Measuring the Impact of Real-time Life Cycle Performance Feedback on Conceptual Building Design

By

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ABSTRACT

Decisions made in the early design stages critically determine a building’s life cycle environmental impact and cost. These decisions are characterized by uncertainty, resulting from downstream decisions that have not yet been made. This paper evaluates the effectiveness of three visualization methods in helping professionals make sustainable building design decisions under uncertainty. A charrette involving 63 architects, engineers, and real estate developers was conducted to measure the effect of a scatterplot, histogram, and tornado diagram on design efficiency and solution quality. Participants were tasked with minimizing life cycle environmental impact and life cycle cost of a commercial office building. Each intervention achieved higher-performing designs than when no feedback was provided, and feedback presented in the form of a scatterplot achieved the best results. The research demonstrates the importance of providing designers with quantitative performance feedback to support sustainable building design decision-making and that the quantity and representation of the data should be carefully considered.

KEYWORDS

life cycle assessment; life cycle cost; energy efficient buildings; sustainable design; real-time simulation; environmental impact feedback

1. Introduction

Buildings have significant economic, environmental, and social impacts. The gross output of the US construction market was $1.35 trillion in 2015 (Bureau of Economic Analysis, 2015) and accounted for 7% of total employment globally (Khasreen et al., 2009). Buildings account for nearly 40% of primary energy consumption (United States Energy Information Administration, 2016) and associated greenhouse gas emissions (United States Energy Information Administration, 2011). Evidence suggests that greenhouse gas emissions from buildings are a significant contributor to the observed increase in the Earth’s surface temperature (United States National Research Council, 2010) as well as smog and ozone pollution, which decreases human life expectancy (Anenberg et al., 2010, Anenberg et al., 2011) and has been shown to reduce crop yields by 2-15% (Avnery et al., 2013). A significant portion of the environmental and economic impacts of buildings is decided upon in the early phases of the design of these facilities (Wood and Agogino, 2005). Understanding how design decisions impact a building’s life cycle performance, therefore, is a critical step towards creating a more sustainable built environment.
Life cycle assessment (LCA) and life cycle costing (LCC) methods exist to predict how a facility will perform over its lifetime, which includes raw material extraction, manufacturing, construction, maintenance, operation, end-of-life, and all intervening transportation impacts. LCA measures a set of environmental, economic, and social criteria (Finnveden et al., 2009), whereas LCC measures economic criteria including capital cost and operating cost (Reich, 2005, Hunkeler et al., 2008). Advancements in building information modelling (BIM) and computer simulation enable design professionals to accurately assess LCA and LCC criteria early in the design process (Flager et al., 2012). However, these criteria are often conflicting: for example, adding insulation with high R-value, photovoltaic panels, or environmentally friendly materials may lower operational energy and reduce environmental impacts while increasing capital costs. Identifying optimal design solutions is therefore a difficult task given the number of possible alternatives and the complex interactions that exist between many design variables (e.g., selection of insulation type). Designers have traditionally relied heavily on intuition and past experience to make the problem more tractable (Parmee, 2005). This practice has been shown to leave large areas of the design space unexplored, which may contain higher performing design solutions (Shea et al., 2005).

Computational design optimization (CDO) methods couple simulation with numerical methods that automatically generate and evaluate alternatives to systematically explore the full range of design possibilities to identify optimal solutions. Application of these methods in the architecture, engineering and construction (AEC) industry has been demonstrated to reduce the time and cost of the design process as well as to achieve significant improvements in building performance compared to conventional methods (Flager et al., 2012, Wang et al., 2005). Despite the potential of CDO methods to yield higher-performing buildings and a growing interest of these methods in the research community (Nguyen et al., 2014), there has been relatively little adoption of these methods in professional building design practice (Hopfe et al., 2005).

Previous research has cited differences in decision-making practice between CDO and conventional design as a possible explanation for the limited adoption of these methods. In particular, CDO typically involves parallel decision-making in which all design decisions are made at once. In contrast, several researchers have argued that sequential iteration more accurately represents most conventional design processes (Kalsi et al., 2001, Smith and Eppinger, 1997). In a sequential design process early design decisions are characterized by uncertainty resulting from downstream decisions that have not yet been made.

