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Interactive Design Selection Process through Visualization and User Guided Search

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A new process is described that assists engineers in making complex decisions during the design process. The Interactive Design Selection Process (iDSP) allows designers to collect design information, compare candidate designs, build user preferences, and ultimately zero in on the best designs. In contrast to traditional black-box optimization approaches, the iDSP involves the designer in each and every step of the process. This involvement gives designers more confidence in the results and allows them to find designs that satisfy all stake-holders. A prototype of the iDSP was implemented by combining an advanced visualization tool with a genetic optimizer using a commercially available process integration environment. A Lunar exploration mission design problem was solved using the guided search technique augmented by design space visualization.

I.   Introduction

Engineering design projects start with many unknowns. In the case of complex systems, design parameters and requirements may not at first be clearly defined. The design process typically involves many incremental learning experiences. As more is understood about the system characteristics and requirements, design goals and requirements often need to be modified or refined. Engineers have difficulties in applying formal optimization techniques to these problems because optimization algorithms generally assume the existence of a well formulated design problem. Another difficulty with formal optimization techniques is that engineers are often left with the feeling that they do not have sufficient control over the direction of the design process. When an optimal design is found, engineers tend to be reluctant to accept it because they do not understand how or why the optimizer found the design.

The design by shopping paradigm proposed by Balling[1] presents the design process as a shopping experience. The designer is like a shopper who visits a dealer's lot to buy a car. The shopper will have some initial idea about the car he or she wants in terms of size, style, gas mileage, price, etc. Chances are that the shopper will reevaluate these expectations and preferences once he or she takes a look at various models available. A truly multi-objective decision making process is going on inside the shopper's mind even though he or she may not perceive it. Such a complex process works by examining car models as a whole and comparing them against other alternatives. When applied to the design process, the shopping paradigm would present a list of good candidate designs to decision makers, and allow them to iteratively refine their preferences before making the final selection.

Two research areas were suggested by Balling to support the design by shopping paradigm[1]. First, efficient methods for obtaining rich Pareto sets are needed. Second, interactive graphical computer tools are needed to assist decision makers in the shopping process. A genetic algorithm optimizer was suggested to support the first need. A multi-objective genetic algorithm (MOGA) approach was used to find a Pareto set that can be presented to decision-

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makers who decide relative importance of the objectives[2]. Researchers at the Applied Research Laboratory (ARL) of the Penn State University developed a design space visualization tool called the ATSV (ARL Trade Space Visualizer)[3,4] that can support the second need. The ATSV uses multi-dimensional visualization techniques to present a large number of design alternatives. The ATSV allows users to apply constraints to the design space using a screening process called brushing and visualize the results of a user's preference structure using preference shading and Pareto frontier display.

This work extends the previous research to realize the design by shopping paradigm. The objective of this work is two-fold. The first objective is to define a step-by-step process that engineers can follow to better understand the design space, build user preferences, and make design selections according to the design by shopping paradigm. It is important to give users the ability to control the design selection process. The second objective is to implement software tools to perform the design selection process in an integrated environment. Each step of the process will require statistical analysis, optimization, or the visual examination of design alternatives. The environment must provide necessary capabilities to allow users to maintain control over the design selection process.

Our proposed design process, the Interactive Design Selection Process (iDSP) is discussed in the following sections. The design selection process is divided into six steps and required tasks for each step are defined. Next, the integration of ATSV with ModelCenter[5] process integration environment is discussed. A discussion of a prototype implementation of iDSP utilizing the User Guided Search (UGS) approach follows. The UGS, in contrast to the black box optimization approach, allows users to interactively influence the automated search of the optimization algorithm. Finally, an example problem of space exploration mission design is discussed followed by concluding remarks.

II. Interactive Design Selection Process

The Interactive Design Selection Process (iDSP) defined here assumes that engineering design activities are a series of learning experiences and decision making steps. Design space visualization techniques help define design objectives and preferences by presenting candidate designs for comparison. In the iDSP framework, design engineers can exercise their judgment throughout the design process, including the selection of design parameters, the choice of preferences, and the selection of candidate designs. The well defined process gives guidance to users and helps them avoid spending resources on design candidates that would not produce customer satisfaction. Figure 1 shows a flowchart of iDSP. A description of each step follows below.
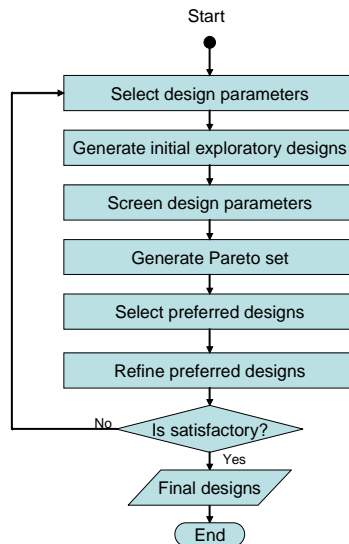
Figure 1: Interactive Design Selection Process.

