Visual Steering Commands and Test Problems to Support Research in Trade Space Exploration

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Designers can simulate thousands, if not millions, of design alternatives more cheaply and quickly than ever before with today's computing power; however, the resulting data can overwhelm designers without proper tools to support multi-dimensional data visualization. In this paper, we discuss the use of a multi-dimensional data visualization tool and visual steering commands which allow designers to navigate multi-attribute trade spaces. The novelty in our work is providing designers with a set of visual steering commands to simultaneously *explore* the trade space and *exploit* new information and insights as they are gained. Specifically, designers can *explore* the entire design space (either sampled randomly or manually) or along the entire Pareto front using the Basic Sampler, Point Sampler, and/or Pareto Sampler. Alternatively, they can *exploit* information they have gained during the exploration process by searching near a specific point of interest or within a region of high preference using the Attractor, Preference Sampler, and/or Guided Pareto Sampler. Examples of each are included in this paper. Meanwhile, a suite of test problems is being formalized to support our trade space exploration – algorithmic development as well as empirical studies involving human decision-makers. This work supports our long-term goal of quantifying the benefits of putting humans back "in-the-loop" during design optimization.

I. Introduction

DESIGNERS can simulate and evaluate thousands, if not millions, of design alternatives more cheaply and quickly than ever before with today's computing power. Even computationally expensive analyses can now be replaced by metamodels (e.g., response surface, radial basis functions, and kriging models) to enable rapid simulation of new design alternatives.[1,2] These advancements are enabling revolutions in trade space exploration processes, particularly for the design of complex systems such as automobiles, aircraft, and satellites; however, the resulting data can lead to information overload and overwhelm designers when appropriate tools to support multi-dimensional data visualization are not employed. Table A provides a summary of the graphical capabilities of 19 commercial and noncommercial software packages that are available and used frequently for multi-dimensional data visualization. This is an updated summary of our software review five years ago.[3]

The basic tenet of trade space exploration is to allow designers to simulate numerous design alternatives and then visualize them while forming their preferences to select the best design – an *a posteriori* approach to decision-making.[4] Often referred to as "Design by Shopping" to credit Balling,[5] trade space exploration entails three basic steps as shown Figure 1. First, a simulation model, M, is created to analyze the system. This model captures the relationships between design inputs, X, and performance outputs, Y, which are often unknown (i.e., the model may be a "black box"). Experiments are then run to simulate hundreds, thousands, or millions of design alternatives depending on available computational resources by varying X and storing the corresponding values of Y for each alternative. Interactive visualization tools are then used to explore the *trade space*, $Z = [X \vdots Y]^T$, to find the most-preferred point Z^*.

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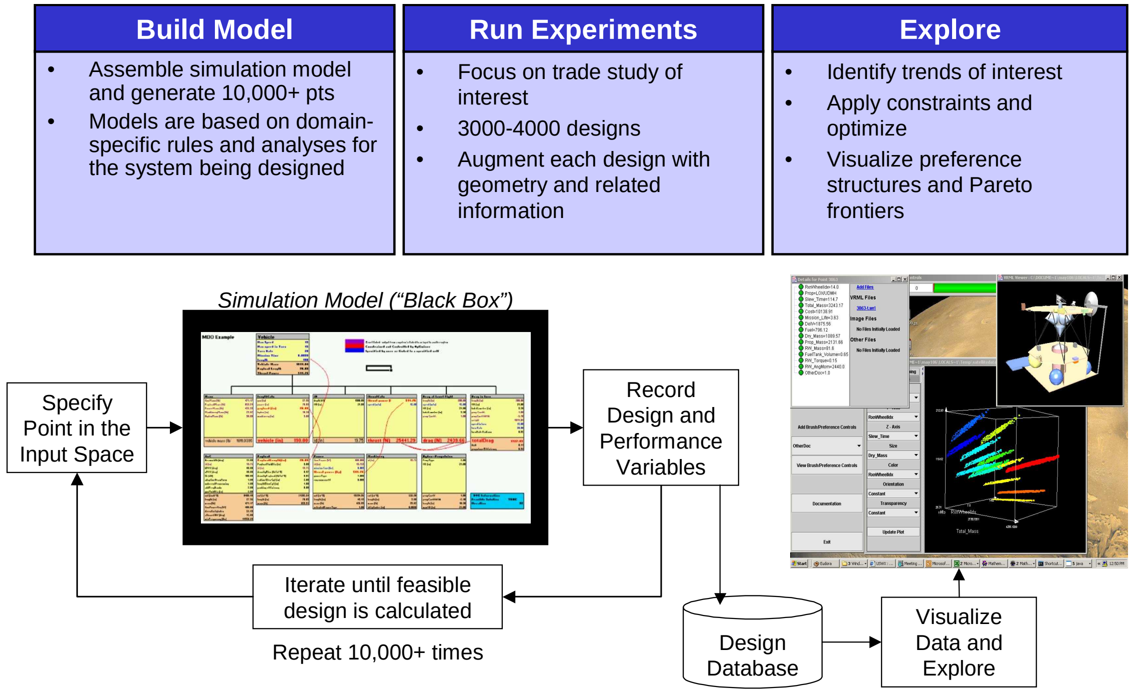


Figure 1. Typical Approach to Trade Space Exploration[6]

This type of approach is advocated by many researchers in the literature. For instance, Messac and Chen[7] were among the first in the multidisciplinary design optimization (MDO) community to propose and demonstrate an interactive visualization method wherein the progress of the optimization is visualized throughout the process. To help optimize architectural layouts, Michalek and Papalambros[8] propose a methodology to "dynamically change the optimization representation on-the-fly by adding, deleting, and modifying objectives, constraints, and structural units." In a similar fashion, Visual Design Steering[9,10] allows users to stop and redirect the optimization process to improve the solution; however, their visualization capabilities are limited to 2-D and 3-D representations of constraints and objectives. Cloud Visualization,[11] BrickViz,[12] and the Advanced Systems Design Suite[13,14] address some of the multi-dimensional data visualization limitations of Visual Design Steering, and recent work by Agrawal, et al.[15,16] provides a novel means for visualizing Pareto fronts that span n-dimensions. Meanwhile, Ross, et al.[17] have introduced a framework for multi-attribute trade space exploration. The emphasis in their work is on the use of multi-attribute utility theory to integrate designers' preferences for multiple objectives, not the visualization of the results, *per se*, as in our case. Our approach for visualizing multi-dimensional data is discussed next and is followed by an overview of the visual steering commands that we have developed to support trade space exploration. Section IV describes the suite of test problems that we have developed to support our research in trade space exploration, and Section V provides closing remarks and discusses ongoing work and future research.