The goal of this paper is to evaluate different interactive visualization methods providing LCA and LCC feedback to support early design processes in which decisions are made sequentially. Section 2 provides background in existing decision support methods under uncertainty as this feature is inherent in sequential processes. Section 3 introduces an experiment that uses a software program to measure the relative effectiveness of three interactive visualization methods to provide LCA and LCC feedback under uncertainty. The experiment involved 63 professional architects, engineers, and real estate developers participating in a charrette and completing an artificial building design problem. The three types of visualizations tested included a scatterplot, histogram, and tornado diagram. The results of the experiment are discussed in Section 4. Finally, the suitability and potential impact of these visualization methods on sustainable building design practice is discussed in Section 5.

2. Design decision support under uncertainty
2.1. Design methods

Early attempts to formally account for uncertainties in engineering design are closely connected with Taguchi (1986). He characterized two primary sources of uncertainty: Type I resulting from uncontrollable noise factors and Type II caused by deviations in the control parameters, e.g., design variables. These sources were subsequently broadened to include deterministic decisions made by other designers in multidisciplinary environments (Chen and Lewis, 1999).

A typical approach for handling uncertainties in engineering design broadly is to use safety factors. Although popular, the safety-factor approach generally results in overly conservative designs, among other serious deficiencies (Koch, 2002). A more exact approach is to introduce ranges of uncertainty in the parameters themselves, or in their derivation, from underlying approximations (Hopfe and Hensen, 2011). A consequence of this approach is that the resulting output criteria used to assess design performance are probability density functions (PDFs) instead of deterministic values. Two noteworthy non-deterministic methods for engineering design are reliability-based methods and robust design methods.

Reliability-based design seeks to reduce the area under the PDF that lies outside of the constraint values by shifting the mean value away from constraint limits (Melchers, 1987). Note that under a reliability-based approach, the mean performance is optimized, however the variation thereof is not minimized. Robust design is different from reliability-based design in that the area under the PDF that lies outside the constraint boundaries is assumed reduced by optimizing the mean performance and minimizing its variation. A robust design is defined as one whose performance remains relatively unchanged and remains feasible in the presence of uncertainty (Taguchi and Cariapa, 1993).

Kalsi et al. (2001) developed a robust design method designed to reduce the effects of uncertainty in the design of complex systems involving multiple decision-makers. The focus was on modelling the interaction among decision-makers and reducing the effect that any one designer can have on decisions made by others. The study assumed a sequential process in which a lead designer chooses a range of satisfactory design configurations instead of a traditional point solution. Subsequent designers are therefore afforded more freedom to find a satisfactory solution to their disciplinary sub-problems. This approach was shown to increase the independence of disciplinary decision-making; however, it does not inform the decision-maker regarding how a given decision might impact product performance or help compare different design alternatives at the decision point.

2.2. Quantitative Visualization Methods

A variety of visualization methods have been employed to communicate uncertainty associated with design variable values and/or evaluation criteria in order to inform decision-making. Hopfe et al. (2013) utilized 1-D error bars to illustrate the range of possible values for various design performance criteria. An analytical hierarchy process (AHP) was then used to fuse evaluations from multiple decision-makers with inconsistent viewpoints. Halecki and Lewis (2002) used PDFs to represent uncertainty associated with variable values impacting coupled sub-systems. These visualizations were used interactively by designers to determine robust design variable values. Mattson and Messac (2005) used 2-D and 3-D Pareto-plot visualizations to communicate the uncertainty associated with performance trade-offs between design alternatives. The points on the Pareto plot representing design alternatives were shifted based on the calculated standard deviation of each performance criteria.
distribution associated with that alternative. Kanukolanu et al. (2006) also utilized three-dimensional Pareto plots, but represented uncertainty using a rectangular cuboid where each dimension of the volume corresponded to the standard deviation of the performance criteria distribution along that axis. This “Brick Visualization” method was implemented into the interactive software BrickViz.

Focusing specifically on methods applied to sustainable buildings in the AEC industry, Radford and Gero (1980) were among the first to apply trade-off diagrams to support early stage design decision-making. The diagrams compared thermal and daylight performance and allowed designers to assess many window configurations on a building exterior for environmental performance. Russell-Smith et al. (2015a) created an analysis tool measuring the ability of design teams to achieve sustainable target values across a building’s entire life cycle. These target values were also used in the coupling of Gantt charts with life cycle environmental impact accrual schedules to account for the variance of impacts throughout a building’s construction process (Russell-Smith and Lepech, 2015b). Basbagill et al. (2013) applied sensitivity analysis and PDFs to help designers determine which early stage decisions contribute the most to embodied environmental impact given only three inputs. Kim et al. (2011) used a data mining approach to analyze energy efficient building designs. By scaling up the data analyzed and integrating projected time series plots of energy costs with early design decisions, the study made accessible large amounts of energy simulation data typically known only late in the design process, thereby increasing the potential for design teams to achieve high-performing results.

