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STUDENTS' EXPLORATION STRATEGIES IN A SUSTAINABILITY-FOCUSED STRUCTURAL OPTIMIZATION TASK

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ABSTRACT

This paper examines students' design exploration strategies in a sustainability-focused structural optimization task. The task was set up as a two-criteria optimization problem with the goal of simultaneously minimizing the weight and an environmental indicator for a pedal bracket design. Forty-two students in an undergraduate computer-aided design class solved this task as a week-long, take-home assignment. Our analysis shows the number of design iterations and the number of failed iterations were significant factors in determining overall performance on the task. We also found that the final shape, the number of material changes, and experiencing conflict in the objective functions between iterations, did not significantly affect task performance. Based on these findings, we discuss implications for computer-aided optimization tools in sustainable product design.

1 INTRODUCTION

The engineering design process often requires balancing multiple competing objectives within specified constraints. This is especially true in sustainable product design, as mitigating a product's environmental impacts can negatively affect other objectives such as its performance, manufacturing cost, and development time. The ability to identify designs that are optimal from this multi-objective perspective requires iterative exploration of the feasible design space. Human input and judgment are a vital part of computer-aided engineering (CAE) tools for design optimization [1]. Therefore, understanding designers' exploration processes is an important step for creating optimization tools in sustainable product design.

In this paper, we discuss exploration strategies adopted by students in a structural optimization task with a focus on sustainability. This task was set up as a surrogate of a real-world sustainable design problem in order to adapt it to a classroom setting. The overall focus of our study was twofold. First, to verify if exploration patterns reported in previous studies—such as poorly executed global searches [2] and challenges in understanding sensitivity of coupled variables [3]—were evident in the sustainability-focused structural optimization task. Second, to discover exploration patterns and usage workflows that can inform the creation of computer-aided optimization tools for sustainable product design.

2 RELATED LITERATURE

2.1 Studies on design exploration

The design exploration process, especially from the point of view of complex systems design has been extensively studied in

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previous work. Fundamental challenges in solving such problems, include problem scale and coupling effects present in the objectives [4]. Increasing the number of constraints and the types of constraints has been shown to be negatively correlated to performance in tasks modeled as constraint satisficing problems [5]. Austin et al.'s [2] study on complex systems optimization found that students searched global spaces poorly, optimized a single input parameter at a time, and preferred a trial-and-error strategy drawing on their design history. Yu et al. [3] studied exploration patterns in the design of a reverse osmosis system. The authors found that participants with more domain knowledge were able to better understand coupling effects in the given design parameters. They also found that the starting point in the design space and making large, consistent step-sizes over iterations correlated to task performance.

Ahmed et al. [6] found novice designers resort to trial and error strategies that negatively affects their overall solution quality and increases the number of iterations. On the other hand, experienced designers avoided these negative effects by performing an evaluation step before implementing their designs. They also report that experienced designers were better aware of involved trade-offs and questioned the future potential of a chosen approach. Ball et al. [7] found that switching from breadth-first mode of problem solving to depth-first modes is indicative of the designer's knowledge on how to effectively search the solution space. Relationships between design features and designers' behavior were explored by Aleyani et al. [8] in a context-free parameter design task. Their study found a moderately negative correlation between the number of actions taken by designers to the overall task performance. On the other hand, the number of actions taken by designers and their overall performance on the task had a weak positive correlation to the error on the task.

Previous work has also looked at designing optimization algorithms based on human behavior. These works include creating novel optimization algorithms based on human behavior [9, 10], and improving optimization algorithms by learning from successful human strategies [11]. Researchers have also explored human-computer partnership in design optimization [12, 13] as well as developing computer-support tools to aid human decision making [14, 15].

2.2 Structural optimization & sustainable design

Structural optimization is a challenging design problem as it can include a wide variety of objectives and constraints. Rules of thumb and guidelines for synthesizing optimal structural members are well established in engineering literature [16], and are a part of existing undergraduate curricula [17]. Designers in the industry often use such principles to guide the synthesis process. CAE tools such as finite element analysis (FEA) are used as a means for validating and refining synthesized designs. Conventionally, the objectives of shape optimization are to (1) induce a uniform stress distribution over as much of the body as possible, and (2) minimize the weight or volume of the material as consistent with cost and manufacturing processes.