II. Multi-Dimensional Data Visualization with ATSV

To support multidimensional data visualization and approaches to trade space exploration, we are using the Applied Research Laboratory's Trade Space Visualizer (ATSV),[18,19] a Java-based application that displays multi-dimensional trade spaces using any combination of glyph, 1-D and 2-D histograms, 2-D scatter, scatter matrix, and parallel coordinate plots, linked views,[20] and brushing.[21] Figure 2 shows several examples of the multi-dimensional data visualization capabilities in ATSV, many of which are common to other commercially available software packages as noted in Table A. We note, however, that the 3D glyph plot (top left of Figure 2) used in ATSV is unique in that it can display up to seven dimensions by assigning different variables to the x-, y-, and z-axes and the size, color, orientation, and transparency of the individual glyph icons. Text can be added to each point in the glyph plot to represent an eighth dimension, and brushing can be used to dynamically vary a ninth dimension; however, we find that most users only visualize 4-6 dimensions at any given time, which we attribute to Miller's 7$\pm$2 rule.[22]

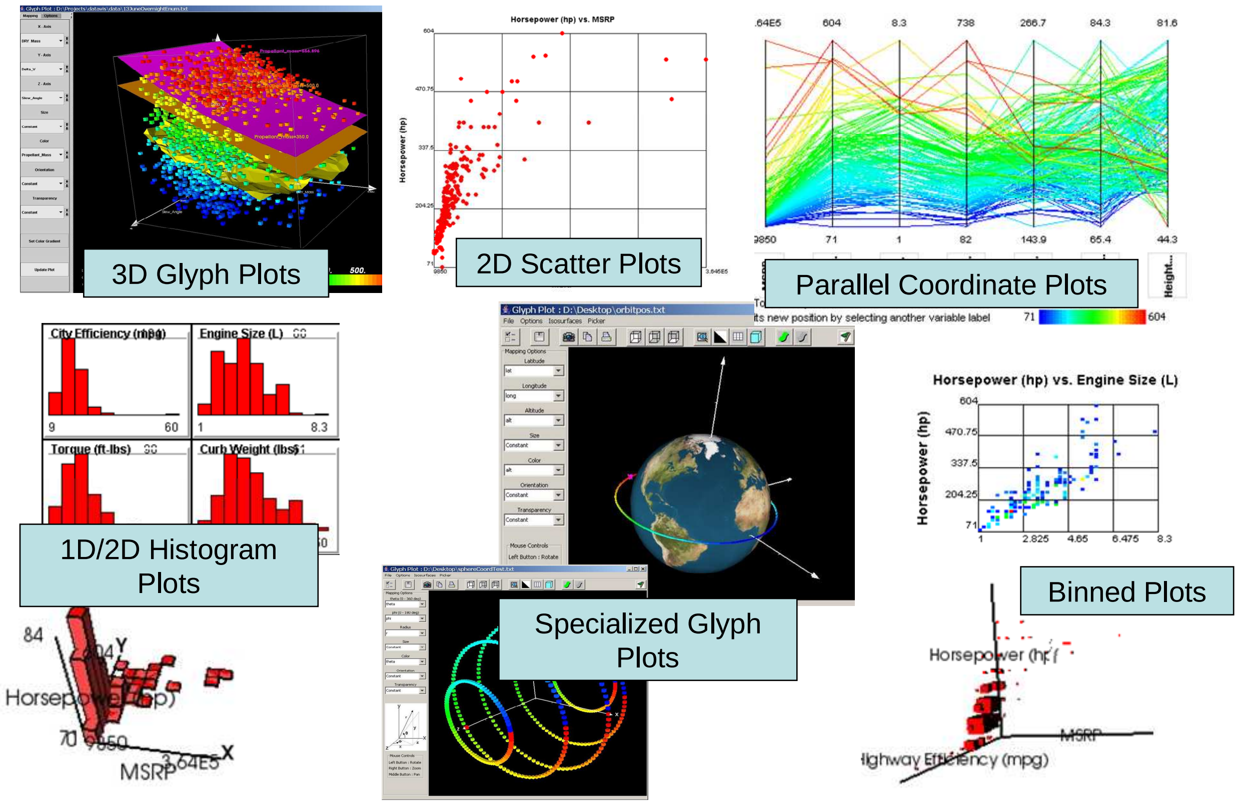


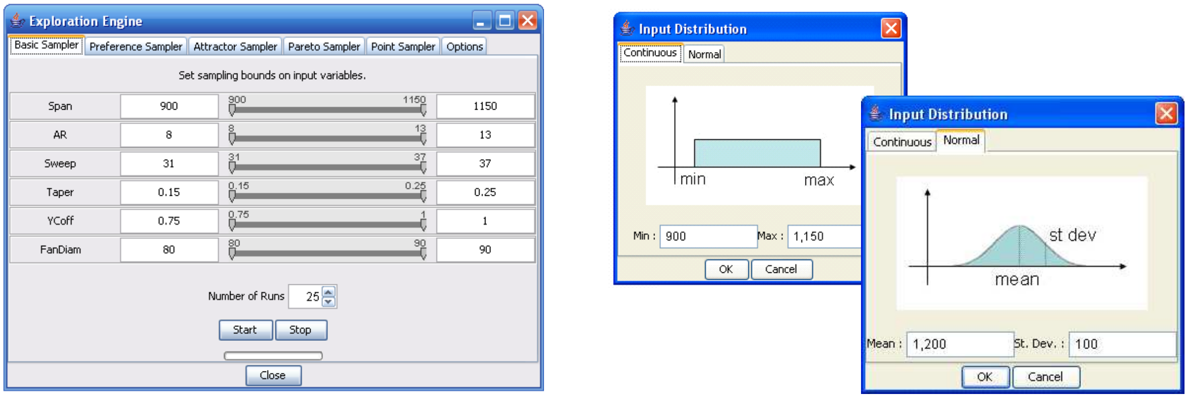
Figure 2. Multidimensional Visualization Examples[23]

The design variable (input) and performance (output) data for different alternatives can either be generated off-line and then read into ATSV for visualization and manipulation (i.e., a "static" dataset) or it can be generated dynamically "on-the-fly" by linking a simulation model directly with ATSV using its Exploration Engine capability.[6] 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.[1,2] Once this link to the simulation model is in place, ATSV provides a suite of visual steering commands to help designers navigate the multi-attribute trade space as discussed next.

III. Visual Steering Commands

The novelty in our approach to trade space exploration lies in providing designers with a set of visual steering commands to simultaneously *explore* the trade space and *exploit* new information and insights as they are gained.[6] Specifically, designers can *explore* the entire design space (either sampled randomly or manually) or along the entire Pareto front using the Basic Sampler, Point Sampler, and/or Pareto Sampler. Alternatively, they can *exploit* information they have gained during the exploration process by searching near a specific point of interest or within a region of high preference using the Attractor, Preference Sampler, and/or Guided Pareto Sampler. A summary of each type of sampler follows using the aircraft wing sizing example described in Section IV. We refer the reader to Ref. 6 for more details on the first five samplers – the Guided Pareto Sampler is unique to this paper.

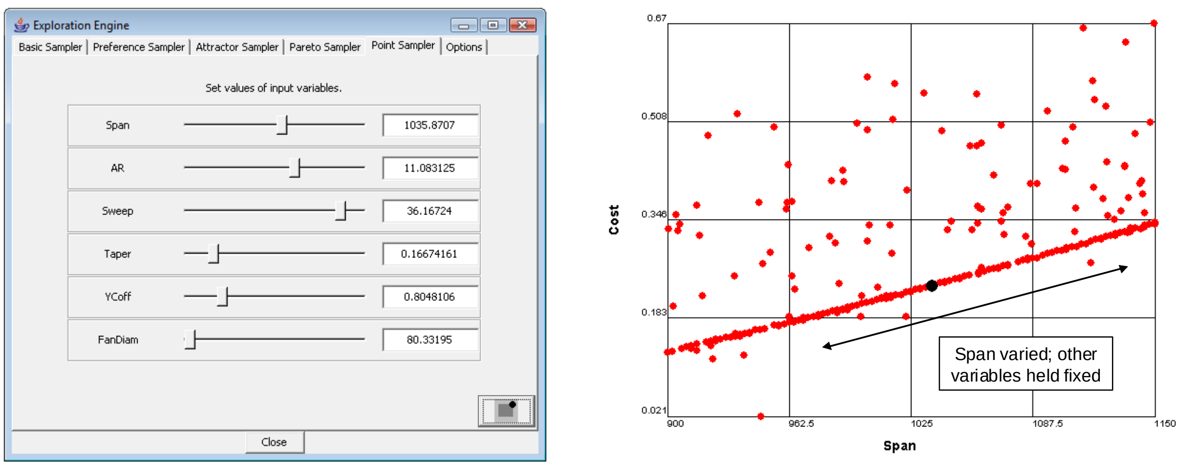
A. Basic Sampler & Point Sampler: These two samplers are used to populate the trade space either randomly or manually and are typically invoked if there is no initial data available, i.e., they are used primarily to *explore* the design space at the start of the trade space exploration process. When sampling randomly, the user specifies the number of samples that will be generated and the bounds of the multi-dimensional hypercube of X as shown in Figure 3a. Monte Carlo simulation then randomly samples the inputs – drawing from a uniform or normal distribution as shown in Figure 3b – and executes the simulation model a user-specified number of times, storing the corresponding output in the database. The bounds of the design variables can be reduced at any time to bias the samples in a smaller region within the design space if desired.