Although the importance of uncertainty in sequential design processes is widely acknowledged and several innovative visualization methods have been developed to represent this information, the precise impact of these methods on design decision-making has not been fully examined. Sanyal et al. (2009) performed a user study to compare the effectiveness of different visualization techniques in communicating the level of uncertainty. The techniques evaluated were traditional error bars, scaled size of glyphs, color-mapping on glyphs, and color-mapping of uncertainty on the data surface. The authors found that the choice of technique had a significant impact on accuracy and response time. However, this study did not go so far as to evaluate how these visualization techniques impacted the decision-making process or to quantify how they compared to conventional decision-making practice. In the data mining study cited above, Kim et al. (2011) suggested using charrettes to test the effectiveness of quantitative interventions on sustainable design practice. Therefore this paper uses a design charrette to test the effectiveness of visualization techniques in supporting quantitative decision-making processes during early stage sustainable building design.

3. Methodology

This section describes an experiment to test the effectiveness of three interactive visualization methods providing LCA and LCC feedback to support early AEC design processes in which decisions are made sequentially. The essential features of the AEC design process that we chose to capture in the experiment are listed below:

1. Design alternatives are evaluated based on multiple performance criteria
2. Some performance criteria have a certain range of values that must be achieved for the design alternative to be considered feasible
3. Multiple decisions are required in order to fully define a design alternative
4. Decisions are made in a sequential fashion
5. Designers strive to develop the highest quality solution possible given a limited amount of time

The experiment involved professional architects and engineers participating in a charrette involving an artificial building design problem. The three types of visualizations tested included a scatterplot, histogram, and tornado diagram. The impact of each visualization on decision-making was measured in terms of design efficiency (or level of design exploration considering number of alternatives evaluated), quality of the final solution, and the rate of improvement in the solution quality over time. The following sub-sections describe the design exercise, the interactive visualization tool, the participants and the experimental procedure.

3.1. Design exercise

Designers were asked to complete four design exercises. Each exercise involved the conceptual design for a 108,000 ft² office building. The design brief indicated that the client would award the design contract to the individual that produced a conceptual design that best matched the owner’s objectives. The decisions required to complete the conceptual design are summarized in Table 1 and included selection of the geometric shape, number of floors, site orientation, window-to-wall ratio, structural framing material, and cladding material. These design variables were selected for the experiment because they typically have a significant impact on a building’s life cycle performance and represent decisions that architects and engineers typically consider during the conceptual design phase. The design objectives and site location varied by exercise to control for subject learning as discussed in greater detail in Section 3.4.

Table 1. Decision variables available to participants in the design exercise

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Footprint shape</td>
<td>“U”, “H”, “L”</td>
</tr>
<tr>
<td>Number of floors</td>
<td>5, 6, 7, 8</td>
</tr>
<tr>
<td>Orientation</td>
<td>0°, 15°, 30°, 45°, 60°, 75°, 90°</td>
</tr>
<tr>
<td>Window-to-wall ratio</td>
<td>30%, 40%, 50%, 60%</td>
</tr>
<tr>
<td>Structural frame</td>
<td>Reinforced concrete, steel</td>
</tr>
<tr>
<td>Cladding</td>
<td>Precast concrete, brick with metal stud, metal curtain wall</td>
</tr>
<tr>
<td></td>
<td>(low-e glazing), brick with metal stud (low-e glazing), metal curtain wall (low-e glazing)</td>
</tr>
</tbody>
</table>

The two site locations chosen were Dallas and Fairbanks since they represented disparate climates. The design objectives are summarized in Table 2 and consisted of embodied carbon, operational carbon, total carbon, first cost, operational cost, and total cost. Total carbon is the sum of embodied carbon and operational carbon, and total cost is the sum of first cost and operational cost.