Papalambros & Chirehdast [18] studied processes used by students for synthesizing a structural member. In this study, student teams designed a bracket that supported a specified load, with constraints such as ease of manufacture, ability to carry the load without failure, and weight reduction. The authors observed students mostly used intuition, some amounts of low fidelity prototyping, and FEA for designing the bracket. Kwak [19] argues that increasing the complexity of the design can inhibit manual modifications to the design. This suggests that designers using simple feature modifications or known shape heuristics are likely to iterate more than those using complex shapes.

In the context of sustainable design, previous studies [20, 21, 22] have looked at integrating computer-aided design (CAD) and sustainability assessment tools. Such tools can help designers estimate the environmental impact of their current designs and explore more benign alternatives. Serfani et al. [23] describe a multi-criteria decision-making method for material selection that utilizes structural optimization. In this work, the part shape is modeled using a set of design dimensions and therefore shape exploration is limited to topology-invariant modification. Russo & Rizzi [24] discuss a software framework that integrates of structural optimization and life cycle assessment (LCA). The discussed framework was not fully integrated and required designers to guide the optimization process using multiple tools.

2.3 Open research questions

While previous work has developed software frameworks for integrating structural optimization and sustainable design (see Section 2.2), very little work has explored their use with designers. We believe this is an important research gap as studies with professional designers have shown design optimization tools are often used as a means for initiating ideation and exploring the design space [25].

Previous research on designers' exploration processes (see Section 2.1) has provided insight into human behavior in design optimization tasks. Observations on the type of search strategy used, extent of search, and influence of domain knowledge on performance, have significant implications for the design of computer-aided structural optimization tools for sustainable design. For example, (1) is it valuable to display failed alternatives to the user?, amd (2) what is the effect of increasing the breadth of the search space based on user domain knowledge?

As a first step towards addressing these questions, our paper examines students' design exploration patterns in a sustainability-focused structural optimization task. In comparison to previous studies on designers' exploration processes, the novelty of our study setup stems from two aspects.

- Reaching an optimal design required an understanding of two domains: mechanical design and sustainable product design.

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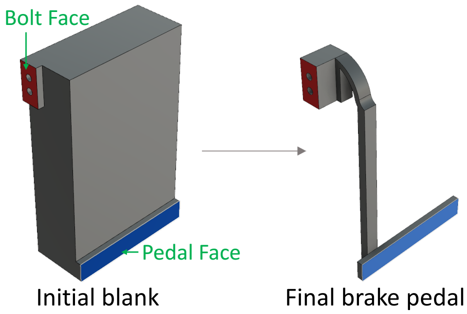

FIGURE 1. Initial blank provided to students for the structural optimization design task. Two bolts on the bolt face attach the brake pedal to a frame, and a 5 psi load is uniformly applied to the pedal face. An optimized design made from the initial blank is shown on the right.

Students in our study were familiar with optimization strategies in mechanical design (i.e. weight reduction), but had limited experience in optimizing for environmental sustainability.

- Exploration via topology modification affords more design freedom in comparison to varying specified design parameters on a numerical scale [26]. This allowed students to explore a wide variety of shapes and made it challenging for them to identify a unique optimal solution.

We also required students to manually optimize the topology of the component, rather than use a topology optimization software such as Autodesk Dreamcatcher[1]. This made students' decisions to retain or remove material more explicit, and made the conflict between weight, structural stability, and sustainability more apparent to the students.

3 METHODOLOGY

3.1 Structural optimization task

The structural optimization task was set up as a two-criteria optimization problem with the goal of simultaneously minimizing the weight (Wt) and an environmental indicator (EI) for a pedal bracket design. For this, students were required to synthesize different pedal brake geometries beginning from a common initial design. The initial design was akin to a "cast blank" from which students could create shapes by removing material. As shown in Fig. 1, the brake pedal is attached to a frame (not shown) using two bolts which holds the bolt face against that frame. A 5 psi load is uniformly applied to the face of the brake pedal. All contacts are assumed to be frictionless for this task.

The primary constraint for the task was that the maximum von Mises equivalent stress in the brake pedal could not exceed the maximum allowable stress. Students could use one of three materials in the task; Cast Iron GGL-NiCuCr (CI), Aluminum 2036 (Al), or Carbon Steel 35S20 (CS). The three materials were chosen such that the choice of material significantly affected the Wt and the computed EI. Additionally, we limited all geometry operations in the task to subtraction (material removal), to mimic real-world manufacturing through machining processes. These constraints also helped us set Wt and EI to be conflicting objectives and make the task challenging. We ensured that the Wt, EI, and maximum allowable stress varied considerably with change in material and geometry. Thus, reaching an optimal solution in this task required students to develop an understanding of the inter-relatedness among these parameters.

