAL STEERING COMMANDS .............................................................................. 10  
  3.1 Visualization Capabilities ............................................................................................... 10  
  3.2 Visual Steering Commands ............................................................................................ 11  
CHAPTER 4 - EXPERIMENTAL SETUP AND USER TRIALS .............................................. 18  
  4.1 Test Problems ................................................................................................................ 18  
    4.1.1 Combustion Chamber Design Model ................................................................. 18  
    4.1.2 Conceptual Ship Design Model .......................................................................... 20  
    4.1.3 Aircraft Wing Design Model .............................................................................. 23  
  4.2 Pilot Study ..................................................................................................................... 25  
  4.3 Preliminary Experiments ............................................................................................... 26  
    4.3.1 Description of User Trials .................................................................................... 27  
    4.3.2 Performance Measures ....................................................................................... 29  
    4.3.3 Reference Data Sets ......................................................................................... 30  
  4.4 Follow-on Experiments ............................................................................................... 31  
    4.4.1 Description of User Trials .................................................................................... 31  
    4.4.2 Performance Measures ....................................................................................... 32  
CHAPTER 5 - ANALYSIS AND DISCUSSION OF RESULTS ................................................ 34
List of Figures

Figure 1 - Multidimensional Visualization Examples - a) Glyph Plot, b) Histogram Plots, c) Parallel Coordinates, and d) Scatter Matrix .......................................................... 11
Figure 2 - Example of Basic Sampler ........................................................................ 12
Figure 3 - Slider Bar Controls for Point Sampler ...................................................... 13
Figure 4 - Example of an Attractor ........................................................................... 14
Figure 5 - Example of Preference-based Sampler ...................................................... 15
Figure 6 - Example of Pareto Sampler (Pareto points denoted by +) ....................... 16
Figure 7 - Combustion Chamber [28] ........................................................................ 19
Figure 8 - Brush/Preference Control Settings for the Geometry Subsystem .......... 20
Figure 9 - Brush/Preference Control Settings for the Thermodynamic Subsystem .... 20
Figure 10 - Conceptual Ship (A- Front View, B- Side View) .................................... 21
Figure 11 - Brush/Preference Controls for the Conceptual Ship Design Problem ....... 23
Figure 12 - Aircraft Wing [32] .................................................................................. 24
Figure 13 - Brush/Preference Controls for the Aircraft Wing .................................. 25
Figure 14 - Comparison of Datasets using NSP as the Metric ................................. 37
Figure 15 - Distribution of NSP Values for both Novices and Experts ....................... 38
Figure 16 - Number of Designs Generated vs. Average Best NSP for Basic Sampler and Novice decision-maker Trials ................................................................. 39
Figure 17 - Additional Comparison of Datasets using NSP as the Metric ................. 41
Figure 18 - Comparison of Datasets using Average Percentage of Feasible Designs as the Metric ........................................................................................................ 43
Figure 19 - Additional Comparison of Datasets using Average Percentage of Feasible Designs as Metric ........................................................................................................ 44
Figure 20 - Percentage of Novice and Expert Users Utilizing Each Visualization and Sampling Tool ............................................................................................................... 45
Figure 21 - Activity Transitions in Preliminary Experiment - Novices without Training
Video......................................................................................................................... 50
Figure 22 - Activity Transitions in Preliminary Experiment - Experts ....................... 51
Figure 23 - Activity Transitions in Preliminary Experiment - Novices with Training
Video......................................................................................................................... 54
Figure 24 - Normalized Sum of the Objectives for the Conceptual Ship Design Model . 56
Figure 25 - Normalized Sum of the Objectives for the Aircraft Wing Design Model ..... 56
Figure 26 - Percentage of Experts using Each Visualization and Sampling Tool........... 57
Figure 27 - Activity Transitions in Follow-on Experiment - Conceptual Ship Design.... 59
Figure 28 - Activity Transitions in Aircraft Wing Design Follow-on Experiment ........ 61
Figure 29 - Novice Ratings of the Helpfulness for each Visualization Technique and
Visual Steering Command ........................................................................................ 62
Figure 30 - Novice Ratings of Potential Support Features ........................................ 64
List of Tables

Table 1 - Inputs and Bounds for Combustion Chamber ................................................... 19
Table 2 - Inputs and Bounds for Conceptual Ship............................................................ 22
Table 3 - Inputs and Bounds for Aircraft Wing................................................................. 24
Preface

Part of this work, namely, parts of the introduction, review of related work, overview of visualization and visual steering commands, and the experimental setup and results for the Pilot Study and parts of the Preliminary Experiment are adapted from a paper written by the author of this thesis for the 2009 ASME Design Engineering Technical Conference (DETC2009-87294). This thesis is an extension of that work in that it provides additional results for the Preliminary Experiment and includes a Follow-on Experiment using trade space exploration problems of varying complexity.
Acknowledgements

I would like to thank my thesis advisor, Dr. Timothy W. Simpson, for the direction and support that he has provided throughout all aspects of this work. I would also like to thank Dr. Xiaolong (Luke) Zhang for his work with the conference paper on which this thesis is based. Additional appreciation goes to Dr. Mary Frecker for acting as a reader and reviewing this thesis. Finally, I would like to thank all of the expert and novice study participants without which this thesis would not be possible.

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CHAPTER 1 - INTRODUCTION

The concept development stage, when the designer needs to consider a large number of design variations, is one of the most important stages in the design process [1]. It is during this stage that the human designer’s knowledge and experience is vital to the success of the product. Continual improvements in computing power and speed allow today’s engineers and designers to simulate and evaluate more design alternatives quicker and more cheaply than ever before [2]. Rapid visualization and analysis combined with model integration can allow decision-makers to explore a multi-dimensional design space quickly and efficiently [3]. Trade space exploration is a promising decision-making paradigm that provides a visual and more intuitive means for formulating, adjusting, and ultimately solving design optimization problems [4]. This is achieved by combining multi-dimensional data visualization techniques with visual steering commands to allow designers to “steer” the optimization process while searching for the best, or Pareto optimal, designs. By keeping designers “in-the-loop” trade space exploration allows decision-makers to form preferences as they explore design options to select the best design [2]. To support trade space exploration researchers at the Applied Research Laboratory (ARL) at The Pennsylvania State University have developed the ARL Trade Space Visualizer (ATSV) [5]. ATSV has become a software platform for conducting research in human-computer interactions to explore how designers use multi-dimensional data visualization techniques to display complex trade spaces.
This thesis presents results from ongoing research toward formalizing methods, tools, and procedures to support trade space exploration and quantify its benefits in engineering design. In particular, we examine how decision-makers use multi-dimensional data visualization to help make decisions during trade space exploration. This thesis first discusses a Pilot Study that was conducted to gain insight into differences between novice and expert decision-makers using a small test group. Then the results of two Preliminary Experiments designed to gain insight into procedural differences in how novices and experts use multi-dimensional data visualization and sampling tools are presented. These Preliminary Experiments seek to measure the novices’ ability to use these tools effectively when solving an engineering design problem. A third Preliminary Experiment is then presented to investigate the ability to train novice users in trade space exploration procedural knowledge. The effectiveness of decision-makers in the Preliminary Experiments was measured through two different methods: (1) their ability to meet the objective of the example problem and (2) the percentage of feasible designs generated. Finally, the results of two Follow-on Experiments conducted with expert decision-makers to compare their decision-making strategies for design problems of varying complexity are presented.

Chapter 2 discusses related work in trade space exploration as well as some background information in expertise and decision-making. An overview of the multi-
dimensional data visualization and visual steering capabilities within ATSV is presented in Chapter 3. Chapter 4 describes the test problems used in this work and the experimental set-up for the Pilot Study, Preliminary Experiments, and Follow-on Experiments. The results and findings are discussed in Chapter 5, and conclusions and future work are outlined in Chapter 6.
CHAPTER 2 - REVIEW OF RELATED WORK

2.1 Decision-Making during Trade Space Exploration

Designing complex systems such as automobiles, aircraft, and spacecraft require tradeoffs between multiple conflicting and competing objectives [4]. Trade space exploration – a more general term for Balling’s “Design by Shopping” [6] paradigm – is a promising alternative to optimization-based approaches for designing such systems as it provides a visual and intuitive means for formulating, adjusting, and ultimately solving multi-objective design optimization problems [4]. As such, designers are able to “shop” for the best design as they explore design alternatives and gain insight into tradeoffs that impact design feasibility. Each design within a trade space may contain many design variables creating a multi-dimensional trade space [7].

Penn State’s ATSV software is used as the research testbed to evaluate the use of multi-dimensional data visualization and visual steering to covert data into knowledge to help solve engineering design problems that involve tradeoffs between multiple conflicting criteria. As an exploration tool, ATSV allows decision-makers to identify relationships between different design variables and to dynamically apply constraints and preferences in real-time by viewing complex design spaces using multi-dimensional visualization techniques [7]. ATSV’s visualization capabilities are
summarized in Chapter 3. Designers using ATSV must populate the trade space with designs either by importing previously generated designs or using ATSV’s visual steering commands, or samplers, which are also discussed in Chapter 3. Trade space exploration is also designed to keep decision-makers “in-the-loop” during the design optimization process [4]. Recent research using ATSV [8] has shown that keeping the decision-maker “in-the-loop” during the design process results in a 4x -7x increase in the number of Pareto optimal designs generated. This improvement is seen regardless of the combination of visual steering commands selected and the order in which they are employed. These studies are promising, but further evidence is needed to substantiate the benefits of trade space exploration.

2.2 User Expertise and Decision-Making

Since ATSV uses visualization as the main form of user feedback from the system, it is important to understand the differences between novices and experts with respect to using visualization tools. Seo [9] states that interactive exploration of multi-dimensional datasets can be challenging because it is difficult to see patterns in more than three dimensions. Klein [10] finds that expertise is based on a person’s ability to recognize and match patterns. The ability to perceive patterns and then to match patterns to actions in decision-making is built up through experience and practice [11]. From these findings, we can gather that novices may not have yet developed the pattern recognition ability of expert users and therefore may struggle with higher dimensional data visualization. Viewing data in more than three dimensions also
makes it harder to discover relationships, outliers, clusters, and gaps in the data [9]. Pattern detection is important especially for developing user-centered methodologies such as trade space exploration because humans are capable of learning from patterns and using this knowledge to improve their performance in a manner that no current algorithm can match [12]. Additionally Petre [13] finds that both perceptual and interpretive readership skill for graphical representations must be learned. Thus there is a clear difference between the way novice and expert users explore visualization tools [14] as less experienced users are unable to utilize graphical cues that may be helpful. Among the strategy differences between novices and experts, Petre [13] states that novices tend to confuse visibility with relevance whereas experts are able to match patterns and disregard irrelevant information.