Table 2. Performance criteria used as design objectives in the design exercise

<table>
<thead>
<tr>
<th>Performance Criteria</th>
<th>Units</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>First cost</td>
<td>USD/ft²</td>
<td>RSMeans</td>
</tr>
<tr>
<td>Operational cost</td>
<td>USD/ft²</td>
<td>eQUEST</td>
</tr>
<tr>
<td>Total cost</td>
<td>USD/ft²</td>
<td></td>
</tr>
</tbody>
</table>
The gray shaded area in Figure 1 shows the phases of the building life cycle that were included in the calculation of the objectives. The embodied carbon and first cost criteria correspond to the raw material acquisition and building material production phases in Figure 1. Operational carbon and cost account for the operational phase in Figure 1, which includes building heating, cooling, lighting, plug loads, and water consumption. Evidence from previous research suggests the included phases, namely raw material acquisition, building material production, and operation account for over 95% of a building’s life cycle environmental impact (Cole and Kernan, 1996). Demolition, construction, transportation, and maintenance, repair and replacement have not been included since impacts associated with these phases have been shown to be difficult to calculate (Pushkar et al., 2005, Schoch et al., 2011) and small when compared with other phases (Scheuer and Keolian, 2002).

Researchers have identified several impact categories that are useful in measuring the environmental impact of buildings, including global warming potential, human toxicity, and acidification, among others (Jolliet et al., 2003). Although the authors recognize the importance of all of these categories in assessing the life cycle environmental impact of buildings, the proposed method considers only global warming potential. The metric used for this indicator is carbon dioxide equivalents (CO₂e), which measures the total amount of greenhouse gas emissions of the building.

Costing data came from RSMeans (2007), operational energy and cost data came from eQUEST (2010), and environmental impact data came from the life cycle assessment programs Athena (2011) and SimaPro (2010). These objectives were chosen since design professionals typically must design for their client’s budget, and total cost and carbon considerations are increasingly becoming more important drivers for sustainable design (Ahn et al., 2013, Häkkinen and Belloni, 2011, Liu et al., 2012, Ugwu and Haupt, 2007).

3.2. Interactive visualization tool

An interactive visualization tool was created that provided a simplified parametric representation of design decision-making that retains the essential features of the AEC design
process described above. It was acknowledged to the participants that a relatively limited range of design alternatives can be expressed using the tool compared to standard software tools available in the industry today such as SketchUp (2016), Revit (2016) or Rhino (2016). The tool was embodied in an online software program that provided participants with dynamic carbon and cost feedback during the design exercises described in the previous section. Figure 2 is a screenshot of the user interface, which consisted of available design decisions (“Variables”), design objectives (“Performance Metrics”), and a Feedback Pane that included a dynamic visualization of the Performance Metrics based on the Variables selected. The visualizations provided varied by design exercise and by participant group as discussed in Section 3.4. The available visualizations included a tornado diagram, scatterplot, and histogram. An axonometric view of the design accompanied the metrics.

![Screenshot of user interface for interactive visualization tool](image)

Participants made selections or de-selections one at a time by clicking on boxes next to parameter values in the Variables pane. Multiple selections for a given parameter were allowed, and the Feedback Pane updated accordingly. The values in the Performance Metrics pane only populated when exactly one selection was made for each of the six parameters, indicating that a complete design alternative had been defined. Note that in the screenshot of the interface shown in Figure 2, a complete alternative is not defined and thus the Performance Metrics values are not populated. At any point participants could deselect all choices for a given parameter by clicking the “Clear” button next to that parameter or for all six parameters by clicking the “Clear All” button.

The visualizations presented to the user updated automatically with each variable value selection to provide LCA and LCC feedback on each sequential decision made. All user actions for each design exercise and the distribution of possible performance values for that configuration of design variables were logged and stored in an online database. This information was then aggregated, normalized, and compared as described in Section 4 to quantitatively compare the impact of each visualization on decision-making in terms of design efficiency, or level of design exploration considering number of alternatives evaluated, quality of the final solution, and rate of improvement in the solution quality over time. The
following sub-sections describe each of the three visualizations tested in the experiment in greater detail.

3.2.1. Tornado diagram

Figure 3 is a screenshot of the tornado diagram used in the interactive visualization tool. The diagram allows a user to visualize the relative influence of each design variable on each output, thereby helping determine which decisions are most and least likely to affect the building performance metrics of interest. The influence values were calculated by pre-computing the performance metrics for each criterion listed in Table 2 for every possible design. The total number of designs equaled the number of possible combinations for the six input variables described in Table 1, or 4,032. The values displayed in the tornado diagram were then calculated from the performance metrics by determining the sensitivity of the performance metrics to changes in each design variable and then normalizing these values to unity, where unity represented the parameter with the greatest influence. All calculated values were stored in an online lookup table and were called and displayed in real time when the user made a change to the design variable configuration.