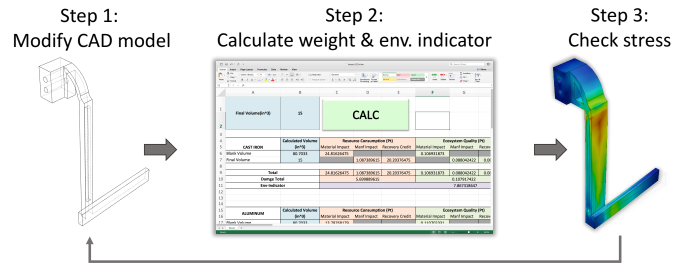

FIGURE 2. Steps involved in a unit iteration for the structural optimization task.

The three steps involved in a unit design iteration are shown in Fig. 2. First, students modified the brake pedal design on a CAD program. Next, they input the volume of the modified design on a Microsoft Excel® calculator that estimated the weight of the part as well as environmental indicators for the three material choices. The reason for providing this calculator was reducing the calculation burden when performing design iterations. Finally, students used an FEA package to verify if the modified design passed the constraint on allowable von Mises equivalent stress. The FEA package also displayed the stress distribution on the CAD model which gave insights into locations for removing additional material.

Equation 1 describes the formula used for calculating the single score cradle-to-gate EI in the Microsoft Excel® calculator. The computed indicator accounts for impacts resulting from material extraction, blank formation, manufacturing processing, and material recovery. Unit impacts for these processes are based on the Ecoinvent 99 (I) method available in SimaPro®.

$$EI = u_1 * W_b + (u_2 - \frac{p}{100} * u_3) * \sum_{i=0}^{n} MRW_i \tag{1}$$

Here,
W_b**:** weight of the initial blank
MRW_i**:** weight of material removed in the i^{th} step
n : total manufacturing steps
p : percentage of material recycled from total material removed

[1] https://autodeskresearch.com/projects/dreamcatcher

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u_1, u_2, u_3**:** single score unit process impacts for material extraction, manufacturing, and material recycling respectively

Table 1 shows the values for u_1 and u_2 for the three materials used in the task. For estimating unit process impacts, all material removal operations for the part $(i : 1, 2, ..., n)$ were assumed to be computer numerical control (CNC) milling. Furthermore, we assumed recycling credit was equal to the impact of material extraction (i.e. $u_3 = u_1$) and that all machined material was recycled ($p = 100\%$). We found these simplifications kept the structural optimization problem at a reasonable level of complexity in earlier studies [27]. All unit process impacts are expressed in Pt/lb. Here, 1 Pt represents 1/1000th of the yearly environmental load of an average European inhabitant.

TABLE 1. Single scores for process specific unit impacts calculated using the Ecoinvent 99(I) method on SimaPro®

	u_1 (Pt/lb)	u_2 (Pt/lb)
Cast Iron (GGL-NiCuCr)	1.4043	0.15836
Aluminum (Al 2036)	1.9238	1.6108
Carbon Steel (35S20)	0.04997	1.21009

3.2 Study procedure

3.2.1 Participants: The structural optimization task was distributed to 70 students in an undergraduate CAD and prototyping course at Purdue University as a week-long take-home assignment. This assignment was one of four assignments in the class and contributed to 3% of the overall class grade. Students in this course were at the junior or senior level and were enrolled in engineering-related degree programs. Submission of the assignment was mandatory for class grade.

3.2.2 Pre-Assignment Instructions: Before distributing the assignment, we conducted a 30 minute lecture that clarified the assignment objectives and constraints. We also demonstrated the CAD program, FEA package, and the Microsoft Excel® calculator by illustrating a design iteration. Students were informed ninety percent of the total assignment grade was based on correctly setting up the CAD model and the FEA problem. To motivate design exploration, the remaining ten percent of the grade was based on performance relative to other students in the class. For this, all final submissions were ranked based on whether both EI and Wt for one submission was lesser than another solution and placed into quartiles. Students were awarded 100%, 75%, 50%, or 25% of the ten percent grade based on their quartile placement. Students were also asked to perform at least three design iterations for the assignment.

3.2.3 Pre-Assignment Guidance: Students could discuss their questions with experts in CAD, FEA, and environmental sustainability assessment during two 90-minute lab sessions. The experts helped students with software problems and conceptual understanding but did not provide any direct design suggestions to students. Along with the assignment, students were also provided with instruction documents, including (1) a step-by-step presentation illustrating the sample design iteration discussed before the assignment, and (2) a document describing the method for computing the environmental indicator.