Many aspects of the trade space exploration process are akin to naturalistic decision-making, which describes how decisions are actually being made in the field. Similar to trade space exploration, naturalistic decision-making pertains to various goals and sub-goals that are likely to change as new information is received and priorities change [2,11]. Trade space problems often contain shifting or competing goals and time constraints, which characterize the circumstances for naturalistic decision-making [15]. Recognition-primed decisions are said to occur in naturalistic decision-making [10], where experienced decision-makers are able to spend more resources assessing a situation rather than assessing different courses of action. Experienced decision-makers do not use their resources to generate a list of possible decisions
before making a decision; rather, they draw from previous experience to accept and reject options one at a time. This provides the user with improved situational awareness and enables the decision-maker to better work under time constraints by continually being prepared to initiate an action [11]. In this way naturalistic decision-making is influenced by the expertise of the decision-maker. Studies have shown [11] that experts do indeed place emphasis on situational assessment while novices emphasize deciding the course of action.

Since expert users have developed the ability to identify the appropriate path to a solution, they process information in a non-goal specific manner [16]. Conversely novices tend to work backwards from the solution, which does not promote knowledge toward non-goal specific problem solving. Since experts use generalities to work toward the solution of a problem they are better able to use their knowledge to solve varying problem types which trade space exploration presents. Another distinction between novices and experts is the relative frequency of which they use specific processes [17]. Novices tend to use a passive strategy of collecting data and seeing what happens whereas an expert’s ability to reason results in a much more varied mix of decision-making processes. In trade space exploration, this would translate into experts using a wider range of visualization tools and sampling techniques to solve a particular problem. Experts will probably use a wider range of visualization techniques to track more variables simultaneously because they are able to better see the big picture whereas novices may become confused by the sheer
number of data elements [10]. This is partially due to the fact that novices treat every piece of information as an independent unit [18] while experts use ‘chunking’ to treat several distinct items of information as a single unit. This allows experts to track more relevant information and have better situational awareness than novice decision-makers [17]. Cognitive Task Analysis [10] can be used to elicit the trade space exploration knowledge from expert decision-makers. Some goals of this analysis are to determine:

- Cognitive skills, rules, strategies, and plans;
- Perceptual learning, pattern recognition, and implicit or tacit knowledge;
- How experts represent a problem and work within the problem space;
- Difficulties in acquiring domain knowledge and skills; and
- Instructional procedures useful for moving a person from novice to expert.

The steps for Cognitive Task Analysis are; locate sources of expertise, evaluate the quality of the expertise, perform knowledge elicitation to get information from the expert decision-makers, process the findings so they can be interpreted to others, and applying the findings. From the Cognitive Task Analysis, a “mental model,” [19] or explanation of someone’s thought process for how something works, can be developed for the expert users during the trade space exploration process.

User expertise affects what a decision-maker needs from a decision-support program such as ATSV. Expert users desire rapid response times, brief and non-distracting feedback, as well as the ability to carry out actions with a limited number of
commands [20]. Novice users, on the other hand, require informative feedback about
task accomplishment as well as effective support methods toward task completion
such as instructions, dialog boxes, and online help. In order for a novice to carry out
tasks successfully, a limited number of actions should be required [20]. Shneiderman
[20] suggests that users be allowed to control the density of information feedback that
a system provides. Similarly they should be allowed to control the density of displays
that ATSV provides, as expert users prefer displays to be more densely packed than
novices. In light of this, a summary of ATSV’s multi-dimensional data visualization
and visual steering capabilities to aid decision-making are described next.
CHAPTER 3 - OVERVIEW OF MULTI-DIMENSIONAL VISUALIZATION AND VISUAL STEERING COMMANDS

3.1 Visualization Capabilities

ATSV is a Java-based application developed to support trade space exploration research [5,7]. As such, ATSV is capable of visualizing multi-dimensional trade spaces using Glyph, 1-D and 2-D Histograms, 2-D Scatter, Scatter Matrix, and Parallel Coordinate plots, linked views [21], and Brushing [1]. The design variables (inputs) and performance data (outputs) for different design alternatives can be generated off-line and then read into ATSV for visualization and manipulation (i.e., a “static” dataset). Alternatively, data can be generated dynamically “on-the-fly” by linking a simulation model directly with ATSV using its Exploration Engine capability [22]. If the simulation model is too computationally expensive to be executed in real-time, then low-fidelity metamodels can be constructed and used as approximations for quickly searching the trade space [23]. Once the simulation model is linked to ATSV, the visual steering commands described in Section 3.2 can be used to help the designer navigate the multi-attribute trade space [2].

Figure 1a shows a glyph plot that can display 8-dimensional information using the spatial position of an icon to represent three variables of a design while an additional five variables can be represented by the size, color, orientation, transparency, and text. Multiple histogram plots can be displayed within a single window as shown in
Figure 1b. Parallel coordinate plots, shown in Figure 1c, represent designs using polylines [24], intersecting parallel axes representing design dimensions. A scatter matrix, pictured in Figure 1d, is used to visualize all possible combinations of 2-D scatter plots. An example of Brushing controls is given in Section 4.1.

Figure 1 - Multidimensional Visualization Examples - a) Glyph Plot, b) Histogram Plots, c) Parallel Coordinates, and d) Scatter Matrix

3.2 Visual Steering Commands

ATSV offers a variety of visual steering commands, as introduced in [22], that allow designers to guide the generation of new designs within the trade space. The visual steering commands currently available include: 1) Basic Sampler, 2) Point Sampler,

*Basic Samplers* are used to randomly populate the trade space and are typically invoked if there is no initial data available. The user specifies the number of samples to be generated and the bounds of the multi-dimensional hypercube. Monte Carlo sampling then randomly samples the inputs – drawing from a uniform, normal, or triangular distribution – and executes the simulation model, storing the corresponding output in the database. The bounds of the design variables can be reduced at any point to bias the samples in a given region if desired. Figure 2 shows an example.

![Figure 2 - Example of Basic Sampler](image)

(a) 100 initial samples (b) 100 new samples in reduced region of interest

*Point Samplers* allow the user to manually sample the design space by moving slider bars for each input variable using controls like those shown in Figure 3. As such, the Point Sampler allows designers to perform one-factor-at-a-time parametric studies of the simulation model if they prefer this to random sampling. After moving a slider
bar, the simulation model is executed at the design point specified by the current setting of all slider bars, and the data is stored in the database.

The *Attractor* is used to generate new sample points near a user-specified location in the trade space. The attractor is specified in the ATSV interface with a graphical icon that identifies an $n$-dimensional point in the trade space, and then new sample points are generated near the attractor – or as close as they can get to it. Unbeknownst to the user, the attractor generates new points using a Differential Evolution (DE) algorithm [25], which assess the fitness of each new sample based on the normalized Euclidean distance to the attractor. As the population evolves in DE, the samples get closer and closer to the attractor. An example is shown in Figure 4 where the user specifies an attractor to fill in a “gap” in the trade space (see Figure 4a). The new samples cluster tightly around Attractor_1 as seen in Figure 4b.

![Figure 3 - Slider Bar Controls for Point Sampler](image)
Preference-based samplers allow users to populate the trade space in regions that perform well with respect to a user-defined preference function. New sample points are also generated by the DE algorithm, but the fitness of each sample is defined by the user’s preference structure instead of the Euclidean distance. An example of the preference-based sampler is shown in Figure 5. Using ATSV’s Brushing and preference controls, the user specifies a desire to minimize Obj1 and maximize Obj3 with equal weighting (see Figure 5a). Figure 5b shows the initial samples shaded based on this preference, and Figure 5c shows the new samples, where the concentration of points increases in the direction of preference, namely, the upper left hand corner of the plot.
Pareto and Guided Pareto Samplers are used to bias the sampling of new designs in search of the Pareto frontier once the user has defined his/her preferences on the objectives. The DE algorithm is again used to accomplish this sampling but is modified to solve multi-objective problems [26]. An example of an un-guided Pareto Sampler is shown in Figure 6. Using the same preferences (i.e., minimize Obj1 and maximize Obj3 with equal weighting), Figure 6a shows the Pareto points in the initial samples while Figure 6b shows the Pareto frontier after executing 7 generations of the DE with a population size of 25 points. The Guided Pareto Sampler [2] combines the power of Attractors with the multi-attribute exploration capabilities of the Pareto Sampler to allow users to modify the search for Pareto points in real-time. The Guided Pareto Sampler allows the user to exploit information that is gained during
the trade space exploration process and interact with the underlying Pareto Differential Evolution algorithm [27] by:

- Selecting specific points within the data visualization window and using these points to seed the initial generation
- Guiding the Pareto search algorithms to regions of interest using an Attractor
- Start, pause, and stop the search with the ability to change initial generations and guide directions.

These interactions allow the users to input, change, and adjust their preferences without being overly burdened by having to constantly input new visual steering commands.

![Figure 6 - Example of Pareto Sampler (Pareto points denoted by +)](image)

These visual steering commands can be used together in any combination to explore the trade space. When used in connection with the ATSV, designers have a powerful multidimensional visualization tool with the capability to “steer” the optimization
process while navigating the trade space to find the best design. The next section describes the experimental set up and test problems used to investigate the use of these tools to support design decision-making during trade space exploration.

To support the experiments discussed in Chapter 4, ATSV was modified to generate a log file of the user’s actions to capture the usage of the visualization and sampling tools described in this Chapter. The log file is generated while ATSV is being used, and it tracks all of the user’s actions such as opening a visualization tool or using a sampling tool to generate designs. The order in which each tool is accessed, as well as the number of designs generated with each sampling tool, is captured.
CHAPTER 4 - EXPERIMENTAL SETUP AND USER TRIALS

In this chapter, the test problems used for the Pilot Study, Preliminary Experiments, and Follow-on Experiments are described. Next, a description of the experimental setup for each user trial is presented. The performance measures for the Preliminary Experiments and the Follow-on Experiments are also discussed.

