Integrating Design Research into the Classroom: An Experiment in Two Graduate Courses

Mary Frecker, Timothy W. Simpson, Joseph H. Goldberg,
Russell R. Barton, Britt Holewinski, and Gary Stump
The Pennsylvania State University

Abstract

As computer technology advances, graphical design environments (GDEs) and visualization tools to support engineering design and decision making are gaining prominence and recognition, particularly in the area of multiobjective design and optimization. In this paper, we discuss an experiment in two graduate courses that was designed to evaluate GDEs through in-class student assignments. For this first set of experiments, a GDE was developed for designing an I-beam cross section with two competing objectives. Within the GDE, students were allowed to vary the values of the design variables and view the corresponding performance graphically in an effort to obtain an optimal design based on a weighted sum of the objectives. Methods for evaluating student efficiency, effectiveness, and satisfaction within a GDE are discussed, and preliminary results from the experiment verify that graphical design environments can improve design quality and overall satisfaction with the design. The importance of rapid graphical feedback in a GDE is also investigated by incorporating time delays in the performance response. The use of graphical design environments to improve student understanding of design tradeoffs in the classroom is discussed, and results from the I-beam experiment are compared with a previous assignment wherein students had to choose an optimal design without the use of a graphical design interface.

I. Introduction

As engineering systems become more complex and design generations exhibit greater leaps in technology and performance, traditional methods of experience-based iterative design become ineffective. Consequently, the use of visualization to support engineering design and decision making is growing rapidly in both industry and academia as computer technology advances and the requisite tools and technology become more readily available. While companies such as Chrysler,[1] Raytheon,[2] and Boeing[3,4] are learning how to harness the power of visualization to expedite and integrate product and process development, the state-of-the-art in optimization visualization is in its infancy.[5] Ng[6] advocates the use of data visualization and interaction to support the designer in making informed decisions and tradeoffs during multiobjective design and optimization. Jones[7] argues that design optimization is more than just algorithm development; appropriate representations (i.e., visualization strategies) are needed to better understand the models, algorithms, data, and solutions obtained during the design optimization process. Finally, Eddy and Mockus[8] argue that visualization should be considered as a solution tool rather than simply a means to present results.

Despite the importance of and recognized need for interactive visualization during the design process, we have found little evidence in the engineering design literature which investigates the *impact* of such graphical design environments on the efficiency and effectiveness of engineering design decisions or the design process. Research on the effect of response time of the design software on user productivity have focused on simple placement, searching, and editing tasks[9-12], or on the loss of information held in short-term memory[13]. Evans, et al.[14] compared the effectiveness of using traditional interfaces and virtual reality interfaces for 3-D spherical mechanism design. There have also been some investigations addressing the effect of software performance on the speed and quality of design; speed of response is critical for certain cognitive tasks. Goodman and Spence[15] examined the effect of system response time on the time to complete an artificial task that was created to mimic design activity. The task was the graphical adjustment of five parameters to change the shape of a function (presented graphically) so that it passed between forbidden regions in the x, $f(x)$ plane. They found an increase in task completion time of approximately 50% for response delays of 1.5 seconds between a parameter adjustment and the resulting shape change for the function. For more complex tasks, system response delays of up to 10 seconds have not had significant impact on the design process.[16]

From an educational perspective, an effective computer interface can also improve the performance of designers by enhancing learning. Lembersky and Chi[17] incorporated artifact representations of logs in their VISION software which enabled timber buckers to position cuts on a log and determine the use for each section (e.g., plank, plywood veneer, pulp, etc.). The software provided immediate feedback on the resulting profit per section and overall profit for the log. At the same time the software computed an “optimal” design for log segmenting and product allocation, and presented the alternative graphically, adjacent to the cutter’s design, in real time. Invariably the “optimal” allocation produced higher profit; however, an interesting result of this study was that the timber buckers using the software improved their own cutting abilities. After one week of practice on the log simulator/design interface, the timber buckers had developed new strategies for cutting and product allocation based on viewing the competing (and superior) “optimal” solutions, thereby improving their own ad-hoc cutting/allocation performance in terms of profitability.

In this paper we present preliminary results from a graphical design environment developed to integrate design visualization research into the classroom to enhance student learning about multiobjective design and optimization. By understanding the *impact* of graphical design environments on design efficiency, effectiveness, and satisfaction, we can improve student understanding of multiobjective optimization and its use for resolving tradeoffs during design. Another objective of this research is to develop and refine technology that can allow fast graphical interfaces for commercial design environments such as Abaqus[18], Patran[19], and I-DEAS[20]. Our results can help to define performance requirements for approximation-based graphical interfaces employed by commercial optimization packages such as VisualDOC [21], OptdesX[22], and iSIGHT[23].