3.2.4 Data collection: A web-based survey was distributed prior to the structural optimization assignment. The goal of this survey was to assess the diversity of the student population and their prior knowledge on mechanical design, structural optimization, and environmental sustainability. Completion of this survey *did not* count towards the course grade.

Data collected from the structural optimization assignment, included (1) a digital copy of the final CAD model, (2) a print out illustrating the von Mises equivalent stress distribution for the final CAD model, and (3) a table detailing the weight, environmental indicator, chosen material, and stress analysis results (pass/fail) for every design iteration. We did not ask students to submit a CAD model for each design iteration as the course instructors felt that it would impose undue burden on the students.

3.3 Research questions and hypotheses

We framed research questions listed below based on literature reviewed in Section 2 and the objectives of this study. To answer these research questions, we framed hypotheses and analyzed them based on data collected from our study.

RQ1: What is the effect of failed design iterations on task performance?

- H1a: Students with one or more failed iterations performed better than students with no failed iterations
- H1b: Total number of failed design iterations is positively correlated to task performance

RQ2: What is the effect of *breadth of the search* on task performance?

- H2a: Students who switched to another material one or more times performed better than students who did not switch materials
- H2b: Total number of material switches is positively correlated to task performance

RQ3: What is the effect of total number of iterations on task performance?

- H3: Students who performed more design iterations performed better on the task

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RQ4: What is the relationship between the final shape and task performance?

H4a: Designs with similar shapes had a similar level of task performance

H4b: High performing designs converged to a unique optimal shape

RQ5: What is effect of experiencing parameter conflicts on task performance?

H5a: Students who experienced one or more parameter conflicts performed better than students who did not experience any conflict

H5b: Total number of parameter conflicts experienced is positively correlated to task performance

4 RESULTS

4.1 Results from the survey

We received a total of 59 responses (response rate = 84%) for the voluntary survey distributed prior to the structural optimization assignment. Among them, 17 students were in the junior year and 42 were in their senior year of their bachelor's program. All students reported to have taken prior courses in either statics, mechanics of materials, or strength of materials. A majority of students (50/59) also had prior experiences with synthesizing structural members in real-world design projects. Given these responses, we expected students to have developed a working knowledge in mechanical design and stress analysis. On the other hand, none of the 59 students had taken prior courses related to sustainable design. Only 1/59 students reported having prior experience with a design project involving sustainable design. Thus, we expected students' limited understanding of sustainable design to pose a significant challenge in the structural optimization assignment.

4.2 Summary of results from the assignment

From the total class of 70 students, 3 students did not submit the assignment and 25 students committed errors in defining physical constants and constraints. The remaining 42 submissions are analyzed in this paper. Table 2 details summary statistics for students' performance in the structural optimization assignment. We found although students were only required to perform 3 iterations for assignment completion, 27/42 students performed additional iterations. Exactly half the students (21/42) reported they had one or more failed iterations (iterations where designs failed the stress constraint). A majority of final designs were either Cast Iron (54.76%) or Aluminum (35.72%). We also found 22/42 students did not switch to a different material along the optimization process. For both final Wt and final EI we found considerable dispersion in the results (see Figure 4). The coefficient of variation for final $Wt = 1.42$ and for final $EI = 0.769$. Figure 3 illustrates the variety in the shape of the final design submitted by the students. The variation in final Wt, final EI, and shape, for finals design submitted by students suggests they adopted very different optimization strategies.

TABLE 2. Summary of results from the structural optimization assignment. Here, *total iterations* represents the number of iterations performed irrespective of failure. *Failed iterations* refers to iterations in which the designs failed to satisfy the stress constraint. The table also illustrates the EI and Wt for the final designs submitted by the students. *Material switches* counts the number of instances where students switched to another material. *Final materials* refers to the percentage of final designs of a particular material.

	Sample mean	**Sample variance**	**Sample range**
Total Iterations	5.64	8.86	$[1,12]$
Failed Iterations	1.33	3.69	$[0,7]$
Final EI (Pt)	16.41	151.25	$[4.39, 48.70]$
Final Wt (lb)	1.63	3.57	$[0.24, 11.16]$
Material Switches	0.83	0.82	$[0,3]$
Final Materials	CI = 54.76%, Al = 35.72%, CS = 9.52%		

As the task objectives were to simultaneously minimize final Wt and final EI, we encoded task performance by defining a design's *class rank*. For each design, we calculated the number of designs from the class that it outperformed (i.e. had a lower final Wt and a lower final EI than the other design). The *class rank* for a design, was computed by sorting all designs in the class using this performance measure. Designs with tied performance were given the same *class rank*.