4.1 Test Problems

4.1.1 Combustion Chamber Design Model

The test problem used for the Pilot Study and the Preliminary Experiments is the combustion chamber design model [28] that is depicted in Figure 7. The original problem was split into two subsystems, Thermodynamics and Geometry, so that two subsystem designers could work on the problem simultaneously for collaborative optimization [29]. These subsystems were combined for the Pilot Study and kept separate for the Preliminary Experiments as explained later. The inputs to both subsystems are five continuous parameters that describe the geometry of the combustion chamber and are confined to the bounds listed in Table 1. The analyses for the problem can be found in Appendix A.
The objective in this problem is to maximize the Specific Power of the combustion chamber, or in this case, to minimize the Negative Specific Power (NSP), which is a function of $b$, $d_i$, $c_r$, and $w$. The corresponding Brush/Preference control settings are shown in Figure 8 and Figure 9 for the Geometry and Thermodynamics subsystems, respectively. As can be seen in these two figures, in addition to having the same objective, there is a global constraint on the engine stroke for both subsystems. The Geometry subsystem has five additional constraints, and the Thermodynamics subsystem has four additional constraints, each of which are a combination of system parameters that must remain less than or equal to zero.

**Table 1 - Inputs and Bounds for Combustion Chamber**

<table>
<thead>
<tr>
<th>Design Variable</th>
<th>Full Name</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b$</td>
<td>cylinder bore, mm</td>
<td>70</td>
<td>90</td>
</tr>
<tr>
<td>$d_i$</td>
<td>intake valve diameter, mm</td>
<td>25</td>
<td>50</td>
</tr>
<tr>
<td>$d_E$</td>
<td>exhaust valve diameter, mm</td>
<td>25</td>
<td>50</td>
</tr>
<tr>
<td>$c_r$</td>
<td>compression ratio</td>
<td>6</td>
<td>12</td>
</tr>
<tr>
<td>$w$</td>
<td>revolutions per minute at peak power, ÷1000</td>
<td>5</td>
<td>12</td>
</tr>
</tbody>
</table>
4.1.2 Conceptual Ship Design Model

The conceptual ship design model is the first of two multi-objective design problems used for the Follow-on Experiment with the expert decision-makers. This model was originally formulated by Sen and Yang [30] and was later adapted by Parsons and Scott [31]. This is a multi-objective design problem where the objectives are to
minimize the Transportation Cost (TC), minimize the Light Ship Weight (LSM), and to maximize the Annual Cargo (AC). The equations for Total Cost, Light Ship Weight, and Annual Cargo are derived in [30,31] and included in Appendix B.

This design problem involves approximating the design of a bulk carrier by varying the input parameters shown in Figure 10 and Table 2. These input parameters are subject to the bounds listed in Table 2.

Figure 10 - Conceptual Ship (A- Front View, B- Side View)
Table 2 - Inputs and Bounds for Conceptual Ship

<table>
<thead>
<tr>
<th>Design Variable</th>
<th>Full Name</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>Length (m)</td>
<td>150</td>
<td>274.32</td>
</tr>
<tr>
<td>B</td>
<td>Beam (m)</td>
<td>20</td>
<td>32.31</td>
</tr>
<tr>
<td>D</td>
<td>Depth (m)</td>
<td>13</td>
<td>25</td>
</tr>
<tr>
<td>T</td>
<td>Draft (m)</td>
<td>10</td>
<td>11.71</td>
</tr>
<tr>
<td>C_B</td>
<td>Block Coeff</td>
<td>0.63</td>
<td>0.75</td>
</tr>
<tr>
<td>V_k</td>
<td>Speed (kts)</td>
<td>14</td>
<td>18</td>
</tr>
</tbody>
</table>

Constraints are also placed on the output values as follows:

\[
\begin{align*}
    L/B & \geq 6 \\
    L/D & \leq 15 \\
    L/T & \leq 19 \\
    T - 0.45*DWT^{0.31} (\text{const}_1) & \leq 0 \\
    T - 0.7*D + 0.7 (\text{const}_2) & \leq 0 \\
    0.07*B - GM_T (\text{const}_3) & \leq 0 \\
    F_n & \leq 0.32 \\
    25,000 \leq DWT \leq 50,000
\end{align*}
\]

A feasible design satisfies all eight constraints and the input parameter bounds. The corresponding Brush/Preference control settings for the constraints and preferences are shown in Figure 11.
4.1.3 Aircraft Wing Design Model

The aircraft wing design model is the second of two multi-objective design problems used for the Follow-on Experiment with the expert decision-makers. This problem was originally formulated by Simpson and Meckesheimer [32] as a single objective problem to minimize Cost; however, a modified version of this problem developed by Carlsen [33] to include two additional objectives is used. These additional objectives are to maximize the aircraft Range and minimize the Takeoff Field Length.

This design problem involves sizing and shaping the layout of an aircraft wing by varying the input parameters shown in Figure 12 and Table 3. These input
parameters are subject to the constraints listed in Table 3. The equations for Cost, Range, Takeoff Field Length, and Buffet Altitude are listed in references [32,33] and are included in Appendix C. These output variables (Cost, Range, Takeoff Field Length, and Buffet Altitude) have been normalized to range between [0, 1] to protect the proprietary nature of the data.

![Aircraft Wing](image)

**Figure 12 - Aircraft Wing [32]**

**Table 3 - Inputs and Bounds for Aircraft Wing**

<table>
<thead>
<tr>
<th>Design Variable</th>
<th>Full Name</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Span</td>
<td>Semi-span</td>
<td>900</td>
<td>1150</td>
</tr>
<tr>
<td>AR</td>
<td>Aspect Angle</td>
<td>8</td>
<td>13</td>
</tr>
<tr>
<td>Sweep</td>
<td>Sweep Angle</td>
<td>31</td>
<td>37</td>
</tr>
<tr>
<td>Taper</td>
<td>Taper Ratio</td>
<td>0.15</td>
<td>0.25</td>
</tr>
<tr>
<td>Ycoeff</td>
<td>Y Coefficient</td>
<td>0.75</td>
<td>1</td>
</tr>
<tr>
<td>FanDiam</td>
<td>Fan Diameter</td>
<td>80</td>
<td>90</td>
</tr>
</tbody>
</table>

Constraints are also placed on the output variables as follows:

- Range $\geq 0.589$
- Buffet Altitude $\geq 0.603$
- Takeoff Field Length $\leq 0.377$
A feasible design satisfies all three constraints and the input parameter bounds from Table 3. The corresponding Brush/Preference control settings for the constraints and preferences are shown in Figure 13.

![Figure 13 - Brush/Preference Controls for the Aircraft Wing](image)

### 4.2 Pilot Study

Using the combustion chamber design model, a Pilot Study was preformed on a small test group in order to gain some insight into what potential differences may be observed between expert and novice decision-makers. Here “expert” refers to the level of expertise in using ATSV to solve engineering design problems, not expertise with the problem itself. In this study, an expert was defined as someone who had used ATSV to solve multiple design problems in the past; novice users had little to no experience with ATSV. For this study the participants acted as both the Thermodynamic and Geometry subsystem designers. This means that they combined the constraints from Figure 8 and Figure 9 to find the feasible design with the lowest NSP.
The Pilot Study was conducted by comparing the actions and results of two novice users and two expert users solving the combined Geometry and Thermodynamics subsystem problem described in Section 4.1. Neither group of users had solved this particular problem before. Each user was given an unlimited amount of time to solve the problem. Both novice users were given an overview of ATSV’s visualization and visual steering capabilities before starting the problem, and an expert user was available to answer any of their questions related to using individual tools in ATSV or clarifying the problem, but not to guide them in their solution of the problem. The Pilot Study was conducted under the direction of Dr. Xiaolong Zhang, Assistant Professor in the College of Information Sciences and Technology, and was observed and video recorded for analysis.

4.3 Preliminary Experiments

For the Preliminary Experiments, the participants solved only the Geometry subsystem for the combustion chamber design model. This was done primarily to reduce the complexity of the problem given the results of the Pilot Study. This subsystem problem was selected because it is a relatively simple model, but also contains many competing constraints and a single objective, which allows for easy comparison of results. The experiment was conducted on three groups: (1) novice decision-makers without a training video, (2) expert decision-makers, and (3) novice decision-makers with a training video. Each of the participants was given the problem description shown in Appendix D.
4.3.1 Description of User Trials

4.3.1.1 Novice Decision-Makers without Training Video

Participants in this part of the Preliminary Experiment were novices at trade space exploration but had experience with many of ATSV’s visualization methods. Data was collected from the results of the giving the Geometry subsystem design problem to these novices. In all, twenty-seven junior and senior undergraduate students from The Pennsylvania State University’s Industrial and Mechanical Engineering Department were selected as the trial group. The experimental protocol for these novices went as follows:

• As part of one of their regularly scheduled classes, the students were introduced to ATSV and its visualization and sampling capabilities, as well as background into the trade space exploration process;
• Students were then given ten minutes to perform their analysis and solve the Geometry subsystem problem; and
• The students submitted the log file and data set associated with their analysis, as well as an informed consent form giving permission to use their data.

The log files were then examined to determine which visualization and sampling methods each student used and to measure how many design alternatives they generated during their trade space exploration process. The data file listed all of the feasible designs generated by each student, from which the number of feasible designs and the best design were extracted.
4.3.1.2 Expert Decision-Makers

Data for the expert Preliminary Experiment was collected by giving the same combustion chamber design problem (Geometry subsystem) to a group of five expert users. These designers were considered expert users because of their experience in solving trade space exploration problems and using ATSV, as well as their general acceptance as experts by their peers. These experts did not have experience solving this particular design problem. The experimental protocol for the experts went as follows:

- The experts were then given ten minutes to perform their analysis and solve the Geometry subsystem problem; and
- The experts submitted the log file and data set associated with their analysis.

Their procedure was video recorded to capture their actions and any insights into their design methodology. Corresponding log files and data files were also collected to compare to the novices.