Step 1: Select Design Parameters

Design engineers should first compile a list of parameters that may be important to the design problem. This should be an inclusive list, since the effects of inputs on outputs may be unknown or unintuitive. It is not necessary to make formal distinctions between design variables, objectives, and constraints at this step. It is enough to decide whether

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the parameter is an input or an output, and decide on typical values for the input parameters, so that bounds are defined for continuous or discrete (integer) variables and a set of possible values for enumerated type (e.g., categorical variables such as material selection).

Step 2: Generate Initial Exploratory Designs

Step 2 is an initial scan of the design space defined in step 1. Various sampling techniques can be used to automatically generate initial candidate designs. For example, a design of experiments (DOE) or a randomly generated sample can be used. The sample size should be large enough to perform statistical analysis of input and output relationship of the system. The computational analysis model will be run for each candidate design and the values of the input and output variables will be recorded. By examining the data set, designers may discover anomalies such as failed runs or nonsensical behavior of the model. Multi-dimensional design visualization is very useful to identify outliers in the data. Such problems should be corrected whenever possible. However, the iDSP process is not hindered from failed runs because it considers individual designs as a whole and compares them each other in a possibly large candidate pool. Failed runs can be penalized or simply excluded from consideration.

Step 3: Screen Design Parameters

The sample data from the previous step is used to find important parameters and their roles. First, statistical analyses such as ANOVA (analysis of variance) can be used to quantify the effects of the inputs on the outputs. A graphical presentation of main effects and interaction effects is useful to identify key input and output variables and to understand overall relationships. The screening process should remove from consideration input parameters of little impact. Second, one or more design goals (e.g., objectives) should be selected. Note that iDSP naturally handles multi-objective design problems. Third, a set of design requirements (e.g., constraints) should be established. Limits can be placed on any of the input or output variables. If there is an important requirement that is not met, users may need to go back to Step 1 and adjust the variable bounds.

Step 4: Generate Pareto Set

When a multi-objective design problem involves conflicting objectives (such as cost and performance), it is not possible to find a design that is best in all aspects. Instead, a set of good designs is sought. If a given design is worse in all objectives compared to another design, it is dominated by the latter. If a design is not dominated by any other design under consideration, it is called a non-dominated design. A list of non-dominated design points that satisfy all design requirements is called the Pareto set (or Pareto trade-off surface). The multi-objective problem can be expressed as:

$$\text{Minimize} \quad f_j(\boldsymbol{x}) \qquad j=1,\ldots, n_{obj} \qquad\qquad (1)$$

$$\text{Such that} \quad g_k(\boldsymbol{x}) \leq 0 \qquad k=1,\ldots, n_{constr}$$

$$x_{lb} \leq x_i \leq x_{ub} \quad i=1,\ldots, n$$

$$\text{where} \quad \boldsymbol{x} = \{x_1, x_2, \ldots, x_n\}$$

where n_{obj}, n_{constr}, and n are the number of objectives, constraints, and design variables, respectively.

If there are enough design points available from previous steps, they can be compared to each other to identify the Pareto set. Alternatively, a Pareto set can be generated by running a multiple-objective genetic algorithm (MOGA). Once the Pareto set is identified, we do not need to consider dominated designs any more because for each dominated design there will always be at least one non-dominated design that will be better than it in all aspects.

Step 5: Select Preferred Designs

The Pareto set contains valuable information because it consists of best designs in a multi-objective sense. The Pareto set can be thought of as an optimal trade-off curve. It tells the user what he or she will have to give up in one aspect in order to achieve gains in another. So the question is: "Which design(s) should be chosen?". This is where user preference comes into the decision making process. In Step 4, objectives were applied without preference. In other words, all objectives were equally important. Now the designer needs to decide which objectives are more important than others. The relative importance of objectives can be expressed through weighting factors in the total figure of merit of a design.

$$F = \Sigma \, w_j f_j \qquad\qquad (2)$$

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The weighting factors, w_j give the relative importance of the *j-th* objective. Given a set of weighting factors, the Pareto designs can be ranked according to the combined merit function *F*. If the weights (e.g., preferences) are determined, the designer can find the best design (e.g., a preferred design). This process can be repeated to produce a handful of preferred designs. Because this process does not require new analyses of design points, visualization tools can quickly present the results to the designer. The designer essentially performs a trade-off study in the preference space. Because the number of objectives is much less that that of design variables in many cases, interactive trade-off studies augmented by data visualization tools are very effective in this step.

Step 6: Refine Preferred Designs

Now that we have selected a few preferred designs, chances are that we can improve upon them. In particular, if the Pareto set was generated from an arbitrary sample without running a MOGA, it is a good idea to perform formal optimization to refine each preferred design. The optimization problem becomes a single objective problem.

$$\textit{Minimize} \qquad F = \Sigma\, w_j\, f_j \qquad j=1,\ldots, n_{obj} \qquad\qquad (3)$$

$$\textit{Such that} \qquad g_k(\boldsymbol{x}) \leq 0 \qquad k=1,\ldots, n_{constr}$$

$$x_{lb} \leq\ x_i \leq x_{ub} \quad i=1,\ldots, n$$

$$\textit{where} \qquad \boldsymbol{x} = (x_1, x_2, \ldots, x_n)$$

The optimization problem would be started from the preferred design. For example, the preferred design can be used as a starting point for a gradient-based optimizer or seeded into the initial population of a genetic algorithm. If better designs are found, the original design can be replaced by the improved design. At this point, it is very likely that at least one design was found that is satisfactory because the designer was in control of the selection process. If there is no satisfactory design found, he or she may need to go back to a previous step or redefine the design problem.