(a) Randomly sample over entire design space (b) User specifies sampling distribution – uniform or normal

Figure 3. Example of Basic Sampler and Input Distributions

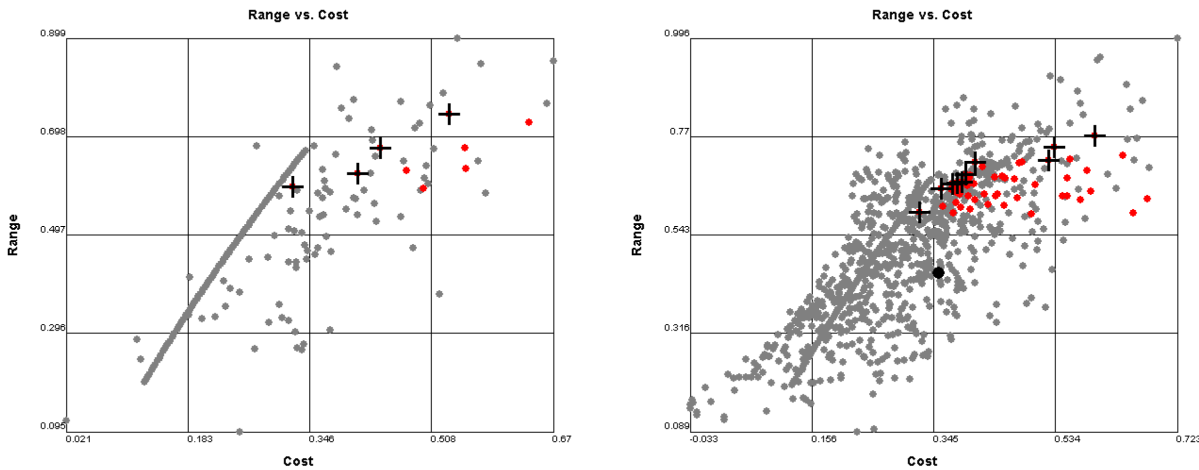
With the Point Sampler, users can manually sample the design space by moving slider bars for each input variable using the controls shown in Figure 4a. As such, the Point Sampler allows designers to perform one-factor-at-a-time parametric studies of the simulation model if they prefer this to random sampling. After moving a slider bar, the simulation model is executed at the design point specified by the current settings of all the slider bars. An example is shown in Figure 4b where the user examined the variation of wing span on system cost while holding everything else at the settings shown in Figure 4a. This variation was performed after randomly sampling 100 points to identify a good starting point for one-factor-at-a-time variations.



(a) Manually vary one factor at a time (b) Visualize impact of specific one-factor-at-a-time variation

Figure 4. Example of Point Sampler for Manual Design Space Sampling

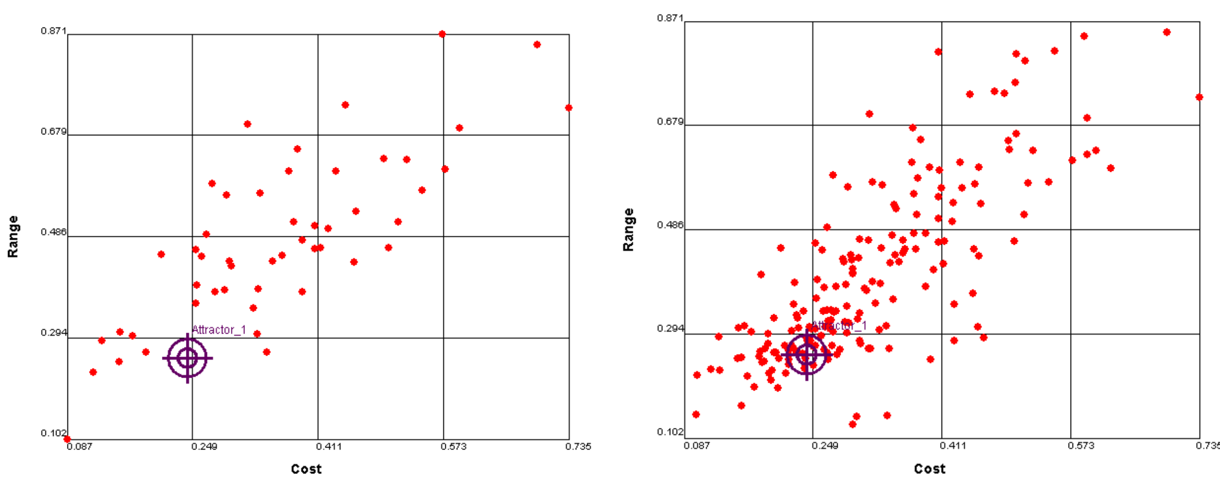
B. Pareto Sampler: The Pareto Sampler generates new points along the Pareto front as the name implies. It is helpful in exploring the trade space, particularly when multiple objectives are important. This requires users to indicate their direction of preference (e.g., minimize or maximize) for each objective of interest. The Pareto Sampler uses the Pareto Differential Evolution algorithm developed by Madavan[24] as the underlying search algorithm. Figure 5 shows an example from the aircraft wing sizing problem where the user wants to minimize cost and maximize range without having to assign importance weightings to either objective. The Pareto points are denoted by +'s in both figures where Figure 5a shows the initial front and Figure 5b shows the front after 500 function evaluations. In both figures, red points are the feasible points after screening off infeasible points based on the constraints (see Section IV.C) while the grey points show all the points that were searched. We are currently working to improve the constraint handling techniques within this search algorithm[23] to make more efficient use of function evaluations when exploring the Pareto front.



(a) Initial Pareto front after using Basic and Point Samplers (b) Pareto front after 500 additional function evaluations

Figure 5. Example of Using the Pareto Sampler to Identify the Pareto Front

C. Attractor: The attractor generates new sample points near a user-specified point in the trade space, allowing users to *exploit* new information and insights that are gained as the trade space is explored. 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. An example is shown in Figure 6 where the user specifies an attractor to generate low cost designs for the aircraft wing sizing problem while also attempting to fill in a "gap" in the trade space (see Figure 6a). The new samples are clustered around Attractor_1 as seen in Figure 6b. Since the attractor can be any point in the trade space, *Z*, it can consist of any *n*-dimensional combination of the inputs, *X*, and outputs, *Y*, and it can consist of discrete and continuous variables. Consequently, we have selected Differential Evolution (DE)[25] to guide this sampling process where the fitness function in DE is defined the Euclidean distance from each sample point to the center of the attractor. For more details on the DE implementation within ATSV and the formulation of the fitness function, we refer the reader to Ref. [6].