The experiment is described in the next section followed by the experimental set-up used for this preliminary study. Analysis of the results is presented in Section IV, and conclusions and future work are discussed in Section V.

II. I-Beam Design Exercise

The purpose of this study is to investigate student interaction with a graphical design environment (GDE) with varying response times and to measure the impact of using a GDE on student learning about resolving design tradeoffs. This example was adapted from a problem in Haftka and Gurdal[24] where the students attempt to determine the optimal design for an ordinary I-beam subject to bending stress. The GDE was developed using Visual Basic 6.0 to visualize the effect of changing the geometry of the I-beam cross-section on the stress and cross-sectional area. The design exercise was completed by students in two graduate courses at Penn State: *Optimal Structural Design* (ME 597I) and *Using Simulation Models for Engineering Design* (IE 578). In the I-beam GDE, students are able to change both the height ($\boldsymbol{h}$) and width ($\boldsymbol{w}$) of the I-beam, thus changing the cross-sectional area ($\boldsymbol{A}$) and the imposed bending stress (σ). As the student changes $\boldsymbol{h}$ and $\boldsymbol{w}$ using slider bars, the corresponding $\boldsymbol{A}$ and σ response appear in the performance space (*xy*-plot of $\boldsymbol{A}$ vs. σ). Since $\boldsymbol{A}$ and σ are competing design objectives, the student seeks to resolve tradeoffs between them by finding the best combination of $\boldsymbol{h}$ and $\boldsymbol{w}$ that minimize both $\boldsymbol{A}$ and σ. This portion of this experiment is called the free-form case.

In the second portion of the experiment, the student seeks to resolve tradeoffs between $\boldsymbol{A}$ and σ using a weighted sum approach, as shown in Equation 1, where normalized measures of $\boldsymbol{A}$ and σ are used in order to avoid scaling problems in the plot. Here, $\boldsymbol{F}$ is a weighted sum of the normalized objectives, α is a scalar weighting factor ranging from 0 to 1, $\boldsymbol{A_{max}}$ and $\boldsymbol{A_{min}}$ are the maximum and minimum possible areas, respectively, and σ_{max} and σ_{min} are the maximum and minimum possible stresses, respectively. The student seeks to determine the best combination of $\boldsymbol{h}$ and $\boldsymbol{w}$ that minimize $\boldsymbol{F}$ for a particular value of α. The weighted sum is appropriate for handling the multi-criteria optimization problem in this case because the problem is convex.

$$\min_{\left\{\begin{smallmatrix}0.2\le h\le 10\\ 0.1\le w\le 10\end{smallmatrix}\right\}} \boldsymbol{F} = \alpha\frac{(\boldsymbol{A} - \boldsymbol{A_{min}})}{(\boldsymbol{A_{max}} - \boldsymbol{A_{min}})} + (1-\alpha)\frac{(\sigma - \sigma_{min})}{(\sigma_{max} - \sigma_{min})} \qquad (1)$$

The student can investigate the quality of a particular design by using the mouse to click on a point in the performance space. The objective contour line (line of constant $\boldsymbol{F}$ with slope α) through that point appears, and the corresponding value of $\boldsymbol{F}$ is displayed. A contour line lies tangent to the optimal design point. The interface is pictured in Figure 1 for $\alpha = 0.9$.

In this portion of the experiment, the impact of the delay time in the display of the performance response is also assessed. The delay time for the response to appear in the performance space is varied during the experiment to be either 0.0, 0.1, or 0.5 seconds. It is important to note that for this simple I-beam example, the analysis is virtually instantaneous, making it easy to study the effect of response delay, since delay can be artificially imposed. For large complex systems, detailed analyses dictate large response delays, and rapid response can only be achieved by using approximations called *metamodels*.[25,26] Our future research will investigate the benefit of rapid approximate analysis using metamodels for such large complex systems.