III. Integration of ATSV Visualization Tool

The iDSP process requires an effective means to present and compare many design alternatives. The ARL Trade Space Visualizer (ATSV) is a tool that was developed to meet such needs. Developed by researchers at Applied Research Laboratory (ARL) at Penn State University, ATSV is a visualization tool that allows users to explore multi-dimensional trade spaces for complex engineering systems. The ATSV visualization techniques include glyph plots, histogram plots, parallel coordinate plots, scatter matrices, brushing, linked views, and Pareto Frontier displays, as shown in Figure 2. Users can select any design and view detailed information pertaining to the design and its behavior.

As a first step in building an integrated environment for the design selection process, the ATSV was integrated into the ModelCenter process integration software. ModelCenter provides integration capabilities for design analysis software tools and advanced optimization capabilities. ModelCenter's plug-in interface was used to integrate ATSV. When a trade study is performed such as DOE, Monte Carlo simulation, or optimization, ModelCenter stores run data into a post processing module called Data Explorer. Multiple ATSV plots can be created inside the Data Explorer infrastructure. The plots are dynamically updated as more data points are computed during trade studies.
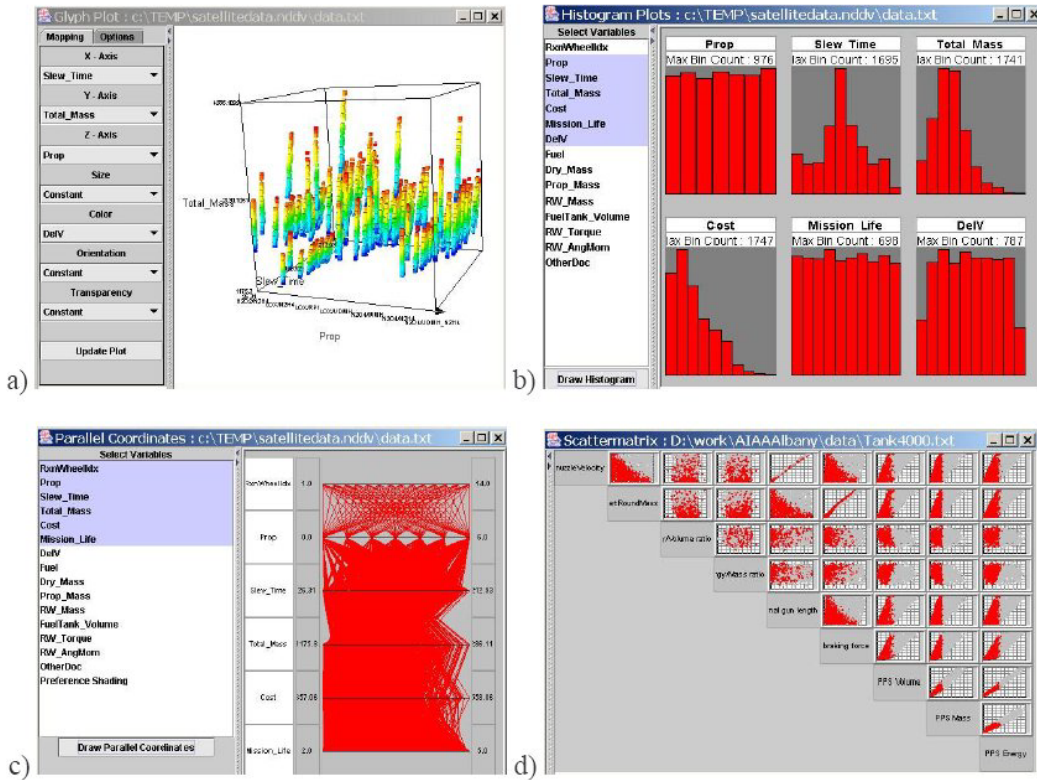
Figure 2: ATSV Visualization tools, a) glyph plot, b) histogram plot, c) parallel coordinates, and d) scatter matrix.