Once a user selected a value for a parameter, the two bars for that parameter would disappear since the parameter in question could no longer affect the results. As a user selected values for design variables, the bars for the unselected parameters would elongate since their relative statistical influence on the performance objectives could only increase. Once selections for all six variables had been made, all bars would disappear to indicate that the performance of the alternative in question had been completely determined.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Clear All</th>
<th>Sensitivity Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shape</td>
<td>Clear</td>
<td>-1.00 Influence +1.00</td>
</tr>
<tr>
<td>✗ U ☑ H ☑ L</td>
<td></td>
<td></td>
</tr>
<tr>
<td># Floors</td>
<td>Clear</td>
<td></td>
</tr>
<tr>
<td>☑ 5 ☑ 6 ☑ 7 ☑ 8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Orientation</td>
<td>Clear</td>
<td></td>
</tr>
<tr>
<td>☑ 0° ☑ 15° ☑ 30° ☑ 45° ☑ 60° ☑ 75° ☑ 90°</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Window to Wall Ratio</td>
<td>Clear</td>
<td></td>
</tr>
<tr>
<td>☑ 30% ☑ 40% ☑ 50% ☑ 60%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Structural Frame</td>
<td>Clear</td>
<td></td>
</tr>
<tr>
<td>☑ Reinforced Concrete ☑ Steel</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cladding</td>
<td>Clear</td>
<td></td>
</tr>
<tr>
<td>☑ Precast Concrete ☑ w/ low-e glazing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>☑ Brick w/ Metal Stud ☑ w/ low-e glazing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>☑ Metal Curtain Wall ☑ w/ low-e glazing</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 3. Tornado diagram used to provide design performance feedback. Black bars indicate the degree to which each parameter impacts building cost performance. Gray bars indicate the degree to which building carbon performance is affected.

3.2.2. Scatterplot

Figure 4 is a screenshot of the scatterplot used in the interactive visualization tool. Before any design decisions were made, the tool would plot all 4,032 possible design configurations as dots. The experiment’s cost objective was plotted on the x-axis, and the carbon objective was plotted on the y-axis. Calculations for each of the six performance criteria came from the data sources outlined in Table 2 and were pre-computed and stored in an online lookup table. The color of the dot indicated whether the given design alternative met either or both performance objectives. As the user selected variable values, the color of certain points would change to gray to indicate design alternatives that could no longer be achieved with the current variable selection. After a single value had been selected for each of the six design variables, only one non-gray design was displayed corresponding to the completed design.

Figure 4. Scatterplot visualization used to provide interactive design performance feedback, here showing all 4,032 designs prior to any design decisions

3.2.3. Histogram

Figure 5 is a screenshot of the histograms used in the interactive visualization tool. Two distributions are displayed: one for each design objective. For each distribution the x-axis was divided into bins showing the performance values, and the y-axis described the percentage of all possible design configurations with a measured performance value that fell within the range of the given bin. The percentage values associated with each bar would change after each variable value selection and always summed to 100. The color of the bar indicated
whether the design configurations in that range always met the performance objective, may have met the objective (indicating that the value fell somewhere within that range), or did not meet the objective.

Figure 5. Histogram visualization used to provide interactive feedback, here showing the proportion of designs meeting the performance objectives

3.3. Participants

Sixty-three design professionals participated in the charrette in a New York City office building that consisted of a series of four design experiments completed with the software program. The participants represented a range of professions, position levels, and years of experience within the AEC industry. It should also be noted that participant recruitment focused on firms with an interest in and/or reputation for sustainable design. Table 3 presents the demographics for the charrette participants. A majority of participants were architects, and position level and years of experience were fairly evenly distributed. Motivations for attending the charrette included testing out a new software program, attending a lecture on life cycle assessment and multi-objective decision-making processes, and receiving professional credits from The American Institute of Architects for attending the charrette.