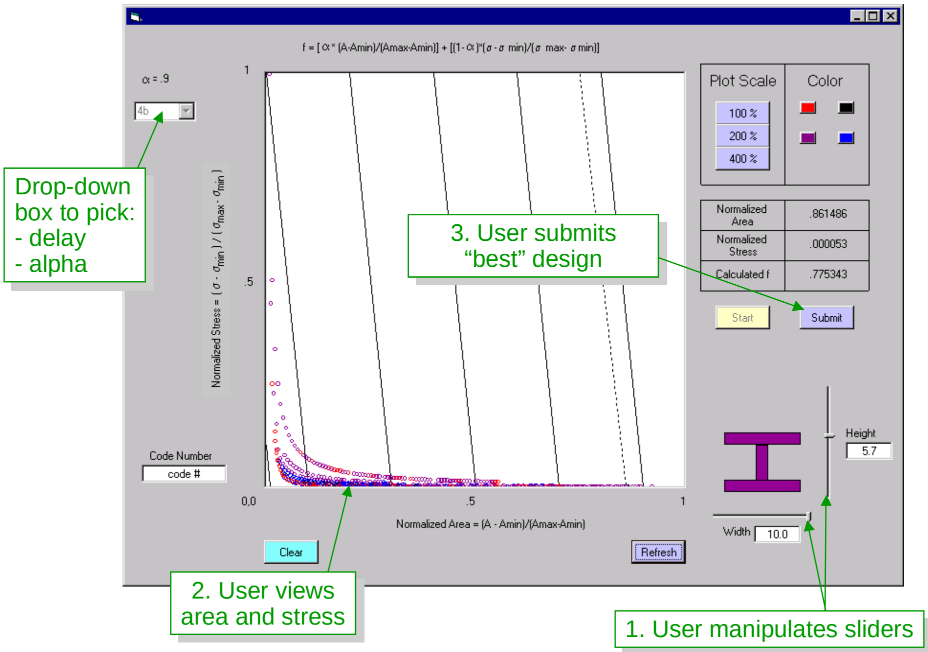

Figure 1. Graphical Design Environment for Weighted Sum Problem

III. Experimental Protocol

Eighteen graduate students designed I-beam cross sections using the graphical design environment shown in Figure 1. The students were asked to manipulate slider bars to adjust design parameters, $\boldsymbol{h}$ and $\boldsymbol{w}$, to resolve tradeoffs between two competing objectives, σ and $\boldsymbol{A}$, and then identify the "best" design. During the weighted sum optimization, the delay before the graphical window was updated after each design change was controlled. The experimental setup is pictured in Figure 2. The students were videotaped during the experiment, and the software recorded the following data for each student:

1. the final designs submitted for each exercise (i.e. design variables, stress, and area),
2. the time to obtain each design, and
3. the time spent on each slider bar.

Figure 2. Experimental Setup

Each student required approximately 15-30 minutes to complete the design exercises. The experiment began with an overview of the experiment, an informed consent form, and a pre-test questionnaire to determine the student's familiarity with multiobjective optimization and computer literacy. The students then completed a simple training example to become familiar with the software. The first task was the free-form design exercise. The students were videotaped during this portion of the experiment and asked to speak aloud and articulate their thinking while designing. The students then completed a mid-test questionnaire regarding ease of use of the software, satisfaction with selected design and anxiety level. Next, students were asked to identify three designs based on three weighted sum combinations of the two competing objectives ($\alpha = 0.1, 0.5, 0.9$). The order in which each student received the three α values and the magnitude of the time delay in the software were varied for each student. The students were also videotaped during this portion of the experiment and asked to speak aloud and articulate their thinking while finding the best design for each α value. The experiment concluded with a post-test questionnaire, where the students were asked to rate the ease of use of the software, their designs and their design process, their learning between tasks, the impact of response delay on the design process, the impact of being videotaped. Suggestions for improving the experiment and/or the software were also recorded.

IV. Results and Analysis

The preliminary analysis of student performance presented in this section follows the segments of the experimental protocol: pre-test questionnaire, free-form design exercise, mid-test questionnaire, design exercises with different weighting (α) values, and post-test questionnaire.

Pre-test Questionnaire Responses

Table 1 summarizes the mean and standard deviation of the student responses to the pre-test questions, where most questions were rated on a scale of 1 to 5. Students felt that they had a fairly extensive knowledge of computers and used them for 10 to 40 hours each week. They were generally familiar with multi-objective optimization, since this topic was covered in both graduate courses, and 1/3 had developed graphical user interfaces for computer programs.

Table 1. Pre-Test Questionnaire Responses

Question	Mean	Std. Dev.
Computer knowledge	3.7	0.8
Weekly computer usage (hours)	26.7	14.0
Video games	2.8	1.1
Understanding of computers	3.7	0.6
Familiarity with multi-objective optimization	3.3	0.7
Ever develop a Graphical Design Environment	5 Yes	13 No

Based on these responses, we expected that the short training period in this test would be sufficient to prepare these students for the design exercises. The results presented in the following sections suggest that students continued to learn how to use the graphical design environment during the first two design exercises.