IV. Combining Visualization and Optimization for User Guided Search

Many engineers find it difficult to apply optimizations to their design problems because they do not have good understanding of workings of the optimizer. If the user lacks understanding of the underlying algorithm, optimizers may not produce useful results. Even when good optimal designs are found, the engineer can be hesitant to accept the results because he or she does not understand why the optimizer chose the design. An alternative to using optimization as a black box is the manual search approach that uses software tools to help visualize the design space and traverse through layers of data. But this can be also a challenging approach for complex design problems with many variables and the engineer is often left with a feeling of arriving at a sub-optimal design.
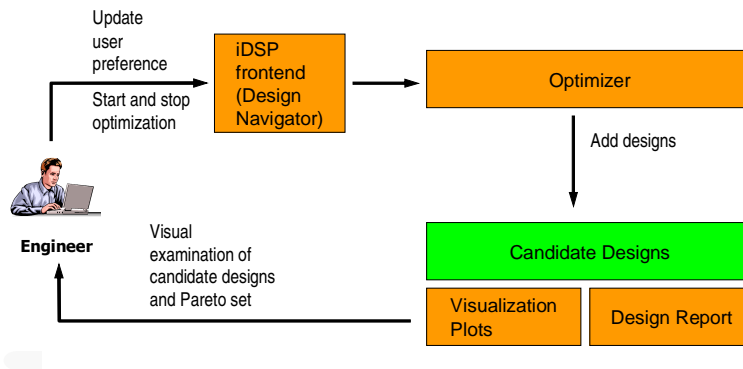

Figure 3: User Guided Search combines visualization and optimization.

The idea of User Guided Search (UGS) is to blend these two approaches by combining the best of both formal optimization algorithms and data visualization techniques. Figure 3 is an illustration of the UGS approach. Note that the design engineer is in the loop of the design search process. The engineer initiates the optimization process by providing initial problem definition. As optimization is running, the engineer gets feedback of the optimization results through visualization and report view of candidate designs. Using the information, he or she makes adjustment to the optimization process to explorer design space more efficiently and focus on area of interests. The UGS approach was adopted to support iDSP, particularly steps 4, 5 and 6 to shape user preferences and refine preferred designs. This section describes the UGS capabilities that are developed as a part of iDSP environment.

A. Problem Definition and Control: iDSP Frontend

To give control of the optimization process to users, a frontend of iDSP was developed called Design Navigator. It provides capability to adjust optimization search criteria on the fly. The user may change objectives of the optimization problem by using slider bars (Figure 4) on the *Goals* tab. Any of the input or output variables can be selected as an objective and more than one objective can be selected to minimize or maximize. Constraints of the optimization problem can be defined using *Requirements* tab (Figure 5). The constraints can be applied to either input variables or output variables. For discrete or enumerated variables, users can select individual values to specify constraints. Darwin genetic algorithm (GA) optimizer[6] was integrated into Design Navigator. The GA can be started and stopped using VCR type buttons on the display (Figure 4). When more than one objective is specified, Darwin can be run in a multi-objective mode that searches for Pareto front. If the Pareto Search option is not active, Darwin uses the combined preference (Eq. 2) for the objective function.
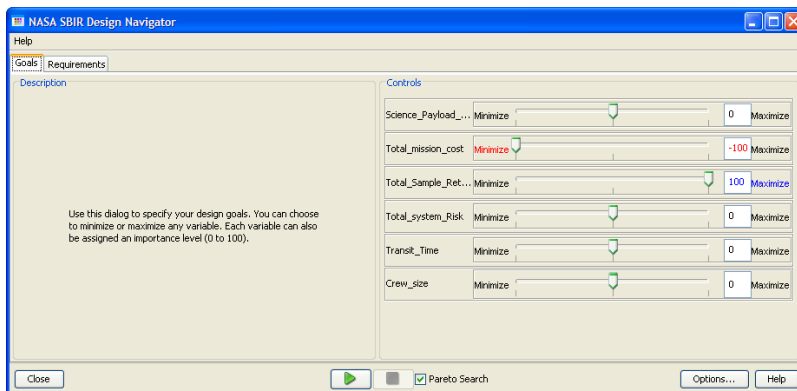

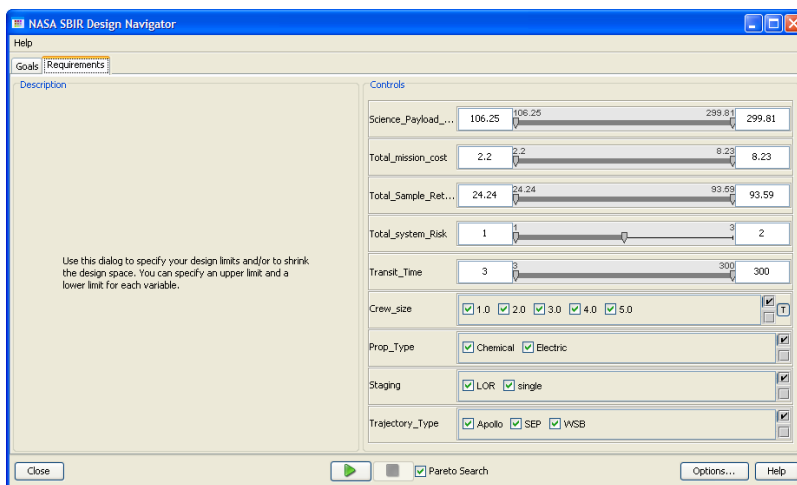**Figure 4: Goals tab to control user preferences.**

Figure 5: Requirements to control constraints.