4.3 Results from hypotheses testing

4.3.1 RQ1: To test the effect of failed iterations on task performance, we computed the Spearman's rho (r_s) between number of failures and the indicators of task performance. We found the number of iterations was significantly correlated to *class rank* ($r_s(40) = -0.4957,\ p < 0.001$), final Wt ($r_s(40) = -0.4809,\ p = 0.0013$), and final EI ($r_s(40) = -0.3317,\ p = 0.0319$). Results from a Wilcoxon's rank sum

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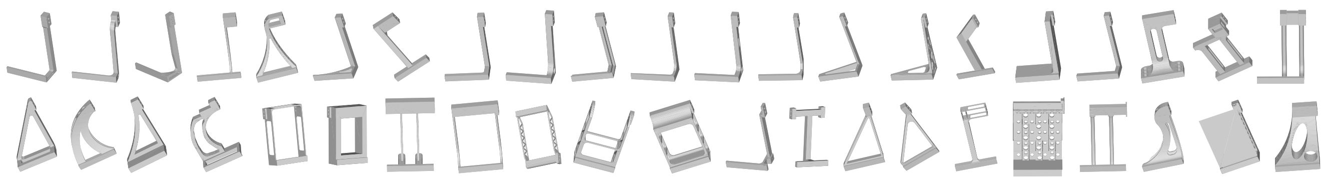

FIGURE 3. Shape of the final designs submitted by students.

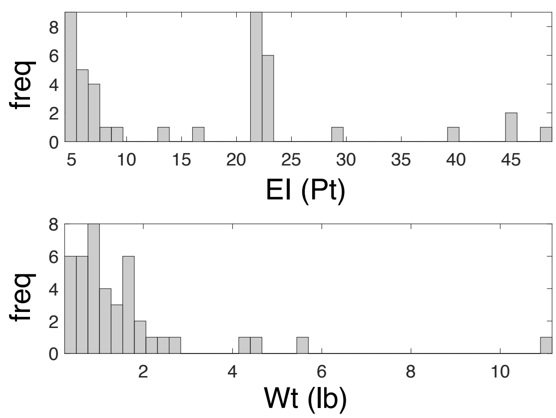

FIGURE 4. Histogram plot for final Wt and final EI.

test also showed *class rank* for students with no failures was significantly greater than students with one or more failures ($Z = 2.6194$, $p = 0.0044$). These results indicate that the number of failed iterations had a significantly positive correlation with task performance.

4.3.2 RQ2:

We used two criteria to determine a student's breadth of search: (1) the number of times they changed materials, and (2) the difference between the students' final Wt & EI from their initial Wt & EI. To see if criterion (1) was an indicator of student performance, we computed the Spearman's rho (r_s) between the number of material changes and the indicators of task performance. We found that the number of material changes was *not* significantly correlated to *class rank* ($r_s(40) = -0.13$, $p = 0.39$). We observed the same absence of significant correlation between the number of material changes and final Wt ($r_s(40) = -0.12$, $p = 0.94$), and final EI ($r_s(40) = -0.18$, $p = 0.25$). A Wilcoxon's rank sum test also showed no significant difference between the *class rank* of students with no material changes and students who changed material at least once ($Z = -0.32$, $p = 0.74$).

For criterion (2), we computed the Spearman's rho (r_s) between Wt difference ($Initial\ Wt - Final\ Wt$) and *class rank*, and between EI difference ($Initial\ EI - Final\ EI$) and *class rank*. While there was no significant correlation between weight difference and *class rank* ($r_s(40) = -0.037$, $p = 0.82$), we found a significant correlation between EI difference and *class rank* ($r_s(40) = -0.49$, $p < 0.001$). This indicates that the magnitude of reduction in EI was significantly correlated with task performance. Additionally, the "breadth of search" with respect to material changes or weight reduction do not significantly correlate with task performance.

4.3.3 RQ3:

The variation in students' final Wt and final EI against $Total\ Iterations$ is shown in Figure 5. Using these data, we computed the Spearman's rho (r_s) for $Total\ Iterations$ and final Wt ($r_s(40) = -0.280$, $p = 0.0725$) as well as $Total\ Iterations$ and final EI ($r_s(40) = -0.3331$, $p = 0.0311$). These results show final EI is negatively correlated to design iterations. We also found a significant correlation between $Total\ Iterations$ and *class rank* ($r_s(40) = -0.4218$, $p = 0.0054$).