Free-Form Design Exercise

For the first exercise, students were asked to find a design to simultaneously minimize both stress and area. Figure 3 shows the normalized stress and area values for the designs created in the first exercise, which are compared with designs created earlier in the semester without the real-time graphical user interface. All of the designs fall close to the Pareto frontier, but designs created using the graphical interface show less variation and are generally better (i.e., closer to the utopia point). We believe that the graphical design environment helped the students resolve tradeoffs between competing design objectives, and the questionnaire responses support this interpretation of the results (see Table 2).

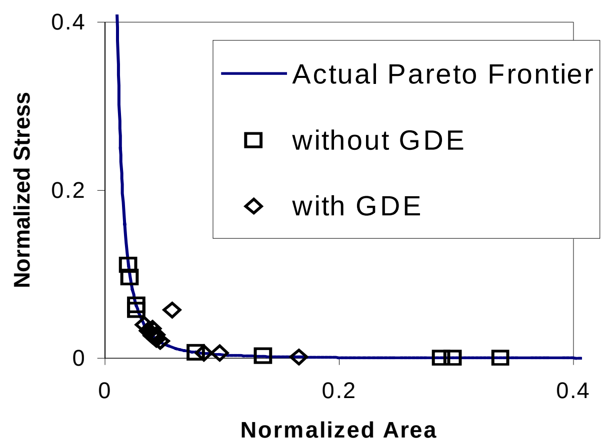

Figure 3. Free-Form Normalized Area vs. Stress for Graphical and Non Graphical Exercises

Mid-test Questionnaire Responses

After completing the free-form design exercise, students thought that the graphical interface helped them find a good design, and they were confident that they had found a good design. They thought that the graphical design environment was easy to use. There were no questions relating to response delay time for the free-form design since no response delays were introduced during this design exercise.

Table 2. Mid-Test Questionnaire Responses

Question	Mean	Std. Dev.
Software helped make tradeoffs	4.0	0.6
Confidence in final design	3.8	0.6
Software easy to use	4.6	0.5
Frustration with software	0.4	0.6

Design Exercises with Three Different Relative Weights (α values)

For the next three design exercises, students were asked to minimize a composite objective function that was a weighted sum of normalized area (weight = α) and normalized stress (weight = 1 - α). The balanced Latin square experiment design prevented confounding of learning effects with effects due to the weight (α = 0.1, 0.5, 0.9) and delay (= 0.0, 0.1, 0.5). Figure 4 shows that the relative weights for the two objectives did not have a significant effect on the quality of the design. On the other hand, Figure 5 may indicate a learning effect: the largest percentage errors in the students' designs generally occurred during the first of these three exercises, regardless of the value of α. Meanwhile, Table 3 shows that the second and third trials tended to have lower errors than the first (3.61% vs. 7.10%); however, the p-value testing this hypothesis was not significant at the 5% level. Figure 5 also shows a general trend indicating that large errors occurred infrequently, but when they did, students who spent more time on to complete each design exercise tended to have lower errors. Figure 6 shows a related phenomenon: students who performed a larger number of controller actions tended to have higher quality designs (smaller percentage error from the optimal objective function value). The effect of learning is also apparent in this figure, since the second and third trials often had lower error for a similar number of alternatives examined.