Table 3. Demographics of the 63 charrette participants

<table>
<thead>
<tr>
<th>Demographic</th>
<th>Values</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profession</td>
<td>Architect</td>
<td>51</td>
</tr>
<tr>
<td></td>
<td>Engineer</td>
<td>35</td>
</tr>
<tr>
<td></td>
<td>Real estate developer</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>7</td>
</tr>
<tr>
<td>Position level</td>
<td>Junior-level</td>
<td>38</td>
</tr>
<tr>
<td></td>
<td>Senior-level</td>
<td>35</td>
</tr>
<tr>
<td></td>
<td>Executive</td>
<td>27</td>
</tr>
</tbody>
</table>
3.4. Experimental procedure

The experimental procedure involved dividing the participants into three groups of 16 and one group of 15. Each group participated in four design experiments involving the conceptual design of an office building as described in Section 3.1. Each exercise involved a different combination of building site locations and design objectives as shown in Table 4. The performance criteria for budget and carbon were equal to the values for the design at the 25% percentile of each metric, meaning a designer had to select a design that ranked in the top 1,008 of all designs for each objective in order to achieve a feasible design alternative that was acceptable to the client.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Site Location</th>
<th>Design Objective</th>
<th>Max Budget ($/ft²)</th>
<th>Max Carbon (lb CO₂e/ft²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Dallas</td>
<td>Minimize first cost <em>and</em> embodied carbon</td>
<td>41.10</td>
<td>229</td>
</tr>
<tr>
<td>2</td>
<td>Dallas</td>
<td>Minimize annual operational cost <em>and</em> annual operational carbon</td>
<td>6.76</td>
<td>96</td>
</tr>
<tr>
<td>3</td>
<td>Fairbanks</td>
<td>Minimize annual operational cost <em>and</em> annual operational carbon</td>
<td>8.72</td>
<td>164</td>
</tr>
<tr>
<td>4</td>
<td>Fairbanks</td>
<td>Minimize total cost(^1) <em>and</em> total carbon(^2)</td>
<td>162.11</td>
<td>5,493</td>
</tr>
</tbody>
</table>

\(^1\)assuming a 30-year service life and 7% discount rate  
\(^2\)assuming a 30-year service life and 0% discount rate

All groups participated in the design exercises in the same order but received a different intervention for each experiment. Interventions consisted of the interactive visualizations presented in the previous section, namely a scatterplot, histogram, tornado diagram, all three visualizations presented simultaneously, or no interventions presented at all representing conventional design practice. A description of the interventions by group is shown in Table 5.
Varying the interventions in this way was meant to offset any learning bias on the part of the participants.

Participants were given a design brief describing the four experiments in Table 4. A ten minute tutorial explained to the participants how to use the interactive visualization tool. Groups had eight minutes to complete each design exercise with a two minute break between exercises. Groups were told they would receive either no feedback or feedback in the form of one intervention or all three interventions simultaneously. However they were not provided Table 5, meaning they could not anticipate the order in which the interventions would be received.

Table 5. Experimental setup showing the order of interventions by design experiment

<table>
<thead>
<tr>
<th>Group</th>
<th>Experiment 1</th>
<th>Experiment 2</th>
<th>Experiment 3</th>
<th>Experiment 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>None</td>
<td>Scatterplot</td>
<td>Histogram</td>
<td>All three</td>
</tr>
<tr>
<td>2</td>
<td>Tornado</td>
<td>Histogram</td>
<td>Scatterplot</td>
<td>None</td>
</tr>
<tr>
<td>3</td>
<td>Histogram</td>
<td>All three</td>
<td>None</td>
<td>Tornado</td>
</tr>
<tr>
<td>4</td>
<td>All three</td>
<td>None</td>
<td>Tornado</td>
<td>Scatterplot</td>
</tr>
</tbody>
</table>

4. Results

The charrette results were analyzed to evaluate the effect of the interactive visualizations, including the scatterplot, histogram, and tornado diagram, on early stage building design decision-making. The impact of the visualization methods was assessed in three categories: (1) design efficiency, measured in terms of the number of design iterations and complete alternatives evaluated by the participants during the time allotted for the design exercise; (2) solution quality, measured in terms of how well the design configurations generated by the participants satisfied the given design objectives for that exercise; and, (3) user feedback, measured in terms of the rating participants provided regarding the effectiveness of each intervention as part of a user survey distributed after the charrette. The experimental findings in each category are discussed in more detail below as well as how well user feedback correlated with participant performance in terms of design efficiency and solution quality.