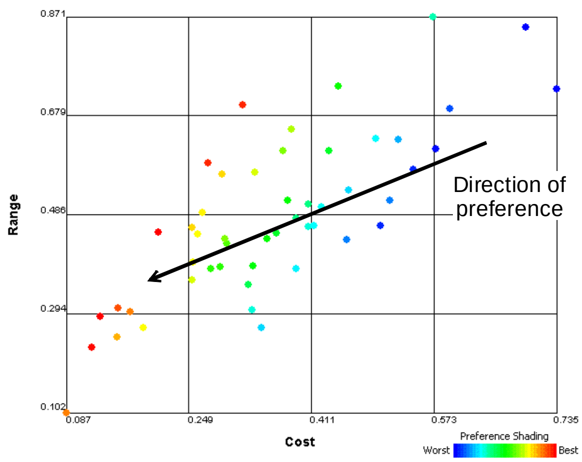


(a) Attractor placed in a promising location in the trade space (b) New samples cluster around the attractor

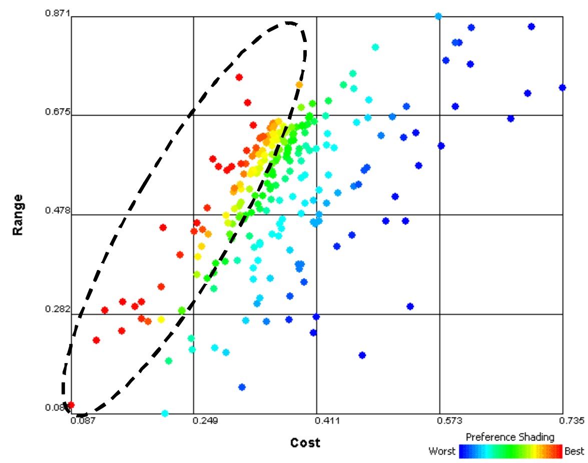
Figure 6. Example of Attractor Used to Exploit Information Gained during Trade Space Exploration

D. Preference Sampler: The Preference Sampler populates the trade space in regions that perform well with respect to a user-defined preference structure (i.e., importance weightings for each objective of interest). New sample points are generated using DE,[25] but the fitness function is now defined by the user's preference structure based on the settings of the Brush/Preference Controls. A linear weighted sum is currently used for the fitness function;[6] however, alternative formulations could easily be implemented within ATSV.

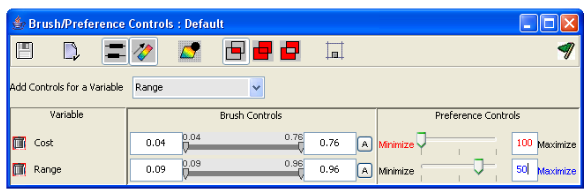
An example is shown in Figure 7 where minimizing cost is deemed to be twice as important as maximizing range. The points are color coded in the plot to indicate the direction of preference (see Figure 7a), and the resulting new samples in the region of high preference are highlighted in Figure 7b. Meanwhile, Figure 7c shows the settings of the Brush/Preference Controls for this particular preference structure.



(a) User-specified preference is indicated by color coding



(b) New samples are generated in region of high preference



(c) Corresponding settings of Brush/Preference Controls

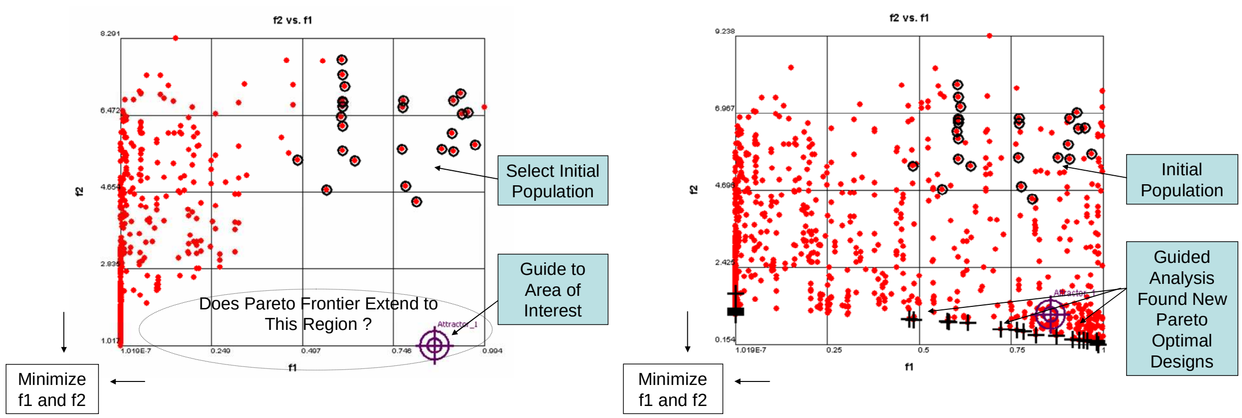
Figure 7. Example of Preference Sampler and Corresponding Brush/Preference Controls[23]

E. Guided Pareto Sampler: The Guide Pareto Sampler 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, exploiting information that is gained during the trade space exploration process. The newest of our visual steering commands, this sampler also uses the Pareto Differential Evolution algorithm developed by Madavan,[24] but the user can now play a supervisory role and interact with the underlying algorithm by:

- Select specific points within the data visualization window and use them to seed the initial generation
- Guide Pareto search algorithms to regions of interest using Attractor icons ⌖.
- Start, pause, and stop the search with the ability to change initial generations and guide directions.

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

An example of the Guided Pareto Sampler is shown in Figure 8. An initial Pareto analysis is performed, where both f1 and f2 are minimized (see Figure 8a). The problem is heavily biased towards f1, and the resulting Pareto frontier includes only one point. The plot shows a large region that has not been explored, and a user runs a Guided Pareto Sampler to search for the frontier in this region. An attractor is first placed in the lower right-hand region of the scatter plot. Additionally, the user has the ability to select points to seed the initial generation before starting the sampler. The Guided Pareto Sampler uses this information to perform its Pareto search, where selection strategies involve each generation's fittest members based on both Pareto optimality and their position relative to the Attractor. Currently, half of each generation's members are selected based on Pareto optimality and half are selected based on closest distance to the Attractor, but this user-setting can be modified as needed. As seen in Figure 8b, the resulting Guided Pareto Sampler has captured new Pareto optimal designs in regions of the trade space that were initially void of data. Our implementation could easily be extended to provide users with more detailed controls, such as allowing users to select each generation's fittest members, change the crossover methodology, or adjust the values of the algorithm's search parameters.



(a) Initial Pareto search to minimize f1 and f2 (b) Pareto search steered toward unexplored region

Figure 8. Process of Using Guided Pareto Sampler to Search Trade Space

IV. Test Problems

A suite of test problems has been developed to support our research in trade space exploration. This suite currently includes complex systems designed for land, sea, air, and space: (1) configuration of vehicle concepts, (2) conceptual design of a cargo ship, (3) sizing of an aircraft wing, and (4) design of the external fuel tank for the Space Shuttle. An overview of each of these problems follows along with visuals of their trade spaces.