Further analysis by splitting results based on the chosen final material showed only designs with Cast Iron exhibited significant correlation between $Total\ Iterations$ and *class rank*/final Wt/final EI ($r_s(21) = -0.5727$, $p = 0.0043$). Please note for a single material type, *class rank*, final EI, and final Wt have the same r_s value as they are perfectly correlated with each other (see Eq. 1). For Cast Iron, $Total\ Iterations$ is significantly correlated with *class rank*, final EI, and final Wt because of two factors (see Figure 6). First, 3 students submitted Cast Iron designs with high final EI and final Wt while performing significantly less iterations than the sample mean. Second, the environmental impact due to machining (u_2 in Table 1) for Cast Iron is significantly lower than for other materials.

4.3.4 RQ4:

To explore relationships between the final shapes submitted by students (see Figure 3) and performance on the task, we clustered the shapes by defining a distance measure based on the Euclidean-distance (D2) shape histogram [28]. For each shape, we first normalized the overall shape to account for scale differences. Next, we computed the Euclidean distance between all pairs of non-identical vertices in a shape. These distances were binned to create a D2 shape histogram. We found a bin size of 100 gave us sufficient discriminating power between the shapes. The distance between any two shapes is given by the distance between their respective D2 shape histograms. In our

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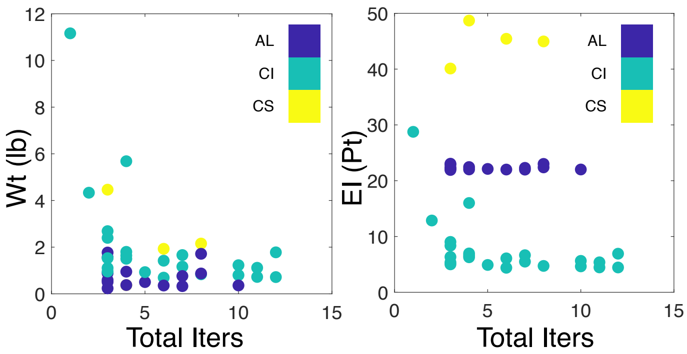


FIGURE 5. Scatter plot for final Wt & final EI against Total Iterations.

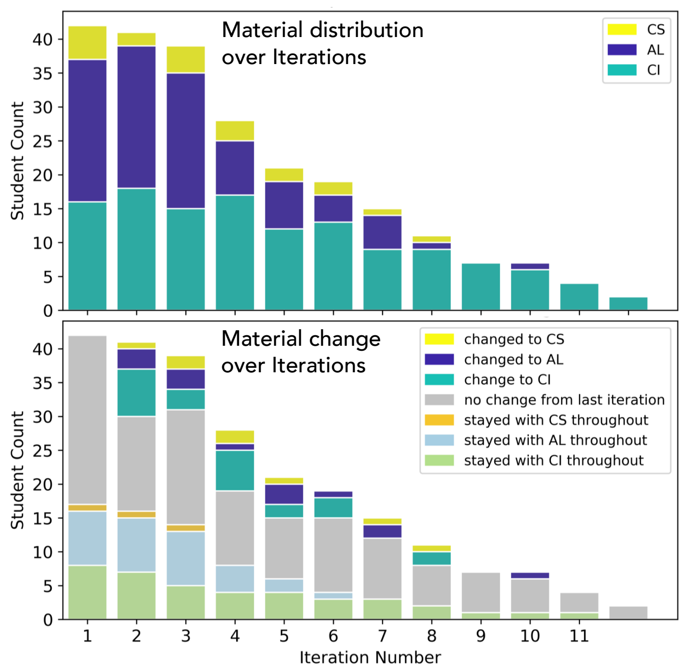
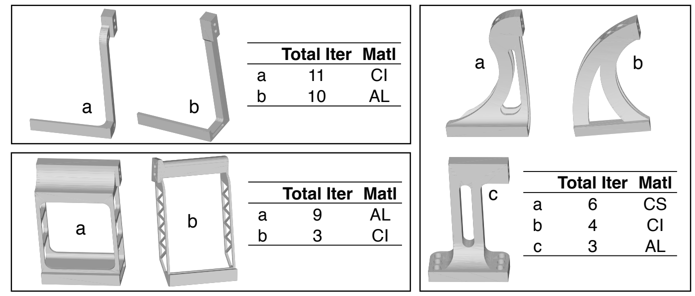