4.3.1.3 Novice Decision-Makers with Training Video

Data for the Preliminary Experiment among novice decision-makers with the training video was collected for the Geometry subsystem design problem similar to Section 4.3.1.1. A total of twenty-seven undergraduate and graduate students from The Pennsylvania State University’s Industrial and Mechanical Engineering Departments were selected as the trial group. This group was selected based on availability and that they met the criteria of being novices with respect to trade space exploration but
have experience with many of ATSV’s visualization methods. This experiment was
designed to give the novices the same introduction to ATSV and its visualization and
exploration capabilities as the novices who were not presented with the training
video. The experimental protocol for these novices went as follows:

- The students were introduced to ATSV and its visualization and sampling
capabilities, as well as background into the trade space exploration process;
- The novices were shown a training video that was designed from principles
learned from the previous two Preliminary Experiments and the Pilot Study.
This short video demonstrated the use of every available visualization and
sampling tool in the context of an example problem (the conceptual ship
design model described in Section 4.1.2) while emphasizing effective usage of
these tools;
- Students were then given ten minutes to perform their analysis and solve the
Geometry subsystem problem; and
- The students submitted the log file and data set associated with their analysis,
as well as an informed consent form giving permission to use their data.

Information was extracted from the log files and data sets as described in Section
4.3.1.1.

4.3.2 Performance Measures

Given that all users were given the same amount of time to complete the experiment,
there were two performance metrics used for the Preliminary Experiment analysis to
assess user efficiency in the trade space exploration process. Since the combustion
chamber design problem has only one objective, NSP, this was the first metric used for comparison. The nature of the objective allows designs to have a very large range of NSP, from as high as a three thousand to negative sixty-six (as seen in Figure 8), which is near the optimum. Noting the larger range of positive NSP values as compared to negative NSP values, and that only negative NSP values are acceptable, it is easy to see how large positive values of NSP can skew the dataset. Thus the Modified Thompson Tau [34] technique was used to discard outlier points. Decision-makers who were unable to generate any feasible points or whose best NSP design was determined an outlier are henceforth referred to as Underperforming Decision-Makers (UDMs). It is important to capture the fact that some users or trials underperformed since a high percentage of UDMs indicates that the decision-makers are having a hard time meeting their objective.

The second metric used was the percentage of feasible designs generated during a single trial. Since relatively few designs were generated by some of the novices during the Preliminary Experiment, this metric is useful because it is less dependent on the total number of designs generated. Thus decision-makers who have a higher percentage of feasible designs generated are considered more successful.

4.3.3 Reference Data Sets
Several reference data sets were generated for comparison to the Preliminary Experiment results. These data sets were randomly generated within ATSV. In particular, data sets for 250, 500, 833, and 1000 designs were generated using the
Basic Sampler to represent random sampling of the trade space. These generation sizes were chosen to show the progression of NSP values as the number of generations was increased, including 883 which was the average number of designs generated by the novices without the training video in the Preliminary Experiment. Ten trials were performed for each desired number of designs with the best NSP value and number of feasible designs recorded for each trial.

4.4 Follow-on Experiments

4.4.1 Description of User Trials

Data for the Follow-on Experiments was collected by giving the conceptual ship design problem (see Section 4.1.2) and the aircraft wing design problem (see Section 4.1.3) to a group of seven expert users. These two design problems were selected because they represented complex design problems involving tradeoffs between multiple conflicting criteria; however, they were solvable in a reasonable timeframe. The decision-makers were considered expert users because of their experience in solving trade space exploration problems and with using ATSV, but they had little to no experience solving these particular design problems. For the conceptual ship design model the experts were given the problem description shown in Appendix E, and for the aircraft wing design model they were given the problem descriptions shown in Appendix F. The experts were given unlimited time for each problem and were told to work until they were satisfied with their final design. Their actions were recorded in the corresponding log files which were collected at the end of each
problem along with the data files as described in Section 4.3.1.1. Additionally, the experts were encouraged to articulate insights into their procedural knowledge, which were recorded by hand by the observer.

### 4.4.2 Performance Measures

The Follow-on Experiments were conducted to understand procedural differences of expert decision-makers while performing trade space exploration design problems of various complexities. As part of this it is also important to understand which exploration strategies are most effective for these multi-objective problems. Since the three objectives for the conceptual ship design problem and the aircraft wing design problem were weighted equally (see Figure 11 and Figure 13, respectively), the expert performance was measured by normalizing the objectives. A value of 0 would represent the worst possible value for that objective and a value of 1 would represent the best possible value for that objective. For example, with the conceptual ship design model, one of the objectives is to minimize Cost (see Section 4.1.2); therefore, a normalized value of 1 would represent the lowest possible value of Cost and a normalized value of 0 would represent the highest possible value of Cost. Likewise, with the conceptual ship design problem another objective is to maximize Annual Cargo. Here a normalized value of 1 would represent the highest possible Annual Cargo value, and a normalized value of 0 would represent the lowest possible Annual Cargo value.
The average of these normalized objective values was taken for each problem. This average is also a normalized value, with 1 representing every objective being met to its full potential. Of course, there are tradeoffs between these objectives; so, a value of 1 is not achievable.
CHAPTER 5 - ANALYSIS AND DISCUSSION OF RESULTS

The data analysis for the Preliminary and Follow-on Experiments focuses first on the performance measures discussed in Sections 4.3.2 and 4.4.2, which were used to evaluate how well the decision-makers were able to explore the trade space and reach their objective(s). Additionally, the extent to which the visualization and sampling tools were used by the groups of decision-makers to solve a given design problem was analyzed.

5.1 Pilot Study Results

Since only four users completed the Pilot Study, detailed analysis of the data was not conducted. Instead, our analysis focused primarily on procedural differences between the two groups, namely, how novices and experts used ATSV to solve the problem. One thing that clearly distinguished expert and novice decision-makers is the use of various visualization tools in understanding multi-dimensional data to guide the change of parameters. After setting initial values for all constraints, experts and novices encountered the same problem, specifically, no feasible designs were observed. While the novices were surprised at the results and did not know what actions should be taken next to analyze multi-dimensional data and generate feasible designs, the experts seemed to expect the initial results and wasted no time before opening multiple visualization tools like Scatter Matrices, Parallel Coordinates, and multiple 3D views to examine what input variables could be manipulated to overcome
this challenge. In adjusting parameters, the experts used visualization tools for guidance and their approaches seemed heuristic, but effective. The novices’ approach was more based on trial-and-error. When feasible designs were finally obtained the experts could recognize them, and they used visualization tools to verify these good designs from various aspects, while novice users remained uncertain about the results.

From this Pilot Study, three notable differences between the novices and experts were observed:

- novice users are not as experienced in understanding multi-dimensional data;
- novice users are less familiar with strategies to use ATSV to solve problems; and
- novice users are not as good at evaluating the results by themselves.

While these differences were not surprising, it was speculated that they may be due to some of the following reasons:

- the lack of a “mental model” for novice users in what tools to use to make sense of complex and multi-dimensional data;
- the lack of a “mental model” for novice users in what tools to use to resolve tradeoffs and solve problems; and
- the inability of our system to help users see where possible results may be and to what extent available data may be close to the final results.
These results supported the development of a model about how people understand multi-dimensional data and how people solve multi-objective design problems. By using survey, interview, and log data analysis we can learn where decision-makers encounter problems or what those problems could be and then take preemptive actions to warn users of potential impasses. We also need to understand how experts overcome these impasses and what tools they use to do this effectively. Based on knowledge gained from expert users, novices could be provided with procedural knowledge based on their situation. These findings guided the development of the Preliminary Experiments.

5.2 Results from Preliminary Experiments

5.2.1 Measuring Performance

For comparison purposes the novice decision-makers were split into three subsets: (1) novices using low-dimensional visualization tools only, (2) novices using higher-dimensional visualization tools, and (3) novices using advanced samplers (samplers beyond the Basic Sampler). Comparison between data sets was performed using two-sample t-tests, with the one-tailed un-paired samples hypothesis test methodology [35]. P-values less than 0.05 indicate a statistically significant change between datasets.

5.2.1.1 Using NSP as the Metric

Figure 14 compares the results of the experts and novices without the video using NSP as the metric. The decision to remove outlier points was made in accordance
with the discussion in Section 4.3.2 since including the outlier points skewed the datasets substantially. Including the outliers in the data would have changed the mean NSP value for all novices without the training video from -42.31 (with no outliers) to 48.01. The distribution of NSP values for all three Preliminary Experiment groups can be seen in Figure 15. Even though a majority of the novices in each dataset performed with similar results, including the outliers would have greatly changed the mean and standard deviation of the datasets. The real value is from the majority of novices from each dataset that performed similarly; however, the percentage of data points that were excluded from each dataset are important to note and are presented later in this section.

![Figure 14 - Comparison of Datasets using NSP as the Metric](image-url)
The average number of designs generated by the novices without the video was just over 883; therefore, the data set of Basic Sampler trials with 883 designs generated each run is the best data set to compare to the novice data. A statistically insignificant difference between these novices without the video and the Basic Sampler with 883 designs in Figure 14 shows that the novices are producing only a small improvement in NSP over purely random sampling. This result is verified by Figure 16, which shows the average NSP values of four Basic Sampler trials against the number of designs generated, as well as a point representing the average NSP value versus the average number of designs generated by the untrained novice decision-makers. As can be seen, the novices barely out-perform random sampling.
This suggests that the novices without the training video are not able to effectively use ATSV’s visualization and sampling tools in a strategic manner and are in essence randomly sampling the trade space.

The data in Figure 14 also indicates that the Basic Sampler of 883 designs outperforms novices using Glyph Plots, the Attractor Sampler, or the Point Sampler; however, this change is only statistically significant with respect to the higher-dimensional visualization tools (Glyph Plots) with a p-value of 0.029. This indicates that these novices are not using the trade space exploration tools effectively. These results also may indicate that, without the training video, novices are not able to choose the appropriate trade space exploration tools during the design process.
Figure 14 also indicates that the overall novice population outperforms novices using Glyph Plots, the Attractor Sampler, or the Point Sampler; however, once again this result is only statistically significant in the case of higher-dimensional visualization tools with a p-value of 0.034.