A. Vehicle Configuration Example: The vehicle configuration example was developed in conjunction with researchers at General Motors and SUNY-Buffalo to evaluate the technical feasibility of new vehicle concepts.[26,27] The model includes five objectives – acceleration, fuel economy, and three measures of interior accommodation – and eleven high-level vehicle design parameters: ten continuous variables that define overall exterior dimensions and positions of the occupants, and one discrete variable that specifies the vehicle's powertrain. This vehicle configuration model also computes vehicle mass, which is neither a design variable nor a performance objective as customers do not usually have a preference on the weight of their car; however, vehicle mass is a function of many design variables and it strongly influences many performance objectives that are important to customers (e.g., fuel economy).[27] The model also computes the total violation of all constraints in the model (= *ConVio*).

Table 1 summarizes the problem definition. Bounds on the 10 continuous design variables are normalized to [0,1], and the objectives are scaled against the baseline model – defined as the feasible point $Y = (1,1,1,1,1,1)$ – to protect the proprietary nature of the data. The design variable, H, defines the powertrain and can take one of six options: [1,2,3,4,5,6]. Finally, the direction of preference for each objective is indicated in the table. While stating these general preferences beforehand may seem counter-intuitive, the end goal is to determine the best point in the trade space, and to do this, we would need to specify weights for each objective to aggregate them into a single objective function using a weighted-sum, for instance; however, these weights are not specified. Alternatively, we could use a multi-objective genetic algorithm to determine the Pareto front as done previously,[27] but that yields a set of non-dominated designs, not a single point; hence, this example lends itself well to trade space exploration.

Table 1. Vehicle Problem Definition

Model Inputs		
Variable	**Lower Bound**	**Upper Bound**
A	0	1
B	0	1
C	0	1
D	0	1
E	0	1
F	0	1
G	0	1
H	1,2,3,4,5, or 6	
I	0	1
J	0	1
K	0	1
Model Outputs		
ConVio	0 → feasible	> 0 → infeasible
Mass	Baseline = 1	Defines weight class
Obj1	Baseline = 1	Smaller is better
Obj2	Baseline = 1	Larger is better
Obj3	Baseline = 1	Larger is better
Obj4	Baseline = 1	Larger is better
Obj5	Baseline = 1	Larger is better

Figure 9 shows an example of the multi-attribute trade space for the vehicle configuration model, which was obtained using a combination of Basic Sampling, Preference Sampling, and Attractors. The glyph plot includes iso-surfaces to indicate different vehicle weight classes, and a promising option is found that improves *Obj3*, *Obj4*, and *Obj5* by 3%, 9%, and 13%, respectively, with only a 2% decrease in *Obj1* and *Obj2*.

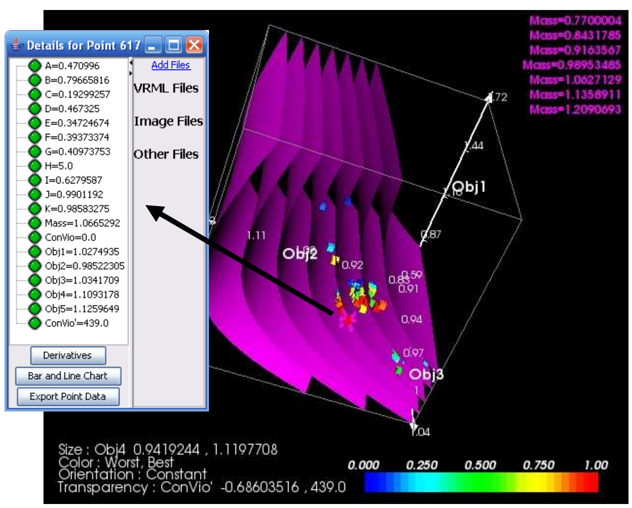


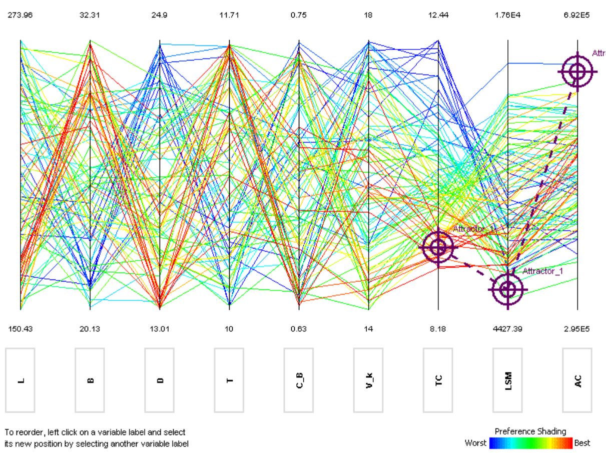
Figure 9. Glyph Plot of Vehicle Trade Space Showing Mass Contours and a Promising Design[6]

B. Conceptual Ship Design: The conceptual ship design example is a multi-objective optimization problem adapted from the literature.[28,29] Following the formulation in Parsons and Scott,[29] the analytical model approximates a family of bulk carriers with deadweight between 3,000-50,000 tons and speeds of 14-18 knots. It has six inputs:

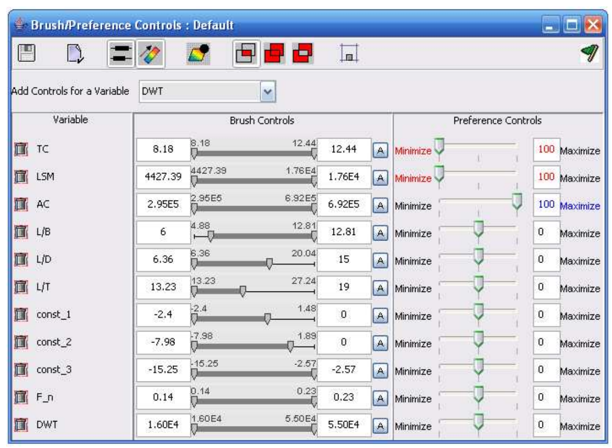
1. Length (m): $150 \leq L \leq 274.32$
2. Beam (m): $21 \leq B \leq 32.31$
3. Depth (m): $12 \leq D \leq 25$
4. Draft (m): $9.5 \leq T \leq 11.71$
5. Block coefficient: $0.63 \leq C_B \leq 0.75$
6. Speed (kts): $14 \leq V_k \leq 18$

Lower bounds have been added to the original formulation for L, B, D, and T to reduce the design space that is searched; however, the reported solutions are encompassed within these bounds. There are three objectives of interest: (1) minimize transportation costs, (2) maximize annual cargo, and (3) minimize lightship weight, and there are 9 constraints in addition to the design variable bounds.[29]

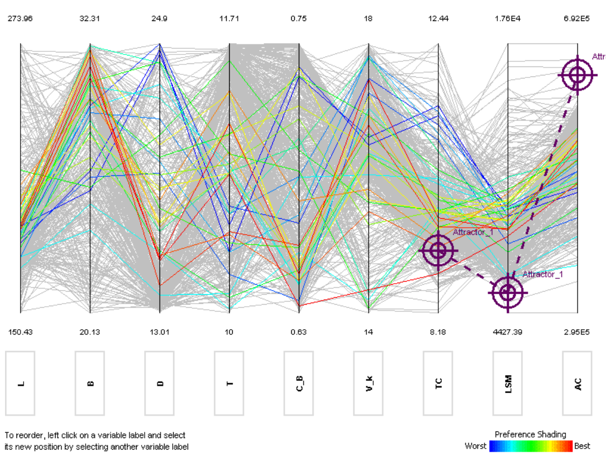
Figure 10 illustrates how parallel coordinates can be used to place an Attractor in more than two dimensions when exploring a multi-attribute trade space. The six design variables and three objectives are shown in Figure 10a based on the results from 100 random samples generated using the Basic Sampler. The Attractor is then placed so as to minimize transportation costs (TC) and lightship weight (LSM) and maximize annual cargo (AC). The lines are color-coded based on this preference (red = most preferred, blue = least preferred) where all three objectives are equally weighted (see Figure 10b). The brush controls in Figure 10b are used to define the feasible trade space, and the resulting solutions after 500 new points are generated with the Attractor as shown in Figure 10c (infeasible points in gray) and Figure 10d (infeasible points not shown). These last two figures are particularly insightful since they indicate that low-to-medium values of L, high values of B, low values of D and C_B lead to highly preferred feasible designs (i.e., the location where bands of red lines cross the vertical line for each design variable). Even though T and V_k seem to vary widely, this information helps reduce the search space for the step in the trade study.