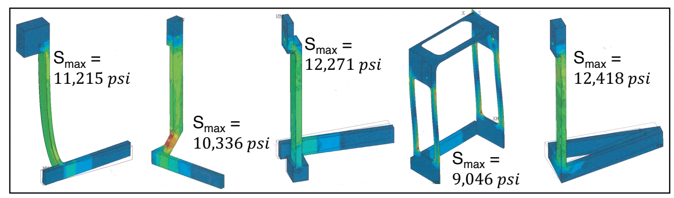
FIGURE 6. Material distribution (top) over iterations, and number of material changes (bottom) over iterations. The bottom plot also shows the number of students who did not change material for any iteration.

case, the distance between D2 shape histograms was computed using the Euclidean norm.

Using the above approach, we generated a 42×42 distance matrix that represents the distance between every shape to the other 41 shapes in in the dataset. We clustered this distance matrix using the affinity propagation algorithm [29] into 7 shape clusters. We found similarities in the shape of the final design did not correspond to similarities in the chosen material (see Figure 7(a)). A Pearson's chi-squared test of independence did not yield a significant correlation between shape clusters and material types ($\chi^2(12) = 15.1255$, $p = 0.2278$). This suggests, students' final shapes did not correlate with material type. Analysis of FEA results also showed that the best performing designs (sorted by *class rank*) did not converge to a unique optimal shape for this problem setup (see Figure 7(b)). We conducted a Kruskal-Wallis one-way ANOVA test to compare the effect of final shape on *class rank* and total iterations for the 7 shape clusters. Results showed no significant difference in *class rank* ($\chi^2(6) = 11.17$, $p = 0.0832$) and total iterations ($\chi^2(6) = 4.49$, $p = 0.6104$) between the 7 shape clusters.



(a) Differences in total iterations, material, Wt, and EI for shapes belonging to the same cluster. Similarity in shape did not correspond to similarity in material or *Total Iterations*.



(b) FEA results and maximum Von Mises equivalent stress (S_{max}) for five designs ranked in the top ten performing designs.The maximum stress in these designs was close to the maximum allowable stress. However, results also show potential for further optimization based on the presence of regions with low stress.

FIGURE 7. Influence of the final shape on performance in the structural optimization assignment.

4.3.5 RQ5: We identified the number of times students experienced opposing changes in Wt and EI, i.e. an increase in Wt from the previous iteration accompanied by a reduction in EI, or vice versa. Using this as a measure of conflicts, we computed Spearman's rho (r_s) between this measure and student performance (final Wt and final EI). We found no significant correlation between the number of conflicts and the final Wt ($r_s(40) = 0.075$, $p = 0.64$), or between the number of conflicts and the final EI ($r_s(40) = -0.18$, $p = 0.26$). A Wilcoxon's rank sum test also showed no significant difference between the *class rank* of students with no conflicts and students who experienced conflicts at least once ($Z = -0.98$, $p = 0.33$).

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TABLE 3. Summary of results from hypothesis testing.

	Results	Explanation
H1a	Accepted	Students with one or more failed iterations performed significantly better than students with no failed iterations.
H1b	Accepted	Total number of failed iterations was positively correlated to performance on the task.
H2a	Rejected	No significant difference was found between the performance of students who changed material at least once over their iterations and that of students who did not.
H2b	Partly Accepted	No significant correlation was found between the number of material changes and student performance, or between weight difference and the task performance. However, the magnitude of difference between the final and initial EI was negatively correlated to task performance .
H3	Accepted	Total number of iterations was positively correlated to task performance.
H4a	Rejected	Final shape did not have a significant correlation to task performance.
H4b	Rejected	Top performing designs did not converge to a unique shape or belong to a any single shape cluster.
H5a	Rejected	No significant difference was found between the performance of students who experienced one or more parameter conflicts and students who did not.
H5b	Rejected	No significant correlation was found between the number of conflicting results between iterations (i.e, Wt and EI changed in opposite directions) and task performance.

5 DISCUSSION

Results from the survey showed students had some previous experience in structural synthesis and a lack of awareness of ES-related concepts. Table 3 summarizes results from the hypothesis tests. We found total number of design iterations was positively correlated to task performance (H3a). Results also showed that students did not converge to a single optimal design and there was significant potential for further optimization in submitted designs (H4a & H4b). These results mirror Austin et al.'s [2] findings that students searched global spaces poorly. Given these findings and the fact that searching large problem spaces with coupling effects is a challenge especially for novice designers [4], there is a need for facilitating exploration of the global design space, for example through the use of computer-aided tools in sustainable design.