Looking back at Figure 15, the novices produced significantly better NSP values with the training video, although there were still a few outlier points. In general, their performance was similar to that of the experts with a couple of the novices actually outperforming some of the experts. Figure 17 shows the comparison of average NSP values for novices with the training video compared to the other novices and the experts. Unlike Figure 14, there is no category separation based on sampling method since all novices who watched the training video used samplers beyond the Basic Sampler. There is a noticeable improvement from Novices without Video to Novices with Video, from an average of -49.24 to -57.41 respectively. This represents a statistically significant improvement in NSP between the two datasets with a p-value of 0.0002. After the training video the novices were able to produce good results while using the higher-dimensional visualization tools. This is in strong contrast to the results shown in Figure 14. The training video not only made the novices more comfortable in using the higher-dimensional visualization tools (as shown in Section 5.2.1), but also taught them how to use these visualization tools effectively.
Figure 17 - Additional Comparison of Datasets using NSP as the Metric

As seen in Figure 23, both groups of novices produced some outliers, which were designated as Underperforming Decision Makers (UDMs) in Section 4.3.2. For effective analysis techniques the percentage of UDMs would approach zero as every decision-maker is able to meet the objective with similar aptitude. Without the training video, 40.7% (11 out of 27) of the novices underperformed. Any NSP values over -31 were determined to be an outlier. On the other hand, only 18.5% (5 out of 27) of novices with the training video were designated as UDMs. These results suggest that overall the training video was able to teach the novices effective trade space exploration strategies.
5.2.1.2 Using Percentage of Feasible Designs as the Metric

Figure 18 presents the results of the trials with percentage of feasible designs as the performance metric. For this analysis we were once again faced with the decision of whether or not to include the outlier points for the novices. Unlike the outliers from the previous section, data points that were removed from these datasets were the best performing points (greatest percentages). Thus, by removing the outliers we are saying that the novices performed worse in the trial then they actually did, which handicaps their results. Another reason to keep the outlier points is that they were not extreme points as seen in Section 5.2.1.1, and they do not skew the overall dataset with their inclusion. Therefore the outlier points were included in this analysis.

Figure 18 shows that even the novices without the training video out-performed the Basic Sampler in every case. Novice decision-makers using glyph plots, the Attractor Sampler, or the Point Sampler produced a higher percentage of feasible designs than the Basic Sampler alone, however this improvement was not statistically significant (p-value < 0.05). Expert decision-makers out-performed All Novices and the Basic Sampler data sets with a p-value < 0.04 in each case. This certainty would be greater if not for the large standard deviation of the expert dataset.

For the novices with the training video, Figure 19 shows that they were able to produce a significantly higher percentage of feasible designs. This suggests that these novices are much more capable of exploring the trade space and focusing their designs in an area of interest. Similar to Figure 18, novices using the higher-
dimensional visualization tools were able to generate a much higher percentage of feasible designs. This emphasizes the impact that the training video had in teaching the novices how to effectively utilize these visualization tools to their benefit.

Figure 18 - Comparison of Datasets using Average Percentage of Feasible Designs as the Metric
5.2.2 Usage of Visualization and Sampling Tools

Figure 20 displays the percentage of novice and expert users that used each visualization and sampling tool discussed in Section 3. Starting with the visualization tools, Figure 20 shows the limited range of visualization methods that the novice decision-makers without the training video used. Almost every novice decision-maker in this category used 2-D Scatter Plots as their primary method for visualizing the trade space. From the log files it could be seen that students used many variations of 2-D Scatter Plots and sometimes used multiple Scatter Plots simultaneously. This result suggests that novice decision-makers are more comfortable using lower-dimension visualization tools. Only 40 percent of the novice decision-makers without...
the video used 3-D Glyph Plots. The performance of these users is explored more in Section 5.2.1.

Figure 20 also shows that the novices without the training video never used any of the remaining four visualization tools (Scatter Matrices, Parallel Coordinates, 1-D and 2-D Histograms), even though they were introduced to these tools during the overview in class. This may indicate a tendency for the novices to use the visualization tools with which they are most familiar and not try new tools when learning how to use ATSV. However, since none of the experts used histogram plots either, this may indicate that this type of plot was not appropriate for this particular design problem.
Unlike the novices without the training video, expert decision-makers used a wide variety of visualization tools both individually and as a group. One of the goals of the training video was to guide the novice decision-makers to use these higher dimensional visualization tools to help them better understand and visualize the trade space. The video sought to encouraging decision-makers to use a wider variety of visualization tools to help them explore the trade space more effectively while also helping them understand when each visualization tool was situationally appropriate. This goal seems to have been accomplished as the novices who viewed the training video took advantage of a wider range of visualization tools similar to the experts. The usage of Scatter and Glyph Plots remained almost constant, but there was a large increase in the percentage of novice decision-makers using the Scatter Matrix or Parallel Coordinate plots after viewing the training video (see Figure 20).

The results for trade space sampling methods detailed in Figure 20 show similar results to the visualization tools. Even without the training video all of the novice decision-makers were able to use Brushing to specify their constraints, and every novice decision-maker also used the Basic Sampler at least once to sample the trade space. Since it is commonplace to start a trade space exploration problem with a Basic Sampler run, we expected this sampling method to be used by every decision-maker. What is interesting though is the number of designs the novices without the video generated through random sampling as opposed to other methods. Most of these novices used the Basic Sampler as their primary sampling method (this is explored
further in Section 5.2.3). They were most likely just trying to sample until they found feasible designs, which indicates that they were goal-oriented but did not have the problem solving strategy necessary to best reach their objective. This supports the goal-specific nature of novice decision-making discussed in Section 2.2. Learning from expert decision-makers to understand effective non-goal-oriented problem solving strategy is desirable.

Although the novices were introduced to all of the sampling methods, only one-third of novice decision-makers without the training video used the Attractor or Point Sampler. Their performance compared to the novices with the training video is explored in Section 5.2.1. A negligible amount of novices without the video utilized the Preference or Pareto Sampler. The expert decision-makers demonstrated the use of a wider range of sampling methods similar to the visualization tools. As demonstrated by the expert’s performance, all of the available sampling methods can be very useful in trade space exploration; therefore, it was a priority in the training video to guide and encourage novice decision-makers to use these tools when appropriate. With the training video, the novices used a much wider variety of sampling methods. As seen in Figure 20, these novices used the Preference Sampler, Attractor Sampler, and Pareto Sampler with much higher frequency. Using the Point Sampler less may have been a consequence of the time constraint and the increased usage of the other samplers. The percentage of designs generated with each sampling
method and the novice’s ability to use these methods effectively is explored in the next two sections.

5.2.3 Activity Transitions between Samplers and Visualization Tools

Figure 21, Figure 22, and Figure 23 illustrate the state transition diagrams of activity [36] for the study groups in the Preliminary Experiment; novices without the training video, experts, and novices with the training video, respectively. In these figures, the circles represent the different samplers used by the decision-makers and the squares represent the different visualization tools used by the decision-makers. The size of the circles are proportional to the percentage of designs generated using that sampling method across the total population of that respective dataset. Similarly, the size of the squares is proportional to the number of times that visualization tool was utilized. The arrows between the squares and circles represent transitions between these tools. The weight (thickness) of each arrow is proportional to the number of times a transition between those tools was performed. Transitions that were not repeated, or occurred a relatively low number of times, are not represented by arrows. The information used to create these diagrams was ascertained from the log files by tracking transitions between tools and recording the number of designs generated with each sampling method.

As mentioned, Figure 21 represents the activity transitions for the novices without the video. From this diagram we can see that the novices relied heavily on the Basic
Sampler and the Brush Preference window. The Scatter Plot was used as the primary method of visualizing the data with the Glyph Plot being used only occasionally. As discussed in Section 5.2.1, these novices did not utilize the Scatter Matrix, Parallel Coordinates, or Histogram plots. The novices used the Attractor Sampler the most frequently; however, over twice as many designs were generated with the Basic Sampler. The Point Sampler and Pareto Sampler were used to generate a relatively smaller number of designs in comparison. In terms of the transitions, there were many transitions between the Basic Sampler and the Scatter Plot as well as between the Basic Sampler and Brush Preferences. There are also quite a few transitions between the Brush Preferences window and the Scatter Plot. Most of these novices’ transitions were between these three tools (Basic Sampler, Scatter Plot, and Brush Preferences) showing that they are primarily utilizing the simplest tools in ATSV. These novices also often used the attractor sampler within the Scatter Plot meaning that they are working with lower-dimensional attractors.
Figure 21 - Activity Transitions in Preliminary Experiment - Novices without Training Video

Figure 22 represents the activity transitions for the expert decision-makers in the Preliminary Experiment. Similar to the novices in Figure 21, the experts utilized the Scatter Plots with the greatest frequency. However, the experts frequently used Parallel Coordinates, Scatter Matrices, and the Glyph Plots when appropriate. One of the greatest differences between the novices without the video and the experts is that the experts used the Basic Sampler much less frequently. Not captured in Figure 22 is that the experts primarily used the Basic Sampler to initially populate the trade space and then only used the more advanced sampling methods thereafter. The experts generated most of their designs using the Pareto Sampler, which is in strong
contrast to the novices without the video. The Attractor and Preference Samplers were moderately used, while the Point Sampler was used to generate only a relatively few number of designs.

From Figure 22 the most common expert transitions can be seen. In particular, Parallel Coordinates to the Attractor Sampler was the most frequent transition, showing that the experts preferred to use multi-dimensional attractors combined with Parallel Coordinates to visualize the trade space. The strongest two-way transition was between the Pareto Sampler and the Scatter Plot. Many experts also transitioned between the Basic Sampler and the Scatter Plots. This shows that after initially populating the trade space, the experts liked to view the designs that were generated before specifying their preferences and constraints. The Pareto Sampler and Glyph Plot also had a large frequency of transitions between them as the experts sometimes
visualized the Pareto surface in multiple dimensions to look for changes as the Pareto Sampler was used.

As can be seen in Figure 21 and Figure 22, there are pronounced differences between the novices without the video and the experts. Thus a training video was created to teach the novices better trade space exploration methodology and encourage the novices to replicate many of the most common expert actions discussed above. The training video was about six and a half minutes long and demonstrated the use of ATSV in solving the conceptual ship design problem described in Section 4.1.2.