At the end of each GA generation, Design Navigator checks to determine if the user has made any changes. If so, the optimization problem is modified and the optimization algorithm is restarted. Instead of restarting from scratch each

time, the optimizer makes use of all of the data generated to that point and does an intelligent *warm start*. This maintains the efficiency of the design process and doesn't penalize the user for modifying the design problem or playing *what-if* scenarios with the data.

B. Real-time Visualization of Optimization Results

When the optimizer is running, all of the visualization plots are updated as new data is available. By observing the various plots, the user is able to monitor the progress of the optimization process. For a multi-objective problem, current Pareto set can be highlighted. The optimization engine may be stopped or restarted at any time from the Design Navigator controls.

C. Report and Comparison of Candidate Designs

Design Navigator provides a report of an individual design. If the user selects a design on a visualization display, a dialog called the *Design Viewer* will be displayed (Figure 6). In this view, the user can see a *critique* of the selected design. The value of each input and output variable is listed in a table, along with the goals and constraints of the design problem. The status of each constraint is highlighted using a simple color scheme: green for satisfied constraints, red for violated constraints, and yellow for marginal constraints. At the top of the dialog, the selected design's ranking relative to other designs in the dataset is indicated. The top designs are marked with 1 to 5 stars (depending on their ranking), other feasible designs are marked with a blue dot, and infeasible designs are marked with a red *X*. This information is automatically updated as the optimizer runs and as the user modifies the goals and constraints of the problem.

The user can use the Design Viewer dialog to navigate and explore the design space. By pressing the *Higher Rank* and *Lower Rank* buttons at the bottom of the dialog, the user may traverse through the design space in rank order according to the combined preference value. After each button press, the dialog will be updated to show information for the new design. The user may also go directly to a specific design by entering either its identification number or its rank in the text box at the bottom of the dialog. If the user presses the *Highlight this Design* link, the current design is highlighted in all open plots. The Design Viewer dialog can be shown for more than one design to compare them side by side.

D. Automatic Adjustment of Preference

Design Viewer also has a capability to adjust the design goals automatically so as to guide the optimizer into area of interests. If the user finds a design that he or she likes, use the *I Like This Design* functionality to automatically adjust the preference weights so that the design will be ranked as high as possible. Design Navigator solves an optimization problem internally to minimize the ranking of the selected design *i*. A downhill Simplex algorithm[7] is used with multi-start to avoid local optima problems.

$$Minimize \quad r_i(\mathbf{w}), \quad ranking\ of\ design\ i\ according\ to\ \text{Eq. (2)} \quad\quad (4)$$

$$where \quad \mathbf{w} = \{w_1, w_2, \ldots, w_{nobj}\}$$

When the weights are adjusted, this will cause the GA optimizer to search for similar designs. The user may also suggest a new design to the optimizer by pressing the *Suggest a Design* link. A dialog will appear that will allow the user to enter any design of their choosing. This allows the user to *nudge* the optimizer to search in desired directions.
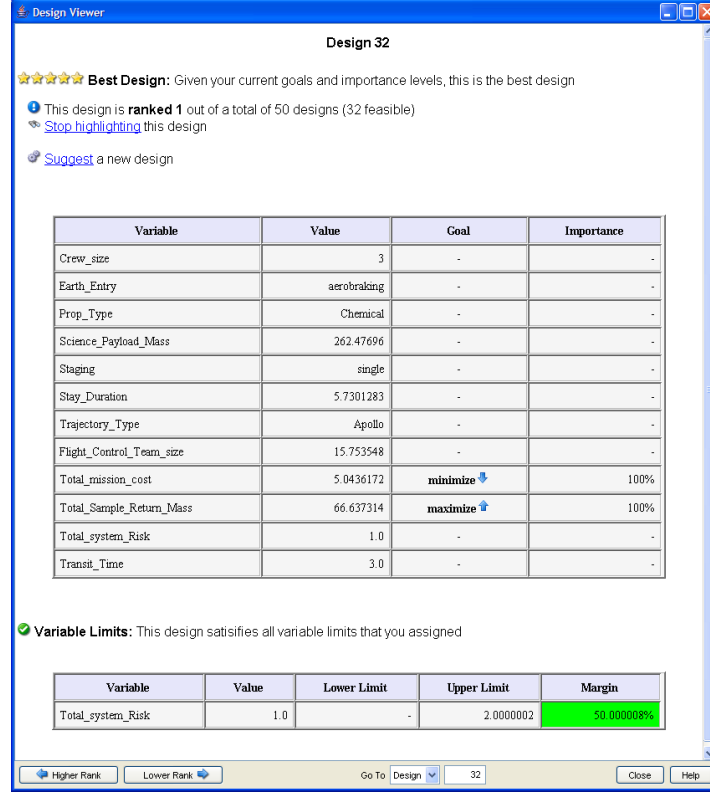
Figure 6: Design Viewer Dialog shows how a design is compared to others for a given preference setting.

