Proceedings of IDETC/CIE 2017
ASME 2017 International Design Engineering Technical Conferences
& Computers and Information in Engineering Conference
August 6-9, 2017, Cleveland, OH, USA

DETC2017-68307

INTEGRATING DESIGN AND OPTIMIZATION TOOLS: A DESIGNER CENTERED STUDY

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ABSTRACT

Exploring design options for additively manufactured parts generally requires separate, sequentially applied software for design, analysis, and optimization. To evaluate the effect of integrating these capabilities within a single tool we conducted a controlled human subjects study. Three tools with different degrees of integration were created for two test cases of structural trusses, and it was found that increased integration improved quality, speed, and efficiency of the design process. After a quarter of their total time with the problems, 50% of designers with a fully integrated tool had a better design than 75% of other designers ever would. After that point, the top 50% of designers went on to explore a design space unreached with other tools. It appears that integration, and in particular the integration of optimization, leads to better performance by making it possible to explore complex designs and achieve outcomes which would be inaccessible to conventional tools.

INTRODUCTION

Historically the challenges of design and manufacturing have been intertwined, with designers increasing the complexity of their designs and pressing manufacturers to comply (the “over the wall” approach [1]). This process has changed dramatically with the development of Additive Manufacturing; it has become possible to produce parts of virtually unlimited intricacy. The reduction of constraints on manufacturing shifts the limitations of production to the designer: we are now design-limited, where it would be possible to make increasingly complex objects (such as the truss structure in Figure 1) if only we could more easily design them. The transition is well captured by Reeves: “Most products are not optimised, as they are ‘designed-for-manufacture’ rather than ‘manufactured-for-design.’” [2]

This shift has created a need for design tools that enable a designer to more effectively and efficiently explore the design complexity afforded by Additive Manufacturing.

Figure 1: 3D-printed aluminum motorcycle [3]

One aspect of the complexity of additive manufacturing is the potential for integration of many different functionalities within a single part. In observing the design principles of 272 part “remixes,” Perez et al. find that more than a quarter of them involve integrations of multiple functions in ways only unique to Additive Manufacturing [4]. Such integrated functionality suggests a need for integrated tools, and indeed one evolution of design tools is to merge design, analysis and optimization together into a single software tool that can leverage the potential intricacy of Additively Manufactured parts and escape the design fixation introduced by designing parts for production using traditional mass manufacturing methods [5–7]. This study uses an experimental approach to explore the potentials of integration. Currently, Additive Manufacturing can involve a number of powerful tools, including computer based design tools, analysis tools such as finite element solvers, and computational optimization tools. The typical use of these tools is to first create a design in one tool, then analyze it in another, and then use that analysis to tweak the design towards optimality. New tools such as Autodesk's DreamCatcher and Altair's Inspire are being developed that integrate all three processes, providing real-time analysis and optimization during design creation. We hypothesize that this integration will reduce the time to manufacture, improve the experience of the designer, and lead to better design outcomes. Research in this area has only examined individual case studies and thus has limited the generalizability of the results [8–12]. To address this gap, we conducted a human subject based experiment for a quantitative answer to the following question:

Compared to using tools serially, how does the integration of design, analysis and optimization into a single tool impact the speed of the design process and the cost and complexity of the resulting design?

It was expected that increased integration of tools would allow for faster, more effective exploration of more complex designs. By evaluating the gains of integration, we hope to enable more appropriate applications of optimization and real-time analysis. Greater understanding of the benefits of optimization tools may motivate a new workflow paradigm, as software companies follow promising directions and organizations garner an understanding of which features are critical to engineering tools.

To investigate this question, we conducted an experiment that involved presenting participants with two design problems , to be addressed with custom tools identical but for differing degrees of integration. The designer's outcomes with these different tools were then compared.

RELATED WORK

A substantial amount of research has been conducted on software tools for design, analysis, and optimization, but the development of particular tools is not our focus. Rather, we are interested in how designers use these tools and how the choice, application, and integration of these tools can impact the design process and its outcome.

Models for early stage design

Many models exist for early stage design process for products and engineered systems, including Pahl and Beitz' systematic approach to engineering design and Ulrich and Eppinger's widely known process for product design and development [13,14]. Underpinning both approaches is the notion of a design specification and/or initial prototype created by an engineering and design team.

Design tools and the designer

Software tools, most notably CAD, are essential to design and production, and a number of studies have considered the impact of these tools on early stage designs. In the exploratory phases of design, studies with practicing engineers and student designers have observed that the use of CAD too early in the design process can have a negative effect on design creativity, known as "premature fixation" [15,16]. High fidelity digital tools require more time and effort on the part of the designer than lower fidelity tools, making designers more invested in a design and less likely to discard it. This is an observation of not only the design tool, but the way that designers use the tools in practice. Our study takes a similar designer-focused perspective on the use of design tools, focusing on exploratory design by formulating constrained but realistic design problems and developing purpose-built tools with minimal interface complexity.