4.1 Design efficiency

The second and third columns in Table 6 show how participants performed in terms of the number of iterations (different variable configurations) explored before arriving at a complete design alternative as well as the total number of complete alternatives evaluated. Each change that a participant made to the configuration of variable values was considered a new design iteration. Thus the minimum possible number of iterations was six, since this equaled the number of design variables in the problem. Not surprisingly, the minimum number of iterations occurred when participants received no feedback. A likely explanation for this result is that in this case no feedback on building performance was provided until a complete alternative was defined. Therefore, participants had little incentive to experiment with different values within a given variable since it would afford no additional information. The histogram, scatterplot and combined interventions resulted in the greatest amount of design iteration. This result is expected since these interventions provided dynamic feedback on carbon and cost performance for each iteration. The mean number of iterations for the tornado diagram was significantly lower than the scatterplot, histogram, or all three interventions. This could be explained by the fact that the tornado diagram only showed the relative influence of each variable on building performance. Participants had no way to compare how
different values for a given variable impacted performance until the alternative was completed.

With regard to the number of complete alternatives evaluated, the results indicate that participants evaluated the most when no feedback was provided. As discussed above, participants were motivated to explore as many alternatives as possible in this case since design performance could not be assessed until a complete alternative was defined. This finding suggests that designers tend to engage in more design iteration when the amount and frequency of feedback is limited, a practice that can be costly for architecture and engineering firms since it often equates to a greater amount of design effort. Participants iterated on the fewest number of alternatives for the scatterplot intervention, suggesting this was a particularly efficient feedback mechanism for achieving the performance objectives specified in the design brief.

<table>
<thead>
<tr>
<th>Intervention</th>
<th>Mean number of iterations to first complete design</th>
<th>Mean number of alternatives</th>
<th>Mean solution quality: cost and carbon</th>
<th>Utility rating¹</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>7.5</td>
<td>21.6</td>
<td>0.59</td>
<td>---</td>
</tr>
<tr>
<td>Scatterplot</td>
<td>15.7</td>
<td>9.3</td>
<td>0.83</td>
<td>3.8</td>
</tr>
<tr>
<td>Histogram</td>
<td>17.4</td>
<td>18.6</td>
<td>0.68</td>
<td>3.1</td>
</tr>
<tr>
<td>Tornado</td>
<td>10.2</td>
<td>11.6</td>
<td>0.59</td>
<td>2.9</td>
</tr>
<tr>
<td>All three</td>
<td>15.8</td>
<td>13.5</td>
<td>0.67</td>
<td>---</td>
</tr>
</tbody>
</table>

4.2. Solution quality

To assess solution quality each of the 4,032 possible design configurations was ranked according to how well it satisfied the design objectives. Design configurations with a lower cost or carbon footprint were ranked ahead of design configurations with higher values. Equal weighting was given to cost and carbon objectives. The best design was given a rank of 1, and the worst design was given a rank of 4,032. These rankings were then normalized to unity: the best performing design was assigned a percentile rank of 1.0, and all other designs were ranked linearly between unity and zero.

The fourth column in Table 6 shows the average solution quality of the best complete design achieved by the participants by intervention. No feedback and the tornado diagram resulted in low solution quality scores. The quality of the best design achieved was in the 59th percentile for both interventions, on average. A possible explanation for the relatively poor performance of the tornado diagram is that unlike the scatterplot and histogram, the tornado diagram did

¹ Users were not asked to rate experiments providing no feedback or feedback from all three interventions.
not provide feedback on incomplete designs. Participants had no way of understanding how their current design was performing relative to the remaining designs and therefore had little incentive to iterate on a design before receiving feedback. This is reinforced by the relatively small number of iterations for the tornado diagram. The scatterplot on the other hand resulted in the highest solution quality metric with participants scoring in the 83rd percentile on average.

4.3 Combined effects of design efficiency and solution quality

Figure 6 plots solution quality against design efficiency by iterations. The figure illustrates that the interventions with the greatest amount of design iteration – the scatterplot, histogram, and all three interventions presented together – generally resulted in higher solution quality scores. This correlation suggests that interventions that provide dynamic feedback after each iteration lead to higher engagement by participants, since they spend more time refining incomplete designs to achieve higher-performing results.

Figure 6. Charrette results comparing mean solution quality against the mean number of decisions per first complete design alternative by intervention. The error bars indicate the standard deviation of the distribution with respect to each axis.