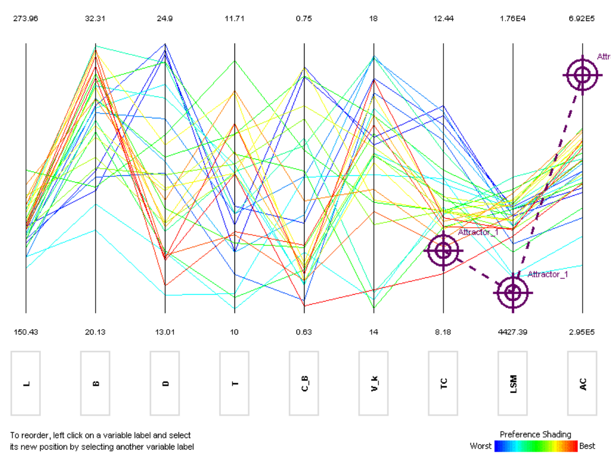
(a) Design variables and objectives after 100 random samples, color shows preference, and Attractor set for each objective



(b) Brush and preference settings for ship design problem



(c) Results after 500 new samples generated for Attractor, color shows preference, gray points are infeasible



(d) Same plot of results but only feasible points are shown, color indicates preference (red = best, blue = worst)

Figure 10. Example of Using Parallel Coordinates to Place an Attractor in Multiple Dimensions

C. Aircraft Wing Sizing Problem: The aircraft wing sizing problem, developed in conjunction with engineers at The Boeing Company, involves sizing the plan view layout of an aircraft wing to minimize its cost subject to constraints on range, buffet altitude, and takeoff field length.[30] The designer can manipulate six design variables over the following ranges:

1. Semi-span: 900 $\leq$ Span $\leq$ 1150
2. Aspect ratio: 8 $\leq$ AR $\leq$ 13
3. Quarter chord sweep angle: 31 $\leq$ Sweep $\leq$ 37
4. Taper ratio: 0.15 $\leq$ Taper $\leq$ 0.25
5. Sparbox root chord: 0.75 $\leq$ YCoff $\leq$ 1
6. Fan diameter: 80 $\leq$ FanDiam $\leq$ 90

These design variables are defined in Figure 11, and the specified ranges define the upper and lower bounds for the design space samplers shown in Figure 3.

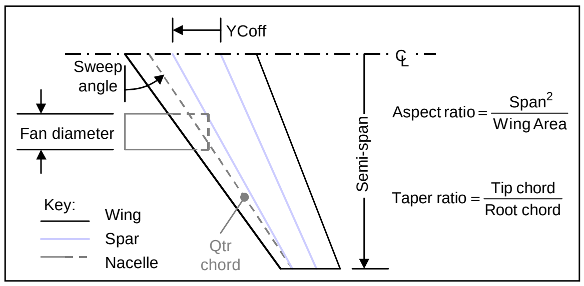


Figure 11. Design Variables for Wing Sizing Problem

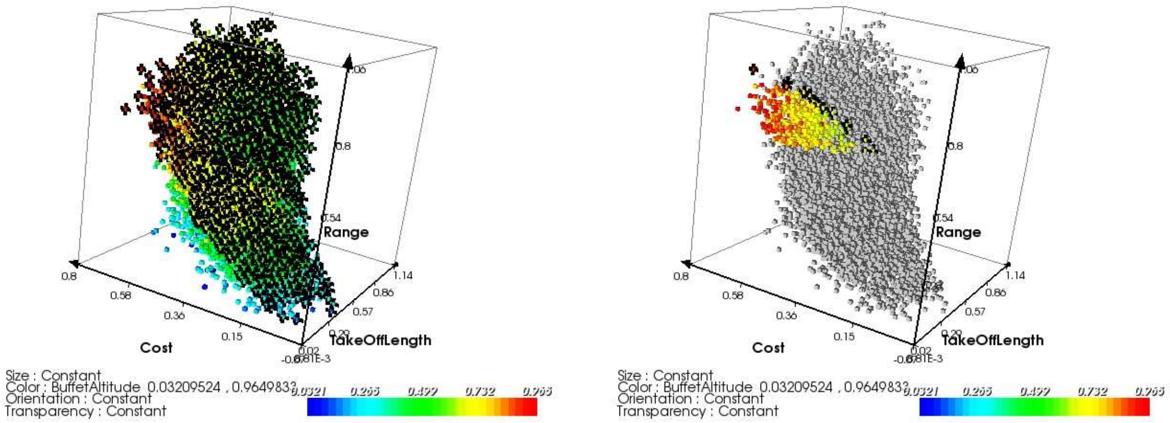
The constraints and objective for the wing sizing problem are evaluated using second-order response surface models constructed from a 243-point orthogonal array – details can be found in Ref. 30. The actual values of cost, range, buffet altitude, and takeoff field length have been normalized to [0,1] based on the minimum and maximum values observed in the sample data due to their proprietary nature. The original optimization problem was stated as:

Minimize:	Cost	(1)
Subject to:	Range $\geq$ 0.589	
	Buffet altitude $\geq$ 0.603	
	Takeoff field length $\leq$ 0.377	

We have made several modifications to this formulation to make the problem multi-objective in nature, including maximizing range while minimizing cost.[23] These new formulations have allowed us to study enhancements to the underlying DE algorithm, including the incorporation of constraint dominance[31] to automatically handle constraints when exploring the trade space. In particular, the domination of two solutions *i* and *j* is modified to be:

A solution *i* constraint-dominates solution *j* if any of the following conditions are true:
1) *i* is feasible and *j* is infeasible: *i* constraint-dominates *j*
2) *i* and j are feasible: if *i* Pareto dominates *j*, then *i* constraint-dominates *j*
3) *i* and *j* are infeasible: if *i* dominates *j* in the constraint-violation space, then *i* constraint-dominates *j*