Design optimization and the designer

An overarching goal of design optimization research is to create tools and systems that can support designers by generating the "best" solutions. The majority of research in design optimization concentrates on the development of better and faster algorithms and strategies, and only limited research has been conducted about how designers themselves reach globally- or locally-optimal solutions, and how this is affected by their tools.

In an early study of how humans deal with coupled problems, Hirschi and Frey compared the time to solve coupled and uncoupled parametric design problems [17]. For uncoupled problems, the time to solve was of the order of $O(n)$ where n is the number of input variables, and increased dramatically to $O(n^{3.4})$ for coupled problems. Notably, coupled problems with more than 4 variables were found to be very difficult and frustrating for the participants. Similarly, human studies by Flager et al. showed that an increase in problem complexity caused a significant decrease in solution quality [18]. A study by McComb et al. showed specifically that more complex 2D trusses led to worse performance [19]. Austin-Breneman et al. found that, despite domain expertise and optimization training, graduate students asked to collaboratively design a simplified satellite had trouble exploring the design space because of the complexity of subsystems and subsystem interactions, and few teams found optimal designs on the Pareto frontier [20]. In interviews with space system designers, they found that teams in industry routinely restricted the information they shared with each other in ways that made exploration much more difficult both practically and theoretically [21]. Yu's study of desalination systems found that software choices could enable novices to explore complex system designs almost as well as experts, with some caveats [22]. Designer satisfaction with rapid prototyping process has been explored by Neeley, et al., who found that designers tended to be more satisfied with design outcomes when given the opportunity to explore more design space initially [23]. Specific questions of how real-time interfaces affect design outcomes were present in the first direct-manipulation CAD software [24], in early studies of the effect of analysis speed on structural design exploration and outcomes [25], and in more recent research on human-computer optimization in circuit-routing [26] and in architectural design [27].

We hope to extend such studies by directly measuring the effects of real-time software decisions and algorithms on design outcomes and process. Previous studies by Barron et al. and Egan et al. [28, 29] have looked at the effects of visualization and search techniques in custom tools exploring different visual representations and search strategies than designers may be accustomed to; in contrast, our study uses familiar visual representations but changes the interaction modalities and underlying mathematical processes. Direct comparisons require design software that is identical except for the change to be measured, and providing statistically meaningful information requires conducting a large number of independent trials.

DESCRIPTION OF SOFTWARE

To conduct the experiments described in this paper we created three software tools for the design of 2D linear truss structures integrating design, analysis, and optimization to different degrees. Studying 3D trusses or incorporating local nonlinear-buckling were tested, but we determined that the increase in solution complexity and need for designers to be comfortable rotating and navigating their structure or being aware of tension and compression would over-restrict our analysis and the field of participants.

Truss performance is measured by mechanical feasibility, and its cost based on the total volume of material the structure uses, determined from the number, length, and diameter of its structural members. While this cost function is a traditional approximation in the field of structural engineering, for traditional trusses other factors (such as the number of different joint angles) are major contribution to a truss's actual cost. In conventional manufacturing, solutions with fewer nodes and larger members may be seen as elegant, but the emerging design strategies of additive manufacturing (particularly topological optimization) favour an elegance of many smaller connections contributing to a biomimetic appearance. With additive manufacturing such complexity is of minimal cost, and so the main cost of a design is much better represented by just the amount of material required. Note that with such a cost function adding a member between the nodes of an existing design should never increase its cost, because if such a member contributes nothing its size can be reduced to 0. Designs which are infeasible (that is, contain axial stresses above the limit) are considered to have an infinite cost. Note that because of the linearity of our structural analysis, the determination of this stress limit is arbitrary; were it to be changed, member sizes and costs scale proportionally.

Evaluations of truss performance are returned in exactly 20 milliseconds (the calculations take less but their return is delayed to provide consistency). This speed (whose effect we plan to study in future experiments), and the fact that using the tools requires a great number of evaluations on partial expressions of a design, mean that the standard concept of a "design iteration" is not appropriately mapped to a structural evaluation. Designer's use of the "save" functionality is probably the concept most similar to an iteration, but usage varied too widely across participants to make this a good basis for comparison across tools. Therefore this study considers un-discretized dynamics of design progressions.

To avoid the effect of subtle differences between our three tools, they differ only in the ways mentioned below; the ability to create such a controlled environment being of course a major advantage to making one's own tools. All tools can create exactly the same designs, and so theoretically share the same Pareto frontier for a given problem.