Figure 23 represents the activity transitions for the novices with the training video. Similar to the novices without the training video, the novices with the video primarily used the Scatter Plot for visualization. However these novices used Parallel Coordinates quite frequently and even utilized the Scatter Matrix occasionally. The greatest difference is that these novices relied significantly less on the Basic Sampler and instead utilized a large variety of sampling methods. The Pareto Sampler, which was not used by the novices without the training video, was used to generate the greatest number of designs. The Preference Sampler was used to generate a large number of designs, most likely in an attempt to generate some feasible solutions as suggested in the training video. The Attractor Sampler was also used to generate a larger percentage of designs; additionally, Parallel Coordinates replaced the Scatter Plot as the preferred visualization tool for the Attractor Sampler. The training video
demonstrated the use of higher-dimensional attractors using Parallel Coordinates, and it appears that many of the novices chose to replicate this method. The novices with the training video also appear to be doing a better job of utilizing the visualization tools to guide their design decision-making. They often visualized the initial population of data before inputting the constraints and preferences, which is similar to the experts’ approach. Their ability to utilize the visualization tools to guide their design generation is also supported by the fact that there were not a lot of transitions between different samplers, but rather they are referencing the visualization tools both before and after new design generation. Figure 23 also shows an even distribution of actions similar to that of the experts in Figure 22. This suggests that they are gaining some procedural decision-making knowledge through training and are not simply relying on repeatedly using the simplest tools as with the untrained novices in Figure 21.
5.3 Results from Follow-on Experiments

5.3.1 Measuring Performance

As discussed in Section 4.4.2, the performance of the experts was measured by taking the average of the normalizing objective values, with a higher value representing a more preferable design based on the objectives. The performance of the experts for the conceptual ship and the aircraft wing design models are shown in Figure 24 and Figure 25, respectively. For the conceptual ship design model, the best performers were Experts #5 and #6. These experts were the only two that used the Scatter Matrix plot or the Point Sampler. Using the Point Sampler most likely allowed them to refine their best design and provide a superior solution. Expert #4 was the only
expert to rely exclusively on the Glyph Plot, and Expert #7 was the only expert to rely exclusively on the Preference Sampler. Relying too heavily on a single visualization or sampling tool may have handicapped this expert’s ability to fully examine the trade space.

For the aircraft wing design model in Figure 25 the best performers were Expert #3 and Expert #6. These experts were the only two to use both the Preference and Pareto Samplers. Expert #4 again only utilized Glyph Plots, and Expert #7 again only utilized the Preference Sampler, which may have been a handicap. For both problems, the experts performing average or above average utilized a larger range of sampling and visualization tools than the lower performers. This suggests that each tool can provide a situational advantage to the decision-maker if used properly. For both of these problems, all experts except Expert #7 relied heavily on the Pareto sampler.
Figure 24 - Normalized Sum of the Objectives for the Conceptual Ship Design Model

Figure 25 - Normalized Sum of the Objectives for the Aircraft Wing Design Model
5.3.2 Usage of Visualization and Sampling Tools

The percentage of experts using each visualization and sampling tool for both the conceptual ship and aircraft wing design problem are shown in Figure 26. Between the two problems there are only slight differences in tools used, which suggests that the experts utilized a common design methodology to solve these problems. The only notable difference was that Parallel Coordinates were used more with the aircraft wing problem (an explanation for this is discussed in Section 5.3.3).

![Figure 26 - Percentage of Experts using Each Visualization and Sampling Tool](image)

In comparison to Figure 20 for the combustion chamber design problem, the experts also commonly used the Scatter Plots and Pareto Sampler. The Basic Sampler and
Brush Preference window were used every time as expected, and the Histograms were not used by any of the decision-makers. The Glyph Plots were frequently used for these three-objective problems in order to visualize the Pareto surface, whereas the best design for the single-objective combustion chamber problem could be easily visualized in a Scatter Plot.

5.3.3 Activity Transitions between Samplers and Visualization Tools

Figure 27 and Figure 28 illustrate the state transition diagrams of activity for the Follow-on Experiments, for the conceptual ship design and the aircraft wing design model, respectively. These transition diagrams were constructed as described in Section 5.2.3 with the size of the squares representing the number of times each visualization method was utilized, the size of the circles representing the percentage of designs generated with each sampling method, and the weight of the arrows representing the relative number of transitions between the samplers and visualization tools.
Similar to the single objective combustion chamber design problem (see Figure 22) the experts solving the conceptual ship design problem relied most heavily on the Pareto Sampler (see Figure 27). Each of the other sampling methods were utilized but only in certain situations. The Basic Sampler was used exclusively at the beginning of the analysis to initially populate the trade space. The Attractor Sampler was primarily used for placing higher-dimensional attractors in Parallel Coordinates, which were placed on the objectives and constraints. The Point Sampler was used at the end of the analysis by a couple of the experts. The objective was to sample around the current best design by varying the parameters of that design in an attempt to fine-tune the result and discover any more-preferable design variations. The Pareto
Sampler had many transitions between the Brush Preferences window as the experts varied the constraints and preference to check for sensitivities. Most of the experts tried to learn which constraints they were violating and proceed accordingly. The experts often preferred to visualize only the Pareto front of designs, usually in the Glyph Plot so that they could visualize all three objectives concurrently and form a Pareto surface. The experts would look at the distribution in this surface to make sure that they were sampling across the whole surface, and they would watch the progression of this surface to see if they were generating better designs.

Figure 28 shows the transition states for the experts solving the aircraft wing design model. This diagram strongly resembles Figure 27 for the conceptual ship design problem suggesting that they were using basically the same strategy for both problems. The Pareto Sampler was used to generate the largest percentage of designs, and the other sampling methods were again only used in certain situations as described for the conceptual ship design problem above. Experts utilized the Brush Preferences window much less in this problem, which can be attributed to the fact that the aircraft wing model had fewer constraints than the conceptual ship model. Since the constraints overlapped the objectives, it was more effective to use multi-dimensional attractors in Parallel Coordinates to improve their design and satisfy the constraints simultaneously; therefore, this problem saw an increase in the number of Attractor Sampler designs created using Parallel Coordinates. The experts again preferred to visualize the three-dimensional Pareto surface using the Glyph Plot. The
Point Sampler was again used to sample around the current best design. In both Figure 27 and Figure 28, the Point Sampler only represents a small percentage of designs; however, it can be seen from the large number of transitions between the Scatter Plot and Point Sampler that the Point Sampler is being used often. This is expected since the Point Sampler generates designs much slower than the other samplers and thus represents a lower percentage of the total designs generated.

![Diagram of Activity Transitions in Aircraft Wing Design Follow-on Experiment](image)

**Figure 28 - Activity Transitions in Aircraft Wing Design Follow-on Experiment**

### 5.4 User Feedback and Additional Results

As part of the experiment with the training video, the novices were asked to fill out a survey after completing the design problem. This survey was aimed at gaining insight into the novice’s perceptions about the trade space exploration process and to
learn ways to better support them in the future. The novices were asked to rate the helpfulness of each visualization tool and visual steering command on a 5-point Likert-type scale (with 1 being unhelpful, 3 being moderately helpful, and 5 being helpful); the results are summarized in Figure 29 (including Standard Error bars).

![Figure 29 - Novice Ratings of the Helpfulness for each Visualization Technique and Visual Steering Command](image)

From this figure we can see that these novices preferred Scatter Plots and Parallel Coordinates for visualizing the trade space, and that they preferred the Pareto Sampler to generate new designs. This is particularly interesting because without the training video the novices did not use these tools (see Figure 20). The novices rated
their previous experience with Parallel Coordinates as only a 1.95 on a 5-point scale (1 being inexperienced and 5 being very experienced). The example problem shown in the training video changed their perceptions about, and their ability to use, these tools. After the training video, the novices placed a greater preference on using the more advanced samplers; however, because of the utility of the Point Sampler seen in the expert experiments, further emphasis should be placed on teaching the novices how to effectively use the Point Sampler in the future. Interestingly the novices did not find the Glyph Plots very helpful. Additional training would be required to prepare them to solve multi-objective design problems such as those presented in the Follow-on Experiment.

Figure 30 provides insight into which support functions the novices would like to see in the future. They were asked to rate the utility (usefulness and likelihood that they would utilize) some listed support features if they were available on a 5-point Likert-type scale (1 being Unhelpful/Unlikely and 5 being Helpful/Likely). The novices rated Sample Problems, Training Video Examples, and Steps for Problem Solving as having the highest utility. Interestingly, the training video created for the Preliminary Experiment met these criteria by focusing on providing problem solving suggestions during the demonstration of an example problem. The novices also rated Error Messages as being the least helpful potential support feature. This may be because Error Messages would only make them aware of a problem, and they prefer more constructive forms of support since they are relatively inexperienced.
Additionally, the novices were asked what the most challenging part of the analysis was for them. This question was posed to understand where additional support features could be provided in the future. Several responses claimed that the hardest part was remembering how to get started or remembering all of the tools available to generate a preferable design. These concerns could be addressed by providing example problems or problem solving steps as previously discussed. Some novices also said that they did not realize how useful it was to sample based on their constraints. Within ATSV’s samplers there is a check box titled “Enable Brushed Constraint” that, when selected, generates designs within the user specified constraints. Even though the training video emphasized selecting this option, very
few novices remembered to use this feature. This is most likely because they assumed that by putting their constraints in the Brush Preferences window that the samplers would automatically take them into account. A helpful modification to the software would be to have “Enable Brushed Constraints” selected as a default at the beginning of the analysis, and then giving the decision-maker the option to turn it off. Finally, many comments simply pertained to the difficulty in remembering where certain buttons and controls were and what they did. This is most likely a result of them being introduced to a large amount of information in a relatively short period of time. Future novices would benefit from additional software orientation time.