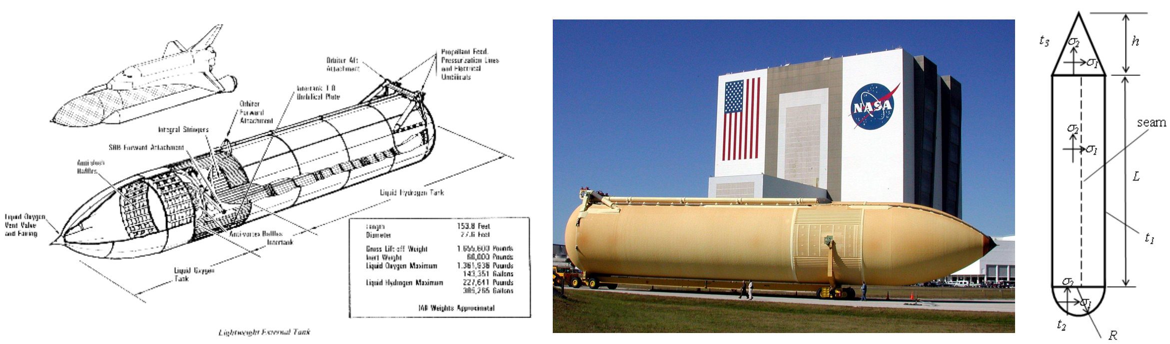
Prior to this work, our general philosophy has been to explore the entire trade space – feasible and infeasible – when searching and then using brushing to filter out infeasible points since some constraint limits may change as the problem evolves. In highly constrained trade spaces, however, this is not an efficient use of function evaluations. An example of the impact can be seen in Figure 12 where the user may think the Pareto front spans a large portion of the trade space when in reality the feasible space is quite small (see Figure 12b). Constraint dominance allows users to make more efficient and effective use of new function evaluations when using the Attractor and various samplers if it is known *a priori* that the problem is highly constrained or has a small feasible trade space; if not, then using brush controls to manually filter out infeasible designs or Attractors to bias samples in the feasible regions are more promising strategies.[23]



(a) Pareto front of entire trade space (b) Pareto front of feasible space (gray points are infeasbile)

Figure 12. Pareto Front with and without Automated Constraint Handling[23]

D. Space Shuttle External Fuel Tank Design Problem: This problem was originally developed by Dr. Jaroslaw Sobieski, formerly of NASA Langley Research Center in Hampton, VA, to illustrate how changes in a problem's objective function influence the resulting optimal design.[32] The overall objective is to improve NASA's Return on Investment (ROI) for the Space Shuttle by resizing its external fuel tank. The external fuel tank is divided into three hollow geometric segments: (1) a cylinder (length L, radius R), (2) a hemispherical end cap (radius *R*), and (3) a conical nose (height *h*, radius *R*), as shown in Figure 13. These segments have thicknesses t_1, t_2, and t_3, respectively. Each segment is assumed to be a monococque shell constructed from aluminum and welded together from four separate pieces of material, resulting in a total of fourteen welded seams. Surface areas and volumes are determined using geometric relations, and first principles and rules of thumb are used to calculate stresses, vibration modes, aerodynamic drag, and cost using the analyses in Ref. 32.



(a) External fuel tank configuration (b) Photo at Kennedy Space Center (c) Geometry

Figure 13. Space Shuttle External Fuel Tank[32]

The optimization problem is formulated based on the original model as follows:

Maximize: ROI (2)

Subject to: Volume constraint:

$$2826 \le V_t \le 3026 \Rightarrow |V_t - 100| - 2926 \le 0$$

Stress and vibration constraints

$$\sigma_{e,i} \le 4 \cdot 10^8 \Rightarrow \sigma_{e,i} - 4 \cdot 10^8 \le 0$$

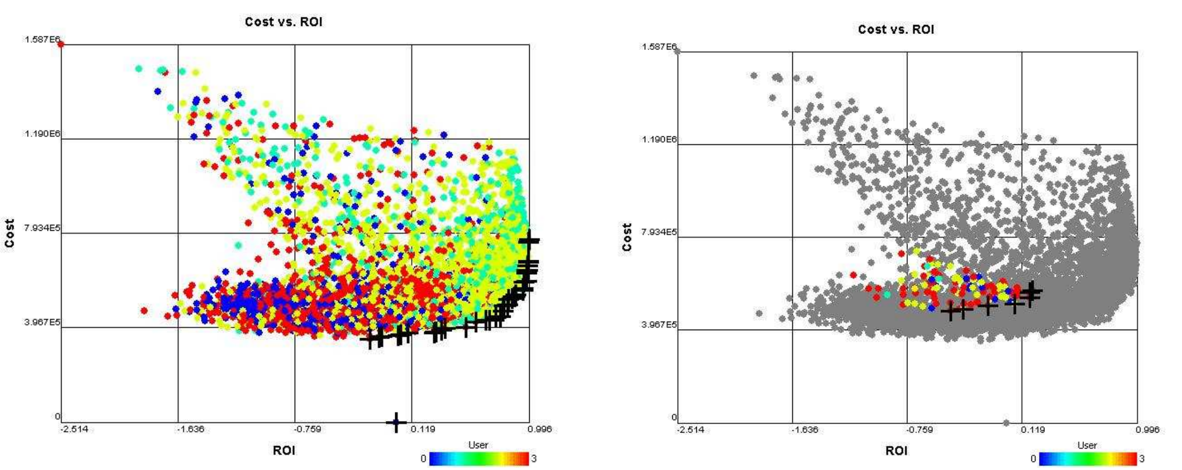
$$0.8 \le \zeta \Rightarrow 0.8 - \zeta \le 0$$

Design variables bounds:

$0.01 \le L_n \le 5.0$	$0.25 \le t2_n \le 2.0$
$0.50 \le R_n \le 2.0$	$0.25 \le t3_n \le 2.0$
$0.25 \le t1_n \le 2.0$	$0.10 \le h/R_n \le 5.0$

The objective is to maximize ROI subject to the constraints on the tank volume and stresses and bounds on the design variables. The restriction on tank volume is an equality constraint (~3000 m^3 +/- 100 m^3), which we have found difficult to meet when using ATSV. The tank volume is dependent upon three parameters (*L*, *R*, *h/R*), and the problem has been reformulated so that the designer can vary any two parameters while the third is dependent upon these two (i.e., specify values for *R* and *h/R* and compute *L* to satisfy the volume constraint). Finally, inequality constraints are placed on the maximum allowable component stress and on the first bending moment of the tank. The equivalent stress experienced by each component cannot exceed the maximum allowable stress of the material is used. Also, the first bending moment of the tank must be kept away from the vibrational frequencies experienced during launch to avoid any potential failures.

This problem is currently being used to test a distributed version of ATSV, one where subsystem designers control their own local objectives (e.g., minimize cost, minimize drag penalty, maximize payload, minimize structural weight) and then collaborate to optimize the overall system.[33] An interesting outcome from these studies is not only how to improve ATSV to support distribute collaboration but also the importance of properly communicating design information between team members. An example is shown in Figure 14 where the color-coding indicates different users. The structural engineer (red points in Figure 14), having the most constraints to satisfy, ends up being the most effective in finding good solutions. The engineers concerned with payload (in green) and cost (in yellow) find many designs that have high ROI and low cost (see Figure 14a), but without any knowledge of the structural engineer's constraints, the majority of their designs turn out to be infeasible once all constraints are considered at the system level (see Figure 14b). By focusing only on their local subsystem constraints during their search, they "overshot" the feasible region from the system's perspective. Even though our findings are preliminary, they stress the importance of proper communication during collaborative trade space exploration.



(a) Pareto front of entire trade space without constraints (b) Pareto front of feasible space (gray points are infeasible)

Figure 14. Trade Space Exploration by Different Subsystem Designers

V. Closing Remarks and Future Work

As discussed in this paper, multi-dimensional data visualization and visual steering commands allow designers to navigate multi-attribute trade spaces in more visual and intuitive ways. The novelty in our work is providing designers with a set of visual steering commands to simultaneously *explore* the trade space and *exploit* new information and insights as they are gained. Designers can *explore* the design space randomly or manually using the Basic Sampler or Point Sampler, respectively, or search for the Pareto front in a multi-attribute trade space using the Pareto Sampler. Designers can also *exploit* information obtained during this exploration process by searching near a specific point of interest using the Attractor, within a region of high preference using the Preference Sampler, or guiding the search for the Pareto front using the Guided Pareto Sampler.