The least integrated tool (D, Figure 2) separates design and analysis views of the designer's structure, and only refreshes the analysis to consider the current design when an "Analyze" button is clicked. This workflow was designed to approximate the cyclic workflow of using a CAD tool such as Solidworks, Inventor or NX followed by a dedicated analysis tool such as Nastran, Abaqus, or Ansys followed by additional iterations of design alteration and reanalysis.

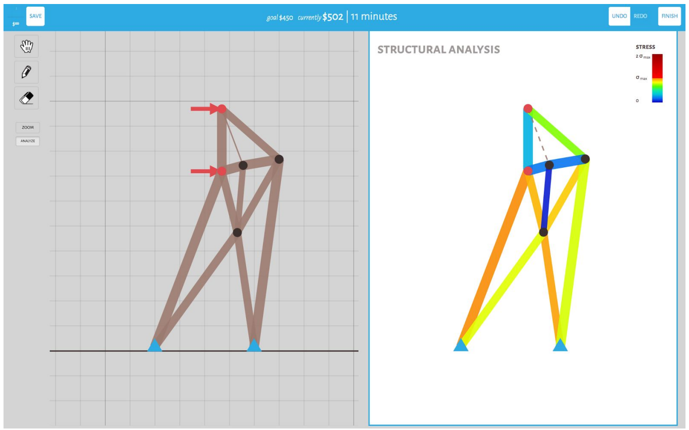


Figure 2: With separate design and analysis views, (D) aimed to be comparable with existing tools.

The second tool (D+A, Figure 3) integrates those two views. In this version we approximate a future tool where real-time analysis is integrated into the design tool. A direction that is being explored by various CAD tool manufacturers. Finally the most integrated tool (D+A+O, Figure 4) dynamically optimizes member size with an established linear programming formulation [30] and indicates in what direction a selected node should be moved to most quickly reduce the structure's cost. (D+A+O) approximates a future workflow based of the design features that might be found in an optimization software package such as Optistruct, Tosca or DreamCatcher where design optimization and analysis are all combined in a single tool.

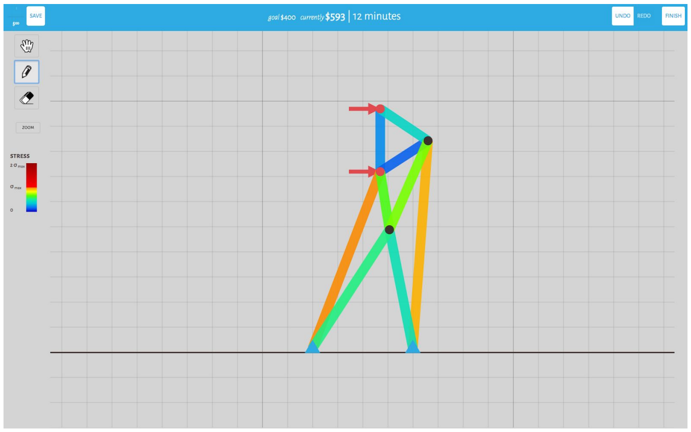


Figure 3: (D+A) presented an interactive/editable analysis.

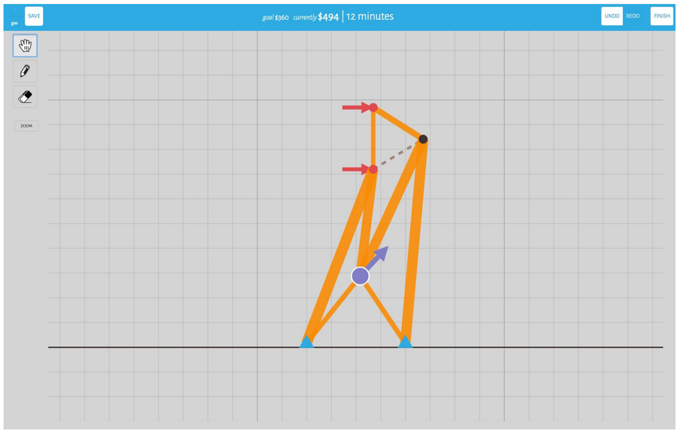


Figure 4: (D+A+O) optimized member size as a linear program and indicated how nodes should be moved to reduce the structure's cost (purple arrow in the screenshot).

(D), the least integrated tool, aims to be comparable to tools currently in use, with serial design, analysis, and optimization. With (D+A), analysis and design are integrated into every user action, and (D+A+O) adds member-sizing optimization and geometric gradient information. By creating our own software we ensured that all differences between tools were variables we intended to test.