Additionally, insights into the expert’s problem solving methodology were gained during the Preliminary and Follow-on Experiments. First, the experts often used color to indicate their preference in many of the visualization windows, especially when the objective(s) was not placed on an axis. Using color to indicate preferences in the visualization tools was emphasized in the training video. Preference coloring also serves to combine multiple objectives so that highly preferred designs can be easily identified. Additionally, a “Guided” Pareto Sampler option [2] was also available where the decision-maker could select existing designs to seed the initial population of the Pareto Sampler. This methodology was also seen in both the expert Preliminary and Follow-on Experiments and was demonstrated in the training video. However for the training video it was suggested that only the “best” current designs be selected as the initial population, whereas some experts in the Follow-on Experiment also selected a few less preferable designs in the initial population. This
was done in order to help prevent falling into a local area of “best” designs, where other more preferable designs exist in another un-sampled region of the trade space.

5.5 Implications of the Results

The results suggest that, without the training video, novice decision-makers were able to use Glyph Plots, the Attractor Sampler, or the Point Sampler with limited success to find trade space regions with more feasible designs. They were not able to significantly improve their single objective in the internal combustion chamber design model compared to purely random sampling. Interestingly, untrained novices using Glyph Plots performed worse than the whole population of novices. This suggests that without proper training, novices are not able to use higher-dimensional visualization plots effectively to find regions with feasible designs.

Since the novices initially performed so poorly while using a limited scope of trade space exploration tools, it was apparent that novice users would benefit from training into using a wider variety of visualization tools and sampling methods. The training video that was created for the Preliminary Experiments was designed for this purpose, as well as to teach the novices strategies for trade space exploration from what was learned from the expert Preliminary Experiment. It is important to understand why novices do not use certain tools and address these issues, whether providing more background and training for tools that they are not familiar with or by guiding them to use each tool when it is most valuable to support decision-making and exploration.
The utility of this strategy was demonstrated through the improved performance among novices who viewed the training video.

Engineering design problems are very diverse, and the most appropriate visualization and sampling tools to use will vary from problem to problem. Understanding in what way individual tools, or combinations of tools, can be used to gain a better understanding of the problem is something that is not easily trained and is perhaps best learned through experience. The training protocols developed in this analysis substantially improved the novices’ average performance by teaching them effective design decision-making strategies and making their approach more comparable to those of the experts. Since novice decision-makers initially do not have a large range of situational experience to draw upon, training protocols helped teach novices how to find patterns in the data and to filter out irrelevant information. Not captured in the results presented is the fact that novices often tended to misuse the visualization tools they selected by not viewing the variables of greater importance. In this way, they exhibited the novice tendency of confusing visibility with relevance [13]. With the training video the novices were better able to visualize the dimensions of higher importance, namely the objective, through Parallel Coordinates, or by placing the objective on one of the axis as suggested by the video.

Interestingly, expert decision-makers in both the Preliminary Experiment and Follow-on Experiments appeared to be split between two different design strategies. Some of
the experts relied heavily on visualization tools to find patterns in the data, and then carefully selected the appropriate sampling techniques. This approach proved to be appropriate for solving any trade space exploration problem regardless of the number of inputs, constraints, and objectives. Other experts took advantage of the ability to rapidly generate new designs. For the single-objective problem they used lower-dimensional visualization tools to watch the progression of the objective function as they applied various sampling techniques to quickly generate thousands of designs. Regardless of the technique used, the expert decision-makers produced consistently high performance; however, the experts that took advantage of the single-objective problem and generated more designs in the ten-minute timeframe performed noticeably better. On the other hand, there was no correlation between the number of designs generated and the expert’s performance (presented in Section 5.3.1) for the multi-objective problems. It is important to see how these differing design methodologies vary in their ability to solve problems with different numbers of inputs, constraints, and objectives.
CHAPTER 6 - CONCLUSIONS AND FUTURE WORK

This thesis presented results from ongoing research that seeks to formalize methods, tools, and procedures to support trade space exploration and quantify its benefits in engineering design. Multiple controlled experiments were performed to examine how novice and expert decision-makers use multi-dimensional data visualization and sampling tools to help make decisions during trade space exploration. This research suggests that novice decision-makers are currently ineffective at using our visualization research testbed, ATSV, in particular, and multi-dimensional data visualization tools, in general, to help solve a design problem. Without proper training, keeping the novice decision-makers “in-the-loop” did not significantly improve design performance over purely random sampling. This can be attributed to the fact that the novices did not effectively use the variety of tools available to them but rather used the same tools repeatedly based on their background and the limited training that they received. Encouraging novices to use a wider variety of visualization and sampling tools improved design performance, corroborating previous research [37].

Cognitive Task Analysis [10] was performed to elicit the trade space exploration knowledge and strategies from expert decision-makers. This information was formulated into a training video so that novices could learn and benefit from the effective use of visualization tools and visual steering commands to support design
decision-making. These training procedures substantially improved the novice’s average performance as they were able to quickly learn strategies for effective design decision-making. Since decision-makers are often left without an orderly approach to explore data [11], this knowledge elicitation pertained to how to effectively use visualization and sampling tools and when they are most beneficial for trade space exploration. Conducting future studies on experts can further develop basic trade space exploration strategies to be given to novice users to aid their exploration of trade spaces with different numbers of variables, objectives, and constraints. Schneiderman [20] states that a “guidelines document” can promote consistency among multiple designers. This document could provide rules of thumb or guidelines to solving trade space exploration problems based on the experimental results presented in this thesis or from future studies. In addition to consistency, guidelines would also help promote non-goal-specific problems solving, which is characteristic of expert decision-makers [16].

There were some limitations associated with this work. For the Pilot Study there was a small population size due to availability of participants, whereas including more people may have given additional insight into the differences between novices and experts. For the Preliminary Experiments, our novice test groups were limited to undergraduate and graduate students who were mostly Mechanical and Industrial Engineers. Some of these novices had experience with optimization but not with the visualization tools, sampling tools, or the test problem they were trying to solve.
More diverse sample populations may have produced different results. For the Preliminary Experiment with the training video, some of the participants were graduate students; whereas, all of the participants in the novice study without the training video were undergraduate students. Although there was no correlation seen between education level and performance in the Preliminary Experiment with the training video, it would have been preferable to use participants of the same education level for both studies. Also, the time that the novices were given to conduct the Preliminary Experiment was limited to ten minutes due to time restrictions. It would have been preferable to give the students more time to explore the trade space and become oriented with the software before and during the analysis. Additionally, the time designated for the training video was limited, especially considering the amount of information presented. Allotting more time for training should help the novices become better oriented with the software and the available tools. Finally, since trade space exploration is a relatively new field, there were also a limited number of experts from which to extract information.

Finally, the work in this thesis did not capture evolving preferences since the decision-maker’s preferences needed to be predefined in order to measure their performance. The a posteriori articulation of preferences [7] is the foundation of the “Design by Shopping” paradigm [6] and should not be forgotten as an important aspect of trade space exploration process. This is perhaps the greatest limitation of this work and should be the focus of future work in this area. It would also be
valuable to understand why novices pick a “best” design when multiple competing objectives are present, as compared to how an expert decision-maker would select a design. Understanding the differences between how novices and experts form their preferences and select the “best” design is important. For the activity transition diagrams, it may have been useful to size the visualization squares based on the time spent using a visualization tool rather than by the number of times that visualization was utilized. This would provide additional understanding into how efficiently decision-makers are able to use these visualization tools. Additionally, more detailed studies into the pattern recognition abilities of novices and experts should be examined. The training procedures tested in this thesis showed that novices could be taught how to effectively use visualization and visual steering tools to explore a trade space; however, even with the training video, the novice’s ability to recognize and understand patterns especially in higher dimensions remained limited. This is perhaps the largest barrier between expert and novice decision-making ability [9,10]. Understanding where the novice’s limitations exist and continually developing training protocols and support features to support effective design methodology is important.
REFERENCES


APPENDIX A - Combustion Chamber Design Model Equations [28,29]

\[
V_p = \left[ \frac{8V_w}{\pi N_c b^2} \right]
\]

\[
FMEP = 4.826(c_r - 9.2) + 7.97 + 0.253V_p + 9.7 \times 10^{-6} V_p^2
\]

\[
\eta_{\text{rad}} = 0.8595(1 - c_r)\gamma
\]

\[
S_v = \frac{0.83 \left( (8 + 4c_r) + 1.5(c_r - 1) \left( \frac{\pi N_c}{V} \right) (b^2) \right)}{(2 + c_r)b}
\]

\[
\eta_t = \eta_{\text{rad}} - S_v 0.083 \sqrt{\frac{1.5}{W}}
\]

\[
\eta_{ovb} = 1.067 - 0.038e^{w-5.25} \text{ for } w \geq 5.25
\]

\[
\eta_{vb} = 0.637 + 0.13w - 0.014w^2 + 0.00066w^2 \text{ for } w < 5.25
\]

\[
\eta_v = \frac{\eta_{ovb}(1 + 5.96 \times 10^{-3}w^2)}{1 + \left( 9.428 \times 10^{-5} \right) \left( \frac{4V}{\pi N_c C_s} \right) \left( \frac{w}{d_j^2} \right)^2}
\]

\[
P_0 = \frac{\rho Q}{A_f}
\]

\[
P_1 = \frac{L_1}{K_1 N_c}
\]

\[
P_2 = \left( \frac{4K_2 V}{\pi N_c L_0} \right)^{0.5}
\]

\[
P_3 = \frac{9.428 \times 10^{-5} \left( \frac{4V}{\pi N_c} \right)}{K_6 C_s}
\]

\[
P_4 = \frac{3.6 \times 10^{-6}}{K_6 Q}
\]
\[ s = \frac{4V}{\pi N_c b^2} \]

\[ Z_n = \frac{9.428(10^{-2}) w_s \left( \frac{b}{d_l} \right)^2}{C_s} \]

\[ IMEP = \eta_c \eta_w P_0 \]

\[ NetSpecPower = K_0 w (FMEP - IMEP) \]

\[ 0.7 \leq \frac{b}{s} \leq 1.3 \]

Min bore wall thickness "MinBoreWallThink" = \( b - P_1 \leq 0 \)

Max engine height "MaxEngineHeight" = \( P_2 - b \leq 0 \)

Valve Geometry and Structure "ValveStructure" = \( d_z + d_g - K_5 b \leq 0 \)

Min valve diameter ratio "MinValveDiaRatio" = \( K_4 d_z - d_g \leq 0 \)

Max valve diameter ratio "MaxValveDiaRatio" = \( d_g - K_5 d_l \leq 0 \)