To support our research in trade space exploration, we have developed a suite of test problems. Four problems are discussed in this paper, spanning land, sea, air, and space applications: (1) configuration of vehicle concepts, (2) conceptual design of a cargo ship, (3) sizing of an aircraft wing, and (4) design of the external fuel tank for the Space Shuttle. The problem formulation and examples from the trade space exploration process are included for each problem, and more complex problems are currently being developed and sought to expand the test suite.

This suite of problems is enabling scientific studies for algorithmic development as well as empirical studies involving human decision-makers. For example, we are fine-tuning the evolutionary algorithm that underlies our visual steering commands to make them more efficient and robust.[34] In conjunction with this, we are developing new samplers to enable the Most Informative Sampler, Most Uncertain Sampler, etc., which support different aspects of the "Design by Shopping" process.[5] We also envision a "detractor" or "repeller" that works in reverse of an attractor, i.e., it generates points that are NOT like the user-specified point. We are also starting to conduct experiments to quantify the benefits of putting humans back "in-the-loop" during the design optimization process. Preliminary results are very promising: designers using the visual steering commands within ATSV to solve the vehicle configuration problem have shown a 4x-7x improvement in efficiency over optimization algorithms running "blindly" without any human intervention.[35] We are currently planning studies involving the entire suite of test problems to further substantiate these findings and generalize our results.

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Appendix

Table A. Summary of Graphical Capabilities and Data Input Formats for Multi-Dimensional Data Visualization Software Packages (Y = has this capability, N = capability not available; $ = least expensive, $$$ = most expensive)

		Graphical Capabilities											Variable		Data Input Format			Other				
Software Name	Reference or URL	Scatter Plot	Parallel Coordinates	Contour Plots	Carpet Plots	Brushing	Pareto Analysis	Shading	Spin Plots	Glyphs	Projection Pursuit	Other Features	Text Input	Slider Bars	Tabular Array	Link to Model	Other	Ability to Modify	Availability	Platform	Developer	Cost
3DVDM	http://www.cvmt.dk/projects/3dvdm/index.html	Y	Y	Y	Y	N	N	Y	Y	Y	Y	3D Grand Tour, Density Plot, Statistical Analysis Tool, Histograms	Y	N	Y	Y	CSV, CAVE	N	As Executable	PC	Aalborg University	N/A
ATSV	http://www.atsv.psu.edu/	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Generate 3D VRML, Histograms, Isosurfaces, Attractor Sampling	Y	Y	Y	Y	TXT, CSV, JAVA	Y	As Executable	PC,UNIX	Penn State	Free
C-Viz	http://www.alphaworks.ibm.com/tech/cviz	Y	N	Y	N	Y	Y	Y	Y	N	N	Edit Design Props., Arbitrary Point Selection, Space Mapping	Y	N	Y	N	CSV	Y	Java Runtime	PC,UNIX	SUNY Buffalo	Free
GGOBI	http://www.ggobi.org/	Y	Y	N	N	Y	N	Y	Y	Y	Y	Bar Charts, Statistical Analysis Tool	Y	N	Y	N	R, PERL, XML	N	As Executable	ALL	AT&T	Free
Glyphmaker	http://www.glyphmaker.com/	N	N	N	N	Y	N	Y	Y	Y	N	Customizable Glyphs, Linked Displays, Assign Glyph to Variables	Y	N	Y	Y		Y	As Executable	ALL	Georgia Tech	N/A
Influence Explorer	http://www.sigchi.org/chi96/proceedings/videos/Tweedie/lt2txt.htm	Y	Y	N	N	Y	N	N	Y	Y	Y	Linked Displays, Histograms	Y	N	Y	Y		N	As Executable	PC	Imperial College	Free
JMP	http://www.jmpdiscovery.com/	Y	N	Y	Y	Y	N	N	Y	N	Y	Main Effects, Statistical Analysis Tool, Bubble Charts	Y	Y	Y	N		N	License	ALL	SAS	$$
Miner3D	http://www.miner3d.com/	Y	N	N	Y	Y	N	Y	Y	Y	N	Heat Maps, Clustering, Trellis Charts, Histograms	Y	Y	Y	Y	TXT, CSV	Y	Registration	PC	Miner3D Inc.	Free
Mondrian	http://www.rosuda.org/Mondrian/	Y	Y	N	N	Y	N	Y	Y	N	N	Mosaic Plots, Histograms, Box Plots, Missing Value Plots	Y	N	Y	N	ASCII	Y	As Executable	ALL	Univ. of Augsburg	Free
N-Vision	http://www.cs.columbia.edu/graphics/projects/AutoVisual/	N	N	N	Y	N	N	N	Y	Y	Y	Isosurfaces, Child/Parent Windows, Multiple Displays	Y	N	N	N		N	As Executable	PC	Columbia Univ.	Free
Partek Pro	http://www.partek.com/	Y	N	N	N	Y	N	Y	Y	Y	N	Analytical Spreadsheets, Histograms, Transformations, Clustering	Y	Y	Y	Y	CSV	Y	License	PC,UNIX	Partek Incorp.	$$
R	http://www.r-project.org/	Y	N	Y	N	Y	N	N	Y	N	Y	Main Effects, Statistical Analysis Tool, Clustering, Bubble Charts	Y	N	Y	Y	GGOBI/XGOBI	Y	As Executable	ALL	All Over	Free
S-PLUS 8	http://www.insightful.com/	Y	N	Y	N	Y	N	N	Y	N	Y	Main Effects, Statistical Analysis Tool, Clustering, Bubble Charts	Y	N	Y	Y	XGOBI	Y	License	ALL	Insightful	$$$
Spotfire	http://www.spotfire.com/	Y	Y	N	N	Y	N	Y	Y	Y	Y	Clustering, Bubble Charts, ANOVA	Y	Y	N	N	SAS, SPLUS	N	License	PC	Ben Shneiderman	$$$
Virtual Data Vis.	Telylingen, Ribarsky, and Mast (1997)	N	N	N	N	Y	N	N	N	Y	N	Customizable Glyphs, Linked Displays, Assign Glyph to Variables	Y	N	Y	Y		N	As Executable	PC	Georgia Tech	Free
VisDB	http://www.dbs.informatik.uni-muenchen.de/dbs/projekt/visdb/	N	Y	N	N	Y	N	Y	N	Y	Y	Stick Figures, Spiral, Axes, Grouing Techniques	Y	Y	N	N	C++	Y	As Executable	UNIX	Univ. of Munich	Free
ViSta	http://www.visualstats.org/	Y	Y	Y	N	Y	N	N	Y	N	Y	Main Effects, Statistical Analysis Tool, Clustering, Bubble Charts	Y	N	Y	Y	ViDAC, Xlisp	N	As Executable	ALL	UNC Chapel Hill	Free
VizEQ	http://www.vizeq.com/	N	N	Y	N	N	N	N	Y	N	N	3D Contours, VRML, Presentation Tool	Y	N	Y	Y	CSV	Y	License	PC	SUNY Buffalo	$
XmdvTool	http://www.davis.wpi.edu/~xmdv/	Y	Y	N	N	Y	N	Y	Y	Y	N	Dimensional Stacking, Pixel-Orient Display, Assign Glyph to Variable	Y	N	Y	Y	OpenGL	Y	As Executable	ALL	WPI	Free