EXPERIMENTAL METHOD

For this experiment, 60 graduate and undergraduate students at MIT were recruited through mass emails to the Mechanical Engineering, Architecture, Civil Engineering, and Aeronautical/Astronautical Engineering departments. The key criteria for participant selection was familiarity with basic mechanics, from either the required undergraduate physical mechanics course or a specialized departmental course. As an incentive, participants were compensated with gift cards from Amazon.com: all were guaranteed to receive $20 and had the opportunity to receive an additional $5 on each problem by reaching a performance threshold, and a further opportunity for another $55 if their design for a specific problem and tool combination was the lowest-scoring among all participants.

Table 1
Demographics (out of 60 participants)

Year

Freshman	4	*Junior*	8	*Master*	11
Sophomore	5	*Senior*	10	*PhD*	12

Gender

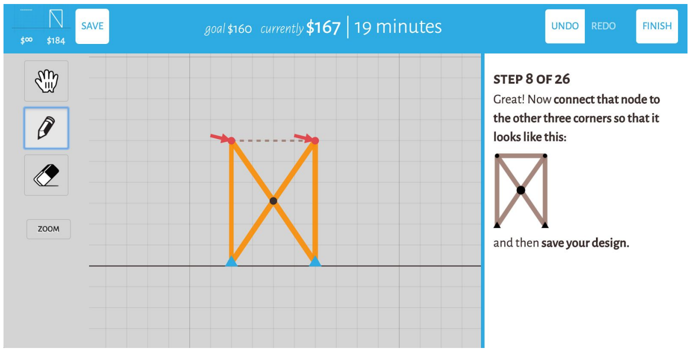
Female	30	*Male*	30

After obtaining informed consent, each participant was given a brief introduction explaining the study and compensation structure before being set up to work individually at a computer workstation, where they were provided the opportunity to change the tracking speed of the mouse for their comfort. Participants were assigned to one of the twelve possible permutations of problem and tool order; while participants were assigned to achieve an equal number of participants with each permutation, the order of the permutations themselves was randomized

Table 2
Problem and tool permutations
(12 sets, each assigned at random to 5 participants)

	Problem 1	**Tool 1**	**Problem 2**	**Tool 2**
1	Bridge	D	Sign	D+A
2	Bridge	D	Sign	D+O+A
3	Bridge	D+A	Sign	D
4	Bridge	D+A	Sign	D+O+A
5	Bridge	D+O+A	Sign	D
6	Bridge	D+O+A	Sign	D+A
7	Sign	D	Bridge	D+A
8	Sign	D	Bridge	D+O+A
9	Sign	D+A	Bridge	D
10	Sign	D+A	Bridge	D+O+A
11	Sign	D+O+A	Bridge	D
12	Sign	D+O+A	Bridge	D+A

Each trial began with a survey on truss structures serving two functions: to establish their understanding of structures, and to teach (as necessary) the basic principles useful for the upcoming design problems. After the structure survey participants went through a computer-guided software tutorial on the creation and analysis of structures and specific properties of the tool they would be use for the first design problem (Figure 5). This tutorial focused on introducing designers to the specific interface of the tool they would be using, rather than training them how to solve problems, and so presented only a simplistic brace problem with no more than six members



STEP 8 OF 26

Great! Now **connect that node to the other three corners so that it looks like this:**

and then **save your design.**

Figure 5: Tutorial for the (D+A+O) tool. The standard interface is displayed next to a series of tasks which must be completed to advance.

After completing the first problem, participants filled out a post-problem survey on their experience. Then they began a second tutorial introducing them to the new tool they would use for the second problem. Because the tools were almost entirely identical, the second tutorial was much shorter, skipping any interface elements present in the other tools (such as undo and member-drawing). They were then given the second problem prompt, design problem and a second post problem survey.

The two design problems, a bridge and a windblown road sign (cantilever), were chosen in part because they allowed the possibility for both simple and complex solutions. The sign problem in particular has a known global optimum in the form of a fractal Michel truss with an infinite number of members [31]. Both problems were also familiar enough that participants could visualize a rudimentary solution, but not so familiar that participants would fixate on any particular solution. To avoid fixation we took care to present the problems without presenting a possible truss-based solution. Each problem was therefore introduced by a brief statement and a carefully chosen illustration (Figure 6).

From consent to the last post-problem survey, trials took less than to an hour to complete. Because of the timed nature of the problems total time depended on how much time each designer spent on the tutorials and surveys.