V. An Application of iDSP: Lunar Exploration Mission Example

As an example, the iDSP was applied to design a lunar exploration mission. The scenario is a manned mission to land on the Moon and explorer its surface. Size of transfer vehicle, trajectory types, mission length, and types of the launch vehicle are considered to compute cost and risk of the mission. The analysis model in an Excel spreadsheet uses simple algebraic equations that run quickly. Excel plug-in of ModelCenter was used to automate execution of the model.

A. Select Design Parameters

As the first step of iDSP, eight input variables and four response (output) variables are selected (Table 1). The input variables contain continuous, discrete and enumerated types. There are four response variables and total system risk and transit time can have only discrete values.

Table 1: Design and response variables of a lunar mission design problem.

Design variables	Values, range
N_c (Crew size)	1, 2, 3, 4, 5
E_T (Earth entry type)	Direct, aerobraking, propulsive
P_T (Propulsion type)	Chemical, electric
M_{SP} (Science payload mass, Kg)	$100 \sim 300$
S_T (Staging type)	Single, LOR (Lunar Orbit Rendezvous)
D_S (Stay duration, days)	$5\sim20$
T_T (Trajectory type)	Apollo, WSB (Weak stability boundary), SEP (Solar electric propulsion)
N_{FC} (Flight control team size)	$10\sim20$
Response Variables	
C_T (Total mission cost, billion dollar)	-
M_S (Sample return mass, Kg)	-
R_T (Total system risk)	1 (low risk), 2, 3 (high risk)
T (Transit time, days)	3, 60, 300

B. Generate Initial Exploratory Designs

The goal is to generate a data set for initial analysis of input and output relationship. 576 design points were generated using a factorial design with two levels for continuous or discrete design variables while all distinct values were included for enumerated design variables. The DOE was performed and the data was collected in a tabular form for further analysis.

C. Screen Design Parameters

ANOVA was performed to evaluate relative importance of design variables. Main effects of design variables on each of the response variables are shown in Figure 7. Crew size was the most important factor both for the total mission cost and the total sample return mass. The system risk depends on type of propulsion system and choice of mission trajectory as well. The mission trajectory was the only meaningful factor for transit time. It turned out that stay duration and the size of flight control team have no effect on any of the response variables and the earth entry type had very small effects. The three variables were removed and were not considered in subsequent design studies.
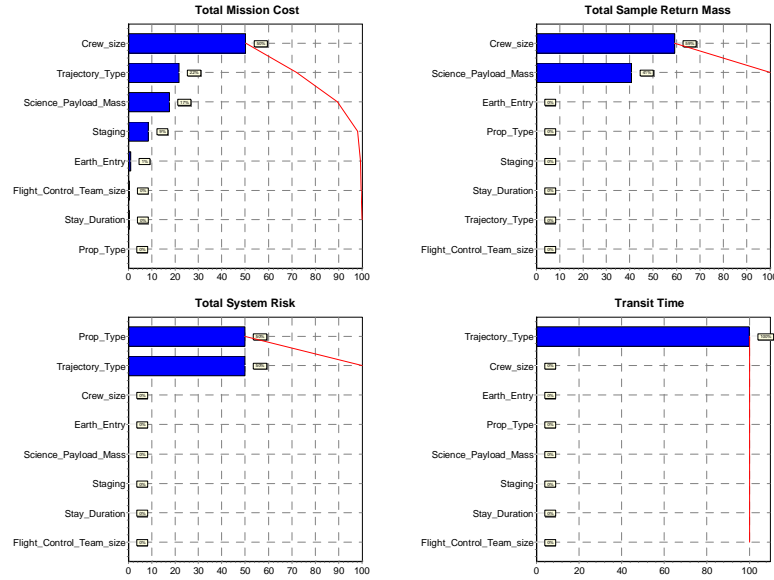

Figure 7: Main effects of design variables.

D. Generate Pareto Set

It was decided to consider three metrics: total mission cost, total sample return mass, and total system risk. The problem is naturally formulated as a constrained multi-objective problem:

$$\begin{aligned} &\textit{Minimize} \qquad C_T \\ &\textit{Maximize} \qquad M_S \\ &\textit{Such that} \qquad R_T \leq 2 \end{aligned} \qquad\qquad (5)$$

We want to minimize the total system cost while minimizing the total sample return mass. The system risk level should be no greater than 2. Genetic optimizer is well suited to this example that contains both continuous and enumerated variables. A random sample of size 30 was generated to seed an initial population of the GA run. The objectives and constraints were set up using the Design Navigator dialog. The Darwin genetic optimizer was run behind the Design Navigator in a multi-objective mode to generate a Pareto set. The progress of the GA run was monitored through ATSV plots available. Since the Pareto designs are of particular interests, they were shown and updated as more data points are computed. Note that iDSP does not require running the multi-objective GA to complete convergence. The GA run can be stopped and continued as necessary by the designer who can visually monitor its progress.