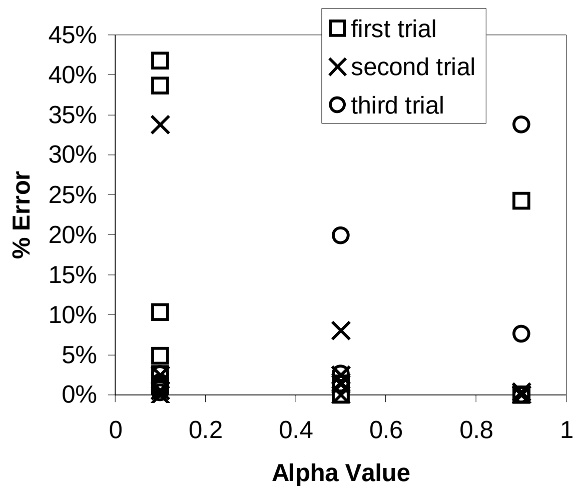

Figure 4. Percent Error in Objective Function vs. Weighting Factor

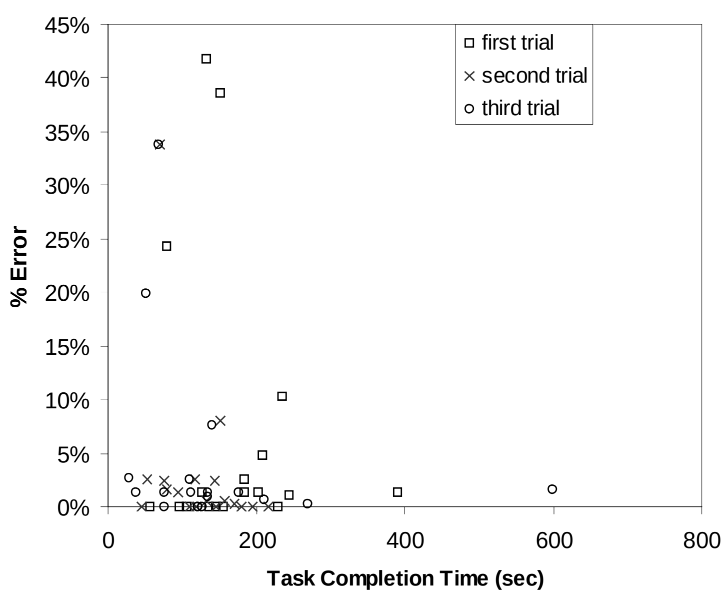

Figure 5. Percent Error in Objective Function vs. Time on Task

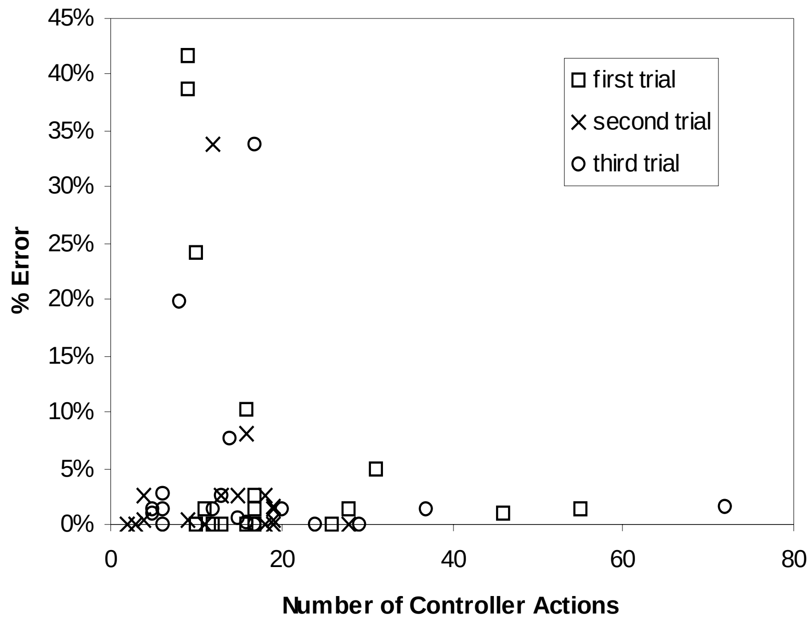

Figure 6. Percent Error vs. Number of Controller Actions

Table 3. Statistical Data for the Learning Effect

Trial	N	Mean	SD	SE Mean
1	18	0.0710	0.1350	0.032
2,3	36	0.0361	0.0832	0.014

P = 0.32

```
                                     Individual 95% CIs For Mean
                                     Based on Pooled SD
Trial      N      Mean     StDev   -----+---------+---------+---------+-
1         18    0.0711    0.1348             (------------*-----------)
2         18    0.0294    0.0799   (-----------*------------)
3         18    0.0428    0.0881      (------------*-----------)
                                   -----+---------+---------+---------+-
Pooled StDev =  0.1038                0.000     0.040     0.080     0.120
```

A primary objective in this study is to determine whether or not small delays in system response affect the design process. Figure 7 shows that a delay as small as 0.1 second may cause deterioration in the quality of a design, in terms of percent increase over the optimal (weighted) objective function value. It appears that the advantage of a graphical design interface for improving design quality depends on the ability to produce near-instantaneous responses to design parameter changes. Shown in Table 4, the average percent error increased from 2.56% to 5.90% when delay was introduced. This difference was not statistically significant with a p-

Proceedings of the 2001 American Society for Engineering Education Annual Conference & Exposition

value of 0.17. On the other hand, Figure 8 shows that in these exercises, added response delay did not have a significant impact on the time to complete the design task.