Table 3
Trial ordering and approximate timing

Overview and consent	15 minutes
Pre-survey	5 minutes
Tutorial for Tool 1	10 minutes
Problem 1	15 minutes
Post-problem survey 1	5 minutes
Tutorial for Tool 2	5 minutes
Problem 2	15 minutes
Post-problem survey 2	5 minutes

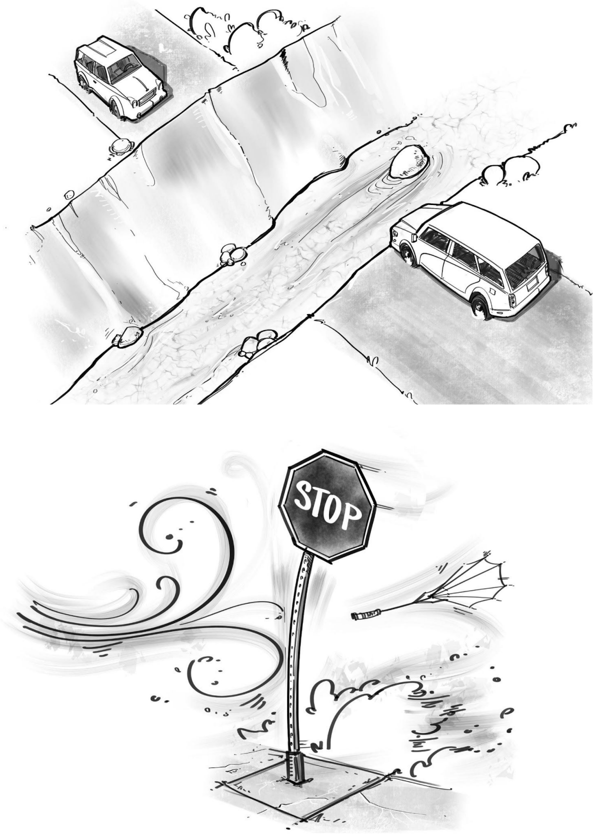


Figure 6: Illustrations used in the problem statements, showing context for a bridge (top) and a windblown sign.

RESULTS

Overall, designers using more integrated tools did explore more complex solutions and got better results quicker. In addition, through the results are noticeable differences between the bridge and sign problems, appearing to spring from the bridge problem's rapidly diminishing returns on complexity. The bridge problem also required more complex solutions, although the symmetry and of truss bridges and their greater familiarity to our participants may have reduced the effects of this. We examined the resultant data set for effects caused by problem ordering and training effects between problems and did not find any significant results.

Comparison of design outcomes

Figure 7 shows the distribution of costs for participant's best designs (note that, here and throughout, a lower cost is better). There is a clear trend of integration tools improving results for the median designer and reducing the spread of scores between the 25th and 75th percentiles. Discarding the outlying worst three scores for each problem-tool combination, Tukey's range test shows an extremely significant difference (p-values < 0.0001) between (D+A+O) and (D) on all problems and between (D+A+O) and (D+A) on the sign problem, a significant difference (p-value 0.025) between (D+A) and (D+A+O) on the bridge problem, and insignificant differences between (D) and (D+A) (p-value 0.155 for the sign and 0.126 for the bridge).

Because of the clear skew of these distributions, the rest of our analysis will focus on quartiles of users instead of averages. In both problems the median (D+A+O) solution closely follows the best solutions achieved with (D) and (D+A); that is to say, the best results of sixty users with unintegrated tools became typical results after a change of software, and the top 50% of (D+A+O) designers worked with costs completely unreached by less integrated tools. For the sign problem this new design space is quite extended, and its density appears symmetric to that above the median; for the bridge these improvements are flattened by the diminishing returns of bridge complexity.

Non-optimizing tools on the bridge problem also showed a trend at the 25th and 75th percentile levels; compared to (D), (D+A) designers had better results at the 25th percentile and median, but worse results at the 75th percentile. Surprisingly, the integration of only analysis with design thus seems to have been a slight hindrance to some designers.