We found students with one or more failed iterations performed better than students with no failed iterations and total number of failed iterations had a significant positive correlation with task performance (H1a & H1b). Coupled with the finding by Ahmed et al. [6] that expert designers are better at questioning the future potential of a chosen approach, these results suggest there may be value in displaying the failure case for a particular exploration direction adopted by novice designers. By providing feedback about when the design reached a limiting constraint, computer-aided tools can help novice designers (1) realize the need for exploring an alternate direction or backtrack, and (2) develop insights about parameter couplings in their designs.

We found the breadth of exploration in materials did not significantly affect overall task performance (H2a & H2b). This could partly be because of how students' strategies in choosing material (see Fig. 6). Results show most students discarded Carbon Steel possibly due to its lack of advantage in weight or EI score. Of the remaining students, some chose Aluminum (in spite of its material extraction impact) and worked to generate a shape optimal for weight and manufacturing impact. Others chose Cast Iron potentially due to its low EI score, and sought to offset the weight by iterating over the shape. This is equivalent to findings by Ball et al. [7], that designers tend to narrow a breadth-first search to a domain that they are more knowledgeable in. Here, the impact of material choice on EI was not a domain students were well-versed in, and hence their material choices were fixed earlier, after which they focused on a domain they *were* well-versed in, i.e. changing the shape of a structure to optimize performance. To bridge the gap , design tools could allow multidimensional exploration of design parameters. Autodesk Dreamcatcher, which provides a range of solutions based on defined constraints and goals, and ShapeSIFT [30], which suggests design options based on prior designs, are examples of such tools that explicate expert-level knowledge and heuristics.

Finally, we found experiencing "conflicts" in design problems—instances when Wt and EI changed in opposite directions (due to a change in material or geometry)—did not significantly correlate with student performance. According to Yu et al. [3], designers with greater domain knowledge were able to understand the coupling effects of design parameters better. Therefore, our finding could partly be due to students' overall lack of experience in simultaneously exploring coupled design parameters such as material and geometry in the context of sustainable design. However, limiting material choice in the task could have also contributed to this finding as fixing material re-

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stricts the possibility of experiencing such conflicts. Most students made a material choice early, and the proportion of students changing material reduced over iterations, reducing the potential for conflicting outcomes. With these two combined factors, it would be difficult to generalize this observation and extend them to other multi-objective optimization problems. However, studying how students manage coupling effects is still a rich area of research, and future iterations of our study will place greater emphasis on this aspect of design behavior.

6 LIMITATIONS

Our study was limited to junior and senior level engineering students in a classroom setting. The task was distributed as a take-home assignment over a one-week period. We did not restrict students from accessing external material and the time for task completion to make it reflective of realistic structural optimization tasks. However, we could not closely monitor students' behavior during the study. The software workflow in our study was more tedious compared to previous studies on parameter-based design exploration. For each iteration, students modified their design on a CAD program and analyzed results using a spreadsheet-based calculator and an FEA package. This may have limited the number of design iterations performed by each student. While using topology optimization and generative deign tools could have eased some of this tedium, they would have prevented us from understanding what changes were initiated by students as opposed to the used computational tools. The grading rubric could have influenced the number of exploration steps performed. While we found that in general students performed more than the recommended 3 iterations, we were unable to ascertain why students stopped their exploration.

7 CONCLUSION AND FUTURE WORK

Our paper examines student's design exploration strategies in a sustainability-focused structural optimization task. The task was given as a week-long, take-home assignment to undergraduate students in a computer-aided design class. We found that the total number of design iterations and the total number of failed design iterations were positively correlated to task performance. We also found that the final shape, number of material changes, and experiencing a conflict in the objectives had no significant relation to task performance. Additionally, among the two objectives, task performance was significantly correlated only to the magnitude reduction in the environmental indicator.

Our findings point to the need for future research on computer-aided design tools in sustainable product design that can explicate relationships between various coupled parameters, and help novices to better explore alternatives in the design space. Findings from our study call for a more controlled study to further examine students' cognitive processes in such tasks. In our future work, we plan on expanding our work by studying novice as well as experienced designers. We also plan on studying designers' exploration processes with and without the use of commercially available topology optimization software. Finally, we will also explore the impact of increasing the material and manufacturing chocies in the exploration process.

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