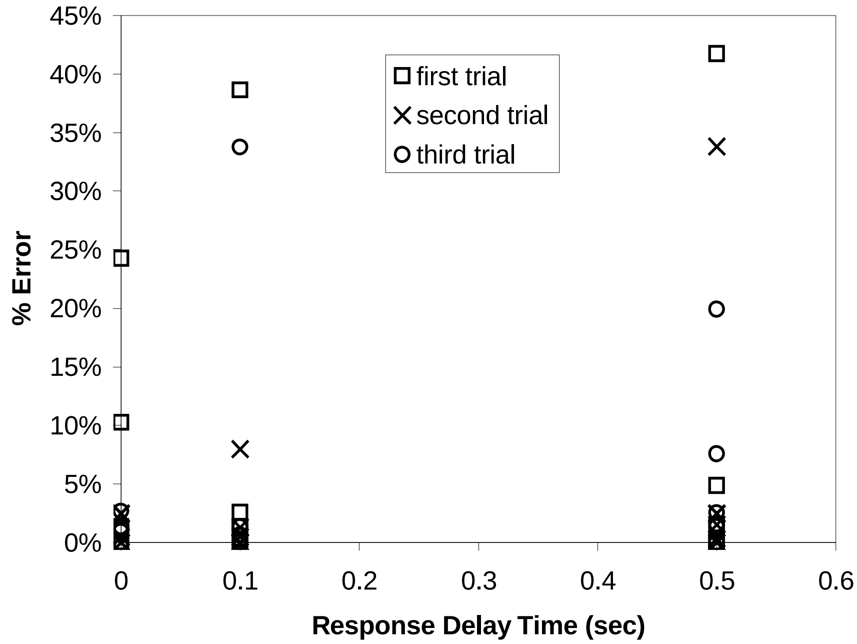

Figure 7. Percent Error vs. Response Delay

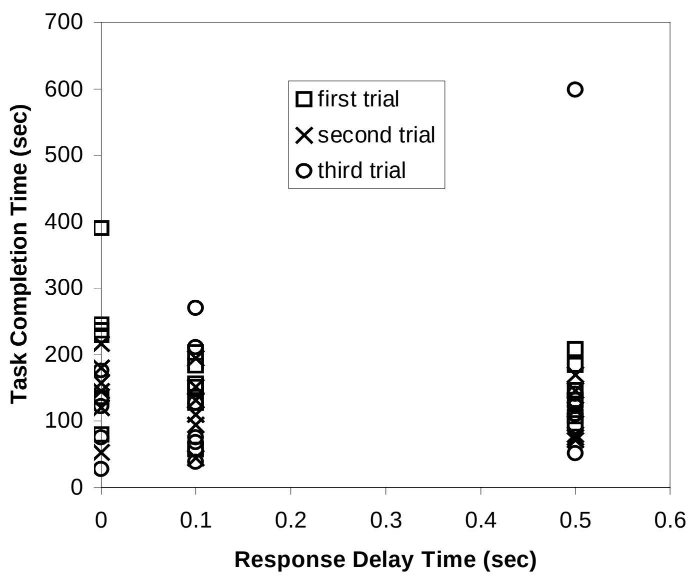

Figure 8. Time to Complete Task vs. Response Delay Time

Table 4. Statistical Data for the Time Delay Effect

	N	Mean	SD	SE Mean
No Delay	18	0.0256	0.0584	0.014
Delay	36	0.0590	0.1190	0.020

P = 0.17

```
                                          Individual 95% CIs For Mean
                                          Based on Pooled StDev
Time Delay  N      Mean     StDev   ------+---------+---------+---------+
0.0        18    0.0256    0.0584   (-----------*------------)
0.1        18    0.0500    0.1165         (------------*-----------)
0.5        18    0.0678    0.1239              (-----------*-----------)
                                    ------+---------+---------+---------+
Pooled StDev =   0.1038                 0.000     0.040     0.080     0.120
```

Post-test Questionnaire Responses

The average and standard deviation of responses to post-test questions are listed in Table 5. The post-test questionnaire showed that the students thought that the software made it easy to resolve tradeoffs between the competing objectives of area and stress, although there was no uniform view of which design exercises were more difficult: the weighted sum exercises or the free-form design. The weighted sum exercises provided objective function contour lines to help the students select a design, and most students found this feature very useful. All but two of the students rated their confidence in their final designs as 4 or 5. All of the students rated the software environment highly, and none of them felt that the videotaping and questions disrupted their design process.