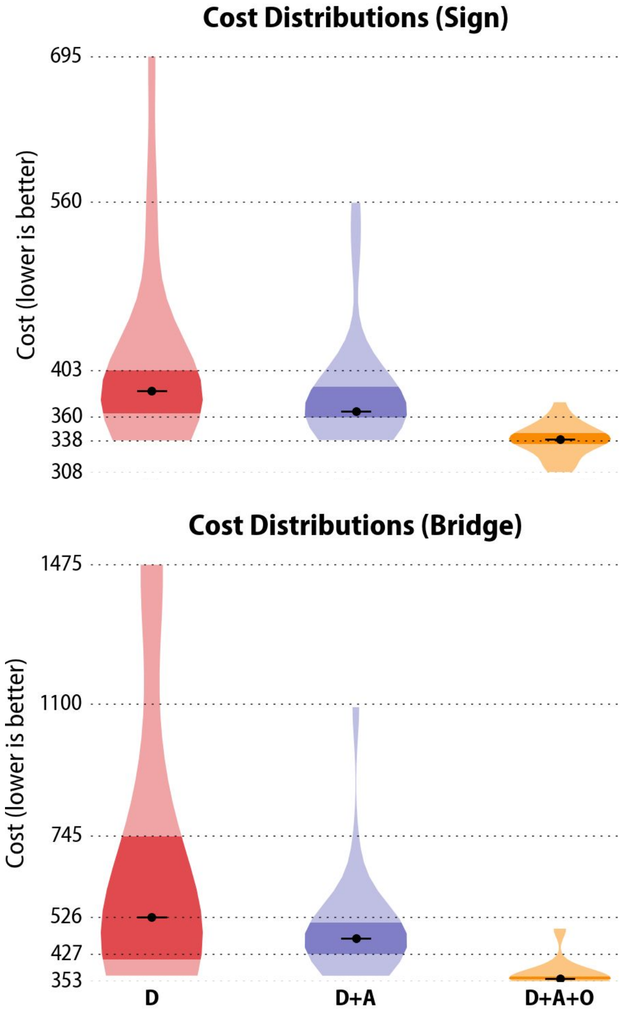


Figure 7: Shapes show the relative number of designers whose best design achieved a given cost. The darker region highlights the 50% of designers between the 25th and 75th percentiles, and the black line shows the median.

Explorations of complexity

In this study we use the number of members in a design as a good proxy for its complexity: each member adds to the design's cost, provides a point of failure, and requires the optimization of another sizing variable. Despite these complications, complexity has clear potential benefits: as shown in Figure 8 and graphed in Figure 9, designs with more members can achieve lower costs. Note that the figure shows each designer's best solution for every complexity they made designs at, a kind of individual Pareto frontier.

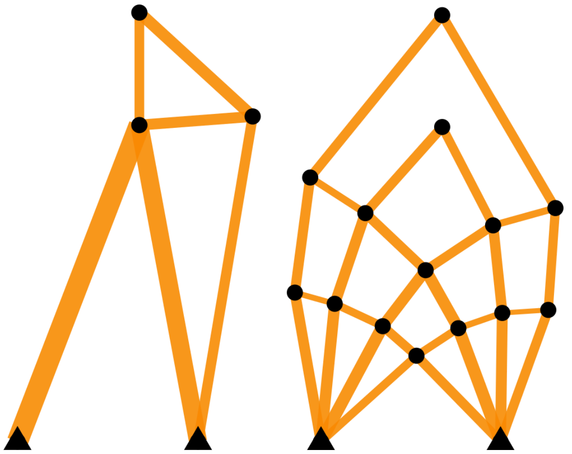


Figure 8: Optimal solutions for the sign problem with low complexity (on the left: 6 members, total cost 360) and high complexity (right: 19 members, cost 306).

Table 4 shows the median number of members in designers' best solutions as well as the maximum tried by at least half of the designers with a given tool and problem.

Table 4
Median final / Median maximum number of members

	Sign	*Bridge*
(D+A+O)	10 / 12	11 / 15
(D+A)	6 / 10	12 / 16
(D)	7 / 10	10 / 15

The median (D+A+O) designer's solution to the sign problem used 50% more members than those made with other tools, despite typically only exploring 20% more complexity. On the bridge problem all designers explored and finished with designs of similar complexity; as can be seen in Figure 9, increasing the complexity of a bridge has only marginal benefit after the first ten members, and at fifteen the benefit of adding another one is less than a dollar of cost; as the software interface did not display fractions of a dollar, this is the point at which a designer adding a new member might see no improvement to their score.

Figure 9 also shows that designs made with (D) and (D+A) get more expensive as complexity increases, diverging from the ever-decreasing theoretical limit. While (D+A+O) users appear to have taken full advantage of every member they used and stay close to that limit, designers with other tools saw costs *increasing* as they added members, facing (and optimizing their solutions for) an environment where complexity decreased the cost of their designs only up to a point. We propose the equation:

$$\textit{cost of complexity} = K\,(\textit{members} - \textit{typical members})^2$$

as a simple fit to these observed costs of complexity, with a 'typical members' value of 8 for the sign and 10 for the bridge and K values of 6, 2, 0 for (D), (D+A), and (D+A+O).