4.4 Improvement rate

Figure 7 shows the rate at which solution quality improved from one decision to the next. This was calculated by averaging the difference in solution quality after every design decision made by the participants until the first design was complete. The figure shows that the scatterplot achieved the greatest rate of improvement, or nearly double that of the tornado
diagram and no feedback interventions. The advantage of using the scatterplot was that each design could be represented on the diagram as a dot, rather than aggregated in a bar, allowing the cost and environmental impact objectives to be visualized simultaneously. This represented a relatively compact way of visualizing two objectives compared to other interventions.

Also of interest is that when all three visualizations (scatterplot, histogram, and tornado) were presented to participants simultaneously, they achieved a lower final solution quality and rate of improvement than when they were provided with only the scatterplot visualization. This finding suggests that too much quantitative information may hinder designers’ decision-making processes. Similarly, receiving no feedback or only the tornado diagram yielded the lowest improvement rates, suggesting these interventions are the least useful at achieving high-performing AEC designs.

Figure 7. Mean solution quality improvement rate by intervention for the first completed design. The error bars indicate the standard deviation of the distribution.

4.5. User feedback

The rightmost column in Table 6 provides a utility rating for each of the interventions. After completing the experiments, participants were asked to rank the three interventions by how useful they found them in successfully meeting the experiment objectives. Users ranked the interventions on a scale from one to five, with one being the least useful and five being the most useful. Utility results correlated well with solution quality, with the scatterplot as the highest-performing intervention receiving significantly higher ratings than the tornado diagram or histogram. Participants also generated far fewer alternatives with the scatterplot, suggesting that participants appreciated the intervention’s ability to efficiently arrive at higher-performing solutions.
5. Discussion and conclusions

This paper presents three interactive visualization methods that provide cost and carbon feedback to architects and engineers to support building design decision-making. The three visualization methods presented included a scatterplot, histogram, and tornado diagram. A design charrette was conducted involving 63 professional architects and engineers to measure the effect of these visualization methods in terms of design efficiency, solution quality and improvement rate.

The results of the charrette show that the scatterplot and the histogram, which provided dynamic feedback after each design iteration, led to the greatest amount of design iteration by the participants and higher solution quality than other interventions. The scatterplot outperformed all other interventions, achieving the highest rate of improvement in solution quality by iteration as well as the highest final solution quality. With the support of the scatterplot intervention, the mean solution quality achieved by the participants was in the 83rd percentile. The histogram intervention achieved the next highest mean solution quality which was in the 68th percentile of all possible solutions. Participants which received no feedback scored in the 59th percentile and took approximately twice the amount of time to arrive at a feasible design solution. Feasible designs were those that scored in the 75th percentile or above considering all possible design solutions.

It is hypothesized that the efficiency and effectiveness of the scatterplot resulted from its ability to communicate the multi-criteria performance of a design alternative with a single point. Other visualizations such as the tornado diagram and the histogram required separate visualization elements (e.g., bars) to represent each performance criteria (i.e., cost and carbon). The data suggests that processing multiple elements places a greater cognitive load on the designer and, therefore, reduces the effectiveness of the visualization. The performance of participants when all three visualizations were presented simultaneously offers additional evidence in support of this hypothesis. In this case, the rate of improvement in solution quality by iteration as well as the highest final solution quality was substantially lower than when the scatterplot was presented alone. The significant impact that the interventions presented had on design decision-making demonstrates the importance of providing designers with interactive performance feedback to support sustainable design decision-making. Further the amount and representation of the feedback data presented should be carefully considered.

The design charrette was limited to six design variables, and each variable had a limited number of options. In addition, only four design exercises were conducted involving one building type and two climates. Future research will integrate with building information modelling and simulation platforms to consider a substantially larger range of design options and to better align with conventional design workflows. Also, only a single environmental impact indicator, CO$_2$e, was presented in this research. The feedback can easily be extended to include additional environmental indicators obtained from the LCA software, such as energy use, acidification, and water use, as well as additional building life cycle phases. In additional, the method can be extended to include other building performance criteria such as energy consumption, acoustical performance, thermal occupant comfort, indoor air quality, as well as other criteria. Finally, the method can be integrated with building energy codes and energy efficiency standards such as the 2030 Challenge. These would provide standardized target values against which design professionals could compare their design’s energy and cost performance.

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