Table 5. Post-Test Questionnaire Responses

Question	Mean	Std. Dev.
Software helped make tradeoffs	4.3	0.8
Confidence in final designs	4.0	0.8
Software easy to use	4.5	0.5
Frustration with software	0.8	1.1
Impact of response delay on choosing designs	2.4	1.3
How much did the contour lines help	4.3	1.0
Ease of use of slider bars and zoom	4.3	0.9
Ease of picking and submitting points	4.8	0.4
Did videotaping/talking interfere with your tasks	2.1	0.5
Satisfaction with part I (free-form) design	3.5	0.9
Which task (free-form or weighted sum) was easier	8F	10W
Rate your overall understanding of the problem	4.1	0.5

Students were not informed of the amount of response delay that would occur in each weighted sum exercise, but they were asked to identify whether delays had any impact on the design process. The responses generally indicated either no effect or a small-to-medium effect.

V. Conclusions and Future Work

The study has provided many insights based on a simple design exercise using a graphical design environment. First, students appreciated the graphical design interface. For the free-form design exercise, designs created with the graphical interface were more consistent and of higher quality than designs created without the interface (Figure 3). Response time delay appeared to affect design quality, but did not affect time to complete the design task; however, students considered fewer design alternatives as response time delay increased. Some students needed more time to become familiar with the graphical interface as evidenced by improved second and third trial design quality and reduced time to complete the design task. Students appeared to have a better understanding of resolving tradeoffs during design after using the graphical design interface. As a result, we intend to include graphical design tools in our graduate and undergraduate courses to enhance student learning about design.

These preliminary results encourage us to expand our investigation of the benefits of graphical design environments for multiobjective design and optimization. We plan to conduct additional experiments using the I-beam design exercise as well as other exercises, including design of a pressure vessel and a desk lamp. Future experiments will also take into account the learning effect that we observed in this experiment. Currently we are developing a GDE which can be linked to simulation packages and/or existing software engines through a JAVA-based interface. Using this interface the study will be expanded to include fast approximation models (metamodels) in order to understand the tradeoff between accuracy, delay, and overall design quality.

VI. Acknowledgements

The authors gratefully acknowledge the support of the National Science Foundation under Grant# DMI-0084918.

Bibliography

1. Jost, K., "Chrysler's ‘Clean Sheet’ V6," *Automotive Engineering International*, Vol. 106, No. 1, 1998, pp. 79-81.

2. Mecham, M., 1997, "Raytheon Integrates Product Development", *Aviation Week & Space Technology*, October 6, pp. 50

3. Mecham, M., 1997, "Aerospace Chases the Software Boom", *Aviation Week & Space Technology*, October 6, pp. 46-48

4. Sabbagh, K., *Twenty-First Century Jet: The Making and Marketing of the Boeing 777*, Scribner, New York, 1996.

5. Messac, A. and Chen, X., "Visualizing the Optimization Process in Real-Time Using Physical Programming," *Engineering Optimization,* Vol. 32, No. 6, 2000, pp. 721-747.

6. Ng, W. Y., "Generalized Computer-Aided Design System: A Multiobjective Approach," *Computer-Aided Design,* Vol. 23, No. 8, 1991, pp. 548-553.

7. Jones, C. V., "Visualization and Optimization," *ORSA Journal of Computing*, Vol. 6, No. 3, 1994, pp. 221-257.

8. Eddy, W. F. and Mockus, A., "Dynamic Visualization in Modeling and Optimization of Ill-Defined Problems: Case Studies and Generalizations," *Technical Report*, Department of Statistics, Carnegie Mellon University, Pittsburgh, PA, 1995.

9. Card, S. K., Moran, T. P. and Newell, A., *The Psychology of Human-Computer Interaction*, Lawrence Erlbaum, Hillsdale, NJ, 1983.

10. Sturman, D. J., Zeltzer, D. and Pieper, S., "Hands-on Interaction with Virtual Environments," *Proceedings of the 1989 ACM SIGGRAPH Symposium on User Interface Software and Technology,* 1989, pp. 19-24.

11. Ware, C. and Balakrishnan, R., "Reaching for Objects in VR Displays Lag and Frame Rate," *ACM Transactions on Computer-Human Interaction*, Vol. 1, 1994, pp. 331-356.

12. Watson, B., Walker, N., Hodges, L. F. and Worden, A., "Managing Level of Detail through Peripheral Degradation: Effects on Search Performance in Head-Mounted Display," *ACM Transactions on Computer-Human Interaction*, Vol. 4, 1997, pp. 323-346.