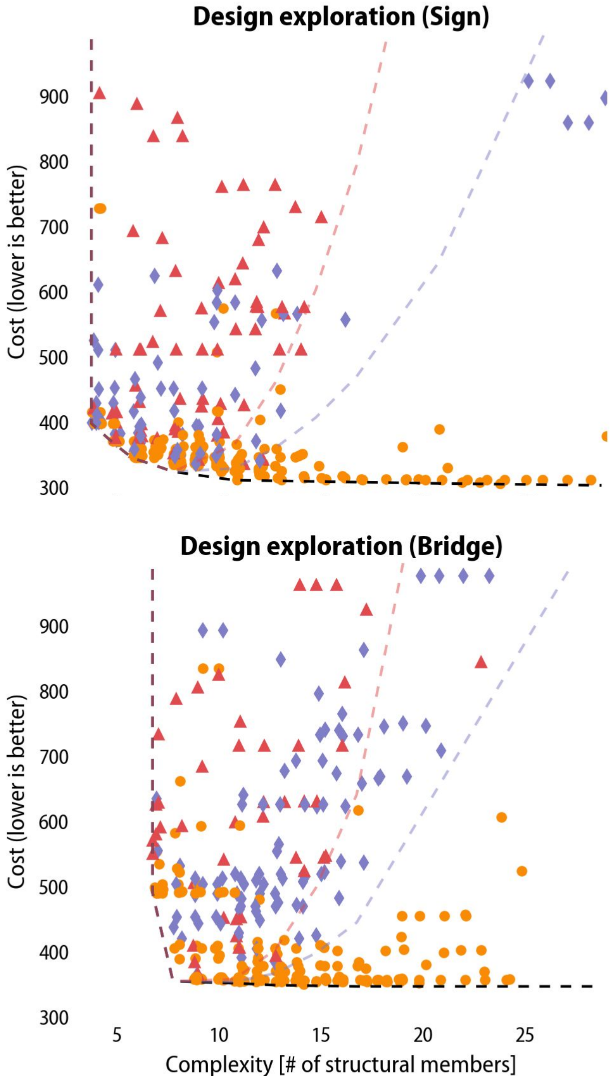


Figure 9: The black dashed line shows the best cost achievable for each problem with a given number of members, while red triangles (D), purple diamonds (D+A) and orange circles (D+A+O) show each designer's best solution for every complexity they made designs at. Colored lines are quadratic fits to the observed cost of complexity.

Efficiency and design progress over time

We can also see the effects of different tools on the time dynamics of solutions. Because individual evaluations were happening in real-time with (D+A) and (D+A+O), cohort analysis over time is a better ground on which to compare tools than number of evaluations. Figure 10 shows that designers with more integrated tools generally converged to their final solution much more quickly: after four minutes the typical (D) designer was 50% from their final solution, while the typical (D+A+O) or (D+A) designer was 5-15% from their final solution (except for (D+A) on the bridge problem, where after four minutes more than 50% of designers had not found a feasible solution).

Figure 11 shows the time trajectories of the quartiles of each tool and problem. After three minutes with the sign problem, 75% of designers with the (D+A+O) tool had a better design than 75% of designers with other tools ever would, while after three minutes with the bridge problem 50% of (D+A+O) designers had better designs than 75% of other designers ever would. In general the distance between the 25th and 75th percentiles shrank over time as large initial improvements were followed by more marginal gains. This tightening (especially between the median and the 75th percentile) is more noticeable with the sign than with the bridge. The high variance of (D) tool outcomes on the bridge problem is also apparent, as its shaded range covers that of (D+A) at almost all times, and even has a better median solution than the more integrated (D+A) for the first 7 minutes.

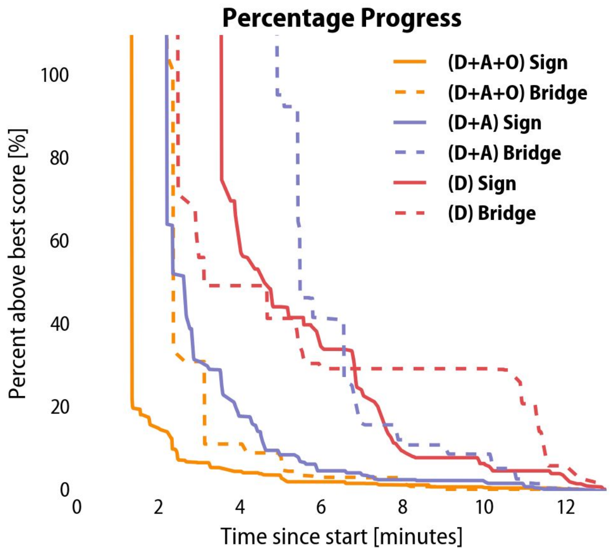


Figure 10: Lines show the median solution's distance in percentage points from its final value.