Max chamber Mach Index "MaxMachIndex" = \( P_3 w - d_l^2 \leq 0 \)

Knock - limited compression ratio "KnockLimit" = \( c_r - 13.2 + 0.045 b \leq 0 \)

Max torque converter rpm "MaxTorqConvertRPM" = \( w - K_7 \leq 0 \)

Min fuel economy at part load "FuelEconomy" = \( P_4 - 0.8595 (1 - c_r^{(1-n^2)}) + S_r \leq 0 \)
APPENDIX B - Conceptual Ship Design Model Equations [30,31]

\[
C_s = 1.3(2000W_g^{0.85} + 3500W_o + 2400P^{0.8}) \\
C_v = 0.2C_s \\
C_v = (C_f + C_p)RTPA \\
C_r = 40000DWT^{0.3} \\
C_a = C_e + C_v + C_r \\
AC = (DWT_c)(RTPA) \\
TC = C_s = \frac{C_a}{AC} \\
W_g = 0.0341B^{0.7}D^{0.4}C_B^{0.5} \\
W_o = L^{0.8}B^{0.6}D^{0.3}C_B^{0.1} \\
a = 4977.06C_B^2 - 8105.61C_B + 4456.51 \\
b = -10847.2C_B^2 + 12817C_B - 6960.32 \\
\Delta = 1.025(L)(B)C_BV_k \\
F_n = \frac{0.5144V_k}{(9.8056L)^{0.6}} \\
P = \frac{\Delta V_k^3}{a + bF_n} \\
W_m = 0.17P^{0.9} \\
LSM = W_g = W_o + W_m \\
RTM = 5000
\[ DC = \frac{(0.19)(24)(P)}{1000} + 0.2 \]

\[ D_{sea} = \frac{RTM}{24V_k} \]

\[ DWT = \Delta - W_{is} \]

\[ DWT_M = 2(DWT)^{0.8} \]

\[ DWT_C = DWT - FC - DWT_M \]

\[ FP = 100 \]

\[ C_f = 1.05(DC)D_{sea}(FP) \]

\[ C_p = 6.3(DWT)^{0.8} \]

\[ FC = DC(D_{sea} + 5) \]

\[ HR = 8000 \]

\[ D_{port} = 2\left(\frac{(DWT_C)}{HR} + 0.5\right) \]

\[ RTPA = \frac{350}{D_{sea} + D_{port}} \]

\[ KB = 0.53T \]

\[ BM_T = \frac{(0.085C_B - 0.002)B^2}{C_BT} \]

\[ KG = 1 + 0.52D \]

\[ const_1 = T - 0.45(DWT)^{0.31} \]

\[ const_2 = T - (0.7D + 0.7) \]

\[ const_3 = 0.07B - (KB - BM_T + KG) \]
APPENDIX C - Aircraft Wing Design Model Equations [32,33]

900 ≤ Semi-span, \( x_1 \) ≤ 1150

8 ≤ Aspect ratio, \( x_2 \) ≤ 13

31 ≤ Sweep angle, \( x_3 \) ≤ 37

0.15 ≤ Taper ratio, \( x_4 \) ≤ 0.25

0.75 ≤ Y Coff, \( x_5 \) ≤ 1

80 ≤ Fan Diameter, \( x_6 \) ≤ 90

\[
\text{Cost} = 0.2854 - 0.005*x_6 + 0.3109*x_5 - 0.0122*x_3 - 0.2095*x_4 - 0.4836*x_2 + 0.4431*x_1 + 0.1037*x_6*x_6 - 0.0592*x_5*x_5 - 0.0204*x_3*x_3 + 0.1057*x_4*x_4 + 0.2494*x_2*x_2 + 0.0218*x_1*x_1 + 0.0581*x_6*x_5 - 0.0025*x_6*x_3 + 0.0034*x_6*x_4 + 0.0502*x_6*x_1 + 0.0326*x_6*x_1 + 0.1254*x_5*x_3 - 0.1362*x_5*x_4 + 0.1664*x_5*x_2 - 0.4223*x_5*x_1 + 0.1039*x_3*x_4 - 0.0155*x_3*x_2 - 0.0735*x_3*x_1 - 0.1281*x_4*x_2 + 0.2183*x_4*x_1 - 0.2109*x_2*x_1
\]

\[
\text{Range} = 0.3576 - 0.0329*x_6 + 0.1978*x_5 + 0.0149*x_3 - 0.0389*x_4 - 0.4652*x_2 + 0.4453*x_1 + 0.0149*x_6*x_6 - 0.051*x_5*x_5 + 0.0075*x_3*x_3 - 0.0229*x_4*x_4 + 0.0987*x_2*x_2 - 0.0188*x_1*x_1 - 0.0524*x_6*x_5 - 0.0272*x_6*x_3 + 0.0281*x_6*x_4 - 0.0147*x_6*x_2 + 0.0083*x_6*x_1 + 0.1018*x_5*x_3 + 0.0563*x_5*x_4 - 0.0349*x_5*x_2 + 0.064*x_5*x_1 + 0.0073*x_3*x_4 + 0.0176*x_3*x_2 + 0.0341*x_3*x_1 + 0.1063*x_4*x_2 - 0.0374*x_4*x_1 + 0.0143*x_2*x_1
\]

\[
\text{Takeoff Field Length} = 0.2884 - 0.2896*x_6 + 0.3376*x_5 + 0.0088*x_3 - 0.0478*x_4 - 0.1448*x_2 + 0.1239*x_1 + 0.0714*x_6*x_6 - 0.029*x_5*x_5 + 0.0148*x_3*x_3 + 0.0068*x_4*x_4 + 0.2251*x_2*x_2 + 0.1654*x_1*x_1 - 0.12*x_6*x_5 - 0.0475*x_6*x_3 + 0.0426*x_6*x_4 - 0.0486*x_6*x_2 + 0.1058*x_6*x_1 + 0.1712*x_5*x_3 + 0.0071*x_5*x_4 - 0.0887*x_5*x_2 + 0.0759*x_5*x_1 + 0.0028*x_3*x_4 - 0.0056*x_3*x_2 + 0.064*x_3*x_1 + 0.0063*x_4*x_2 + 0.0456*x_4*x_1 - 0.2902*x_2*x_1
\]

\[
\text{Buffet Altitude} = 0.617 - 0.1221*x_5 - 0.0485*x_3 + 0.0141*x_4 - 0.4507*x_2 + 0.6968*x_1 + 0.0248*x_5*x_5 + 0.0277*x_5*x_3 + 0.011*x_4*x_4 - 0.0873*x_2*x_2 - 0.295*x_1*x_1 - 0.061*x_5*x_3 - 0.0789*x_5*x_4 + 0.0546*x_5*x_2 - 0.1674*x_4*x_1 - 0.008*x_3*x_4 + 0.0422*x_3*x_2 - 0.0371*x_3*x_1 + 0.017*x_4*x_2 - 0.0507*x_4*x_1 + 0.2845*x_2*x_1
\]
APPENDIX D - Instructions for Combustion Chamber Design Problem

Your goal is to optimize the design of a combustion chamber for an internal combustion engine. Assuming a flat head design as depicted in Fig. 1, the design variables you can manipulate are the cylinder bore ($b$), compression ratio ($c_r$), exhaust valve diameter ($d_E$), intake valve diameter ($d_I$), and the revolutions per minute at peak power ($w$). The objective is to minimize the NegSpecPower, which is a function of these five variables, while satisfying a set of constraints.

Minimize: \[ \text{NegSpecPower} = f(c_r, w, b, d_I, d_E) \]
Subject to:
Constraints:
1. Stroke: $0.7 \leq b/s \leq 1.3$
2. MinBoreWallThick $\leq 0$
3. MaxEngineHeight $\leq 0$
4. ValveStructure $\leq 0$
5. MinValveDiam $\leq 0$
6. MaxValveDiam $\leq 0$

Bounds: As limited within ATSV
The corresponding Brush/Preference Control settings should look like this:

Using ATSV, find the best design, i.e., the settings of b, d_E, c_r, and w that minimize NegSpecPower while satisfying all 6 constraints.
APPENDIX E - Instructions for Conceptual Ship Design

Your goal is to optimize the parameters of a conceptual ship design. There are six design variables that you can manipulate; Length (L), Beam (B), Depth (D), Draft (T), Block Coefficient (C_B), Speed (V_K); some of which are shown in Figure 1. The objective is to optimize the three objectives, which are functions of the six input variables, while satisfying the constraints.

![Figure 1: Ship Parameters (A- Front View, B- Side View)](image)

Objectives:
- Minimize: Transportation Cost (TC)
- Light Ship Weight (LSM)
- Maximize: Annual Cargo (AC)

Subject to:
Constraint:

1. \( L/B \geq 6 \)
2. \( L/D \leq 15 \)
3. \( L/T \leq 19 \)
4. \( \text{const}_1 \leq 0 \)
5. \( \text{const}_2 \leq 0 \)
6. \( \text{const}_3 \leq 0 \)
7. \( F_n \leq 0.32 \)
8. \( 25,000 \leq \text{DWT} \leq 50,000 \)
Input Bounds: As limited within ATSV

The corresponding Brush/Preference Control settings should look like this:

![User Settings Diagram]

Using ATSV, find the best design that optimizes the objectives while meeting the constraints.
APPENDIX F - Instructions for Aircraft Wing Sizing

Your goal is to optimize the design of an aircraft wing. As shown in Figure 1, there are six design variables that you can manipulate; Semi-span (Span), Aspect Ratio (AR), Sweep Angle (Sweep), Taper Ratio (Taper), YCoff, and Fan Diameter (FanDiam). The objective is to optimize the three objectives, which are functions of the six input variables, while satisfying the constraints.

![Figure 1: Aircraft Wing](image)

**Objectives:**
- Minimize: Cost
- Minimize: TakeOffLength
- Maximize: Range

**Subject to:**
**Constraint:**

1. TakeOffLength ≤ 0.377
2. Range ≥ 0.589
3. BuffetAltitude ≥ 0.603

**Input Bounds:** As limited within ATSV

The corresponding Brush/Preference Control settings should look like this:

![User Settings](image)

Using ATSV, find the best design that optimizes the objectives while meeting the constraints.