13. Waern, Y., *Cognitive Aspects of Computer Supported Tasks*, John Wiley & Sons, New York, 1989.

14. Evans, P. T., Vance, J. M. and Dark, V. J., "Assessing the Effectiveness of Traditional and Virtual Reality Interfaces in Spherical Mechanism Design," *ASME Journal of Mechanical Design*, Vol. 121, No. 4, 1999, pp. 507-514.

15. Goodman, T. and Spence, R., "The Effect of System Response Time on Interactive Computer-Aided Design," *Computer Graphics*, Vol. 12, 1978, pp. 100-104.

16. Foley, J. D. and Wallace, J. D., "The Art of Natural Graphic Man-Machine Conversation," *Proceedings of the IEEE*, Vol. 4, 1974, pp. 462-471.

17. Lembersky, M. R. and Chi, U. H., "Decision Simulators Speed Implementation and Improve Operations," *Interfaces*, Vol. 14, 1984, pp. 1-15.

18. Hibbitt, Karlsson and Sorensen, Inc. (2001). ABAQUS, Superior Finite Element Analysis Products, http://www.hks.com/.

19. MSC,Software (2001). MSC.Patran 2000 Native NT (v9.0), http://www.mechsolutions.com/products/patran/patran2000.html.

20. SDRC Software (2001). I-DEAS, http://www.sdrc.com.

21. Vanderplaats Research and Development Inc. (2001). VisualDOC, http://www.vrand.com/software.htm.

22. Design Synthesis (2001). OptdesX, http://www.et.byu.edu/~optdes/.

23. Engineous Software Inc. (2001). iSIGHT 5.5, http://www.engineous.com/.

24. Haftka, R. and Gurdal, Z., 1992. *Elements of Structural Optimization*, 3rd Revised and Expanded Edition, Kluwer Academic Publishers.

25. Simpson, T. W., Peplinski, J., Koch, P. N. and Allen, J. K., "Metamodels for Computer-Based Engineering Design: Survey and Recommendations," *Engineering with Computers*, 2000, in press.

26. Barton, R. R., "Simulation Metamodels," Proceedings of the 1998 Winter Simulation Conference (WSC'98) (Medeiros, D. J., Watson, E. F., et al., eds.), Washington, DC, IEEE, December 13-16, 1998, pp. 167-174.

MARY FRECKER
Mary Frecker is an Assistant Professor of Mechanical Engineering at Penn State. She is a member of ASME, SAE, SPIE, and ASEE, and has developed a graduate course in structural optimization at Penn State. Dr. Frecker received a bachelor's degree in Mechanical Engineering from the University of Dayton in 1991, and a M.S. degree in 1994 and Ph.D. degree in 1997 in Mechanical Engineering from the University of Michigan. She has also held engineering positions at General Motors and Ford Motor Company.

TIMOTHY W. SIMPSON
Timothy W. Simpson is an Assistant Professor in Mechanical Engineering with a joint appointment in Industrial & Manufacturing Engineering. He is a member of ASME, AIAA, and ASEE and is actively involved with the Product Realization Minor at Penn State. Dr. Simpson received a B.S. degree in Mechanical Engineering from Cornell University in 1994 and a M.S. degree in 1995 and a Ph.D. degree in 1998 in Mechanical Engineering from the Georgia Institute of Technology.

JOSEPH GOLDBERG
Joseph Goldberg is an Associated Professor in Industrial & Manufacturing Engineering. He teaches and conducts research in the field of Human Factors Engineering, specializing in eye tracking and human-computer interface design. Dr. Goldberg received a B.S. in 1979 in Psychology, an M.S. in 1980 in Industrial & Operations Engineering, and a Ph.D. in 1985 in Industrial & Operations Engineering and Psychology from the University of Michigan.

RUSSELL R. BARTON
Russell R. Barton is Professor of Industrial Engineering at the Pennsylvania State University. He spent ten years in industry, primarily at RCA, before entering academia in 1987. At Penn State he developed undergraduate courses in concurrent engineering and laboratory-based statistics, as part of the Product Realization Minor. He developed a graduate course in using simulation models for engineering design, one of his primary areas of research. He is a member of ASEE and has served as DEED program chair or co-chair twice. He was Co-editor for the Proceedings of the 2000 Winter Simulation Conference, and serves as Secretary/Treasurer in the INFORMS College on Simulation.

BRITT HOLEWINSKI and GARY STUMP
Britt Holewinski and Gary Stump are research assistants working toward their M.S. degrees in Mechanical Engineering at Penn State University. Britt received a B.S. degree in 2000 in Aerospace & Mechanical Engineering from the University of Notre Dame. Gary received a B.S. degree in 2000 in Mechanical Engineering from Penn State University.