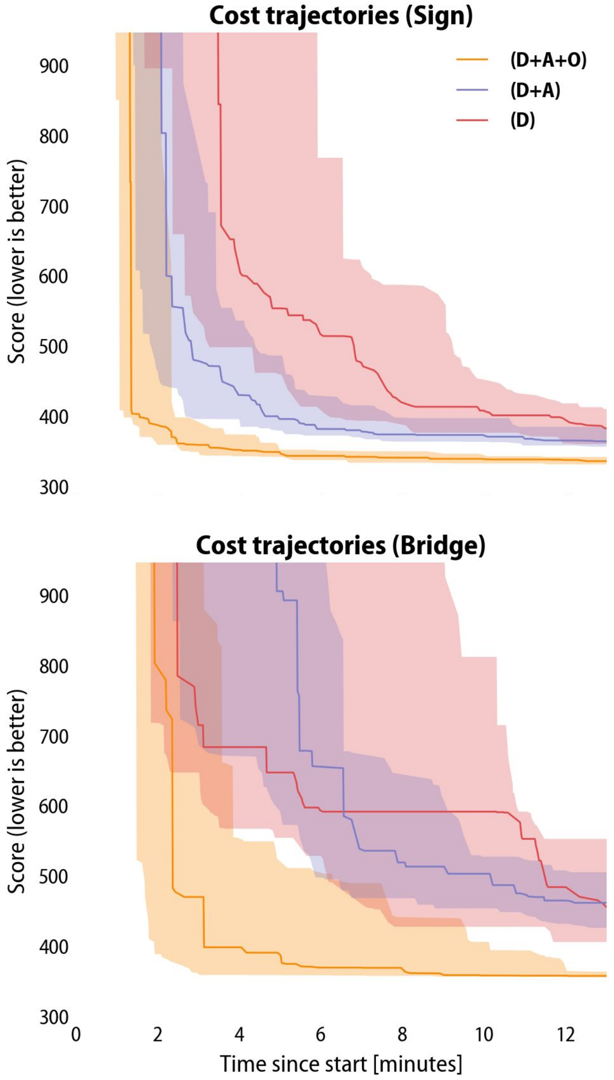


Figure 11: The solid line represents the median solution at a given time, and the shaded region spans between the 25th and 75th percentiles.

CONCLUSIONS AND FUTURE WORK

In this study we set out to quantify the benefits of integrating design, analysis, and optimization software by creating three different 2D design tools for a sixty-participant study:

Compared to using tools serially, how does the integration of design, analysis and optimization into a single tool impact the speed of the design process and the cost and complexity of the resulting design?

The primary conclusion of this study is that while integrating analysis with design led to a tool better than an unintegrated tool, integrating optimization led to such improvement that it's difficult to even compare it to less-integrated tools. After three minutes with the sign problem, 75% of designers with the (D+A+O) tool had a better design than 75% of other designers ever would; after three minutes with the bridge problem 50% of (D+A+O) designers had better designs than 75% of other designers ever would. In both problems, the median (D+A+O) solution closely followed the best solutions achieved with (D) and (D+A); that is to say, the best results with unintegrated tools became typical results after a change of software, and the top 50% of (D+A+O) designers explored a design space completely unreached with other tools.

Meanwhile, (D+A) designers suffered less from complexity than (D) designers and had better final designs (especially between the 100th and 50th percentiles). However, analysis of the bridge problem shows surprisingly that (D+A) was not strictly better than (D): between the 35th and 10th percentiles, or over most percentiles in the first six minutes of the problem. One explanation might be that (D+A) designers would "miss the forest for the trees", spending their time optimizing member sizes instead of exploring the design space. Given the limited scope of this phenomenon it is also possible that preconceptions about bridge shapes muted some of the expected benefits for (D+A) users. It would be interesting to conduct additional work to further explore this phenomenon.

Future work on this project will transition it from an in-person experiment to one that can be conducted without direct oversight, so as to reach a broader population of potential participants and allow further studies to study smaller effects and more options for tools. Studies comparing multiple optimizing tools within the domain of structural trusses will be able to directly quantify the benefits of both interface elements (such as gradient visualizations) and algorithmic properties (such as speed, accuracy, and fidelity). The benefits of optimization in these 2D truss problems seem great enough that the best way to quantify them will be such apples-to-apples comparisons.

Similar studies could also find other engineering domains where the processes of computers and human designers could be integrated into the design tool, and grow our understanding of how human designers solve engineering problems at the same time as it motivates new CAD interfaces and optimization algorithms that let designers explore and exploit the complex potentials of Additive Manufacturing.

ACKNOWLEDGMENTS

We gratefully acknowledge the support of this work by MIT Lincoln Laboratory. We also acknowledge the efforts of Eeway Hsu, Merry Mou, and Megan O'Leary, who helped design and engineer the (D+A+O) tool's initial version, Nathan Cooke who illustrated the test problems, and Kathy Wu, Ambika Kamath, and Esther Jang, who helped edit and clarify this paper. The opinions, findings, conclusions and recommendations expressed are those of the authors and do not necessarily reflect the views of sponsors and contributors.

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