GA results after 5 generations are shown in Figure 8. Out of the 106 designs evaluated so far, the Pareto designs are shown with crosses. The color map of the design points is based on the combined preference according to relative

weights of the two preferences (cost and sample return mass) that were equally important in this case. Red points have higher combined preference values. Infeasible design points are shown in gray color. The designer may decide to continue the Pareto search. Alternatively, the designer can adjust the preferences to narrow down candidate designs, as was performed in the next step.
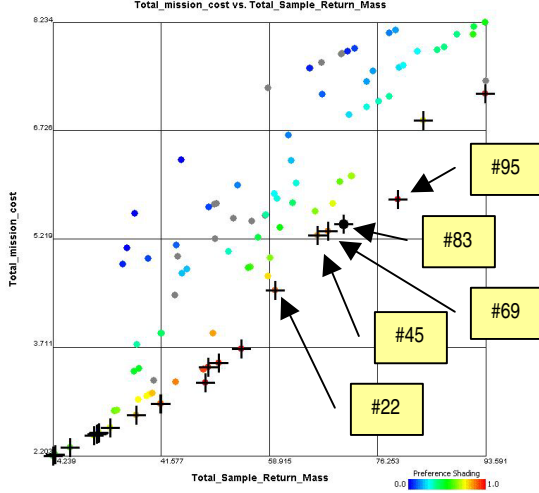

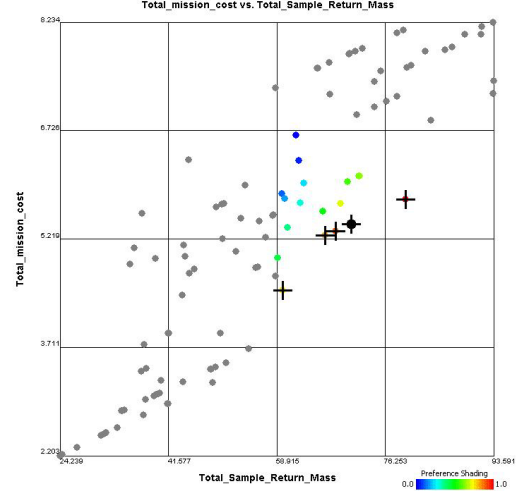**Figure 8: Results after 5 generations of the multi-objective GA run.**

Figure 9: Preferred objective space of mid cost and high return.

E. Select Preferred Designs

In theory, designers can select any of the Pareto points as an optimal design. However, designers may have reasons to like one over the other. A scatter plot in the objective space such as Figure 8 is useful since it shows typical ranges of design objectives. The designer may decide that designs of mid-cost and high performance are preferred. For example, design #83 is a Pareto point that fits the criteria. Double clicking the design point shows the Design Viewer that reports that the design is ranked 9 out of the 106 designs. The values of variables are listed in Table 2. One way to find more designs like this is to adjusted relative weights of preference so that the selected design ranks as high as possible. Automatic adjustment of importance level was used that was available from the Design Viewer and the design was ranked 4 after weight adjustment: 43% for total mission cost and 56% for total sample return mass. Another way to infuse designer's judgment is to impose bounds on the objective values. Since we prefer mid-cost and high return designs, new requirements were introduced:

$$3.7 \leq C_T \leq 6.7 \qquad\qquad (6)$$
$$58.9 \leq M_S \leq 93.59$$

Table 2: Preferred designs considered.

Design Variables	Design #83	Design #22	Design #45	Design #69	Design #95	Design #176
N_c (Crew size)	4	4	4	4	4	3
P_T (Propulsion type)	Chemical	Chemical	Chemical	Chemical	Electric	Chemical
M_{SP} (Science payload mass, Kg)	219.5	289.1	191.0	202.3	278.0	294.3
S_T (Staging type)	Single	Single	Single	Single	Single	Single
T_T (Trajectory type)	Apollo	Apollo	Apollo	Apollo	Apollo	Apollo
Response Variables						
C_T (Total mission cost, billion dollar)	5.427	4.507	5.263	5.328	5.764	5.197
M_S (Sample return mass, Kg)	70.86	59.91	66.68	68.33	79.58	71.37
R_T (Total system risk)	1	1	1	1	1	1
T (Transit time, days)	3	3	3	3	3	3

Figure 9 shows that there are five Pareto points including design #83 that fall on the constrained objective space. Their design values are listed in Table 2 (Designs #83, 22, 45, 69, and 95). It was found that the first four designs

belong to a family of the same configuration with different science payload mass. Design #95 belongs to a different family that uses electric propulsion instead of chemical one.

F. Refine Preferred Designs

Darwin GA was performed to explorer more design points in the constrained objective space. This time Darwin was run in a single objective mode that maximizes the weighted sum of the objectives. Figure 10 shows the objective space after 6 generations that contains 199 designs. Note that design #83 is not a Pareto point anymore because a new design (design #176) was found that dominates it. In fact, three designs in the original Pareto set are dominated and the new Pareto set consists of seven designs. By focusing on area of interests, we were able to improve a set of preferred designs more effectively. If we compare designs #83 and #176 from Table 2, the latter trades crew size by one to increase the science payload mass. And the net effect was increased sample return mass and lower cost.
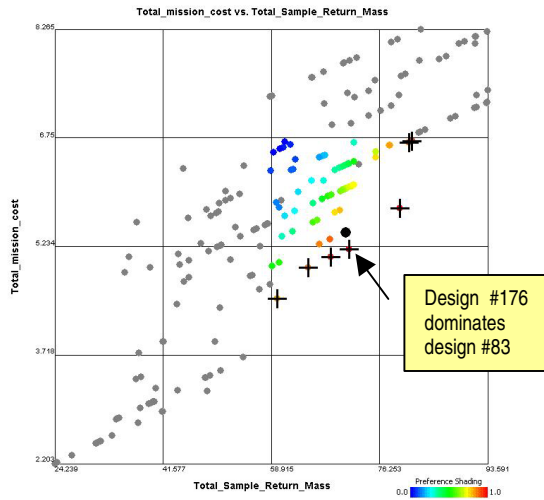
Figure 10: Improved design point after 6 generations of GA run.
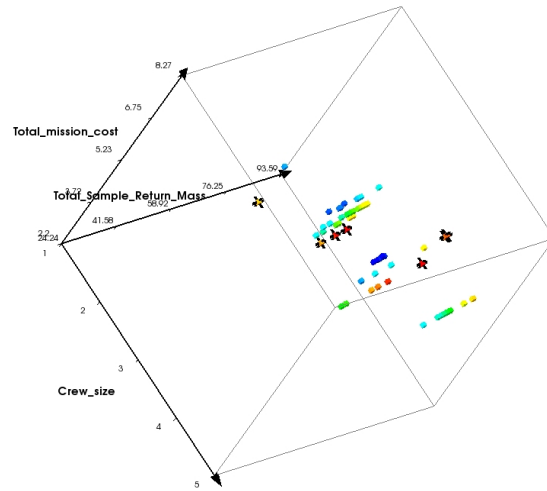
Figure 11: Glyph plot highlights location of Pareto design points.

Although we have illustrated this example using 2D scatter plots, combination of different plots was also used to examine the data set in different views. Figure 11 shows feasible design points out of the 199 designs in a 3D glyph plot. The Pareto points were shown with crosses and it can be observed that the Pareto points have crew size of between 2 and 4.

VI. Concluding Remarks

Engineering design is a complex decision making process. This paper defined a new design process that helps designers collect design data and make informed decisions at each step in the process. The new process called Interactive Design Selection Process (iDSP) follows the design by shopping paradigm that allows designers to build preferences through comparison of candidate designs. iDSP is an inherently multi-objective design process and it covers entire design selection process including design problem definition, Pareto set search, user preference definition, and final down-select. Interacting through design space visualization tools, users maintain control throughout the design selection process. As a result, the user is much more likely to find a satisfactory design compared to the traditional black box optimization approach.

A prototype of iDSP was developed by integrating ATSV, an advanced design space visualization tool, with the ModelCenter process integration tool. The ATSV plug-in has capabilities to visualize candidate designs generated by ModelCenter. Multiple plots can be presented so that the same data can be examined in different perspectives at the same time. The iDSP implementation utilized the concept of the User Guided Search to provide capabilities of

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interactive design space search by combining visualization and optimization. The iDSP frontend enables users to influence the automated search of an optimizer by adjusting objective preferences or constraints on the fly.

A Lunar space mission design problem was presented to demonstrate the iDSP techniques. ANOVA analysis was used to screen variables of little importance. The GA optimizer was first run to find a Pareto set. Characteristics of the promising design points were examined using the design report view. It helped refine the preference and requirements of the design problem and the GA optimizer was run to find more designs in the area of interests. As a result, better designs that dominate previous Pareto designs were found. The iDSP capabilities are being extended to provide a step by step guidance so that non-expert users can perform design studies more effectively.

Acknowledgments

References

1. Balling, R., "Design by Shopping: A New Paradigm," Proceedings of the Third World Congress of Structural and Multidisciplinary Optimization (WCMSO-3), 1999, Buffalo, NY., pp.295-297.
2. Schaumann, E., J., Balling, R., and Day, K., "Genetic Algorithms with Multiple Objectives," AIAA Paper 98-4974.
3. Stump, G., M., Simpson, T., W., Yukish, M., and Bennett, L., "Multidisciplinary Visualization and Its Application to a Design by Shopping Paradigm," AIAA Paper 2002-5622.
4. Stump, G., M., Yukish, M., Martin, J., D., and Simpson, T., W., "The ARL Trade Space Visualizer: An Engineering Decision-Making Tool," AIAA Paper 2004-4568.
5. Phoenix Integration, Inc., "Improving the Engineering Process with Software Integration," a white paper, 2002, see also http://www.phoenix-int.com.
6. Soremekun, G., Gürdal, Z., Kassapoglou, C., and Toni, D., "Stacking Sequence Blending of Multiple Composite Laminates Using Genetic Algorithms", *Composite Structures*, Vol. 56, No. 1, 2002, pp. 53-62.
7. Luersen, M. A., Le Riche, R. and Guyon, F., "A Constrained, globalized, and bounded Nelder-Mead method for engineering optimization," *Structural and Multidisciplinary Optimization*, Vol. 27, No. 1-2, 2004, pp. 43-54.