Design Creativity: Using Pareto Analysis and Genetic Algorithms to Generate and Evaluate Design Alternatives

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ABSTRACT
When presented with a design problem, engineers, architects and visual-effects artists routinely generate multiple, competing design alternatives. Generating alternatives enables designers to explore the creative space along multiple parallel and orthogonal dimensions. This paper examines a new design practice called *design optioneering*, which uses parametric modeling, Pareto analysis and genetic algorithms to simultaneously generate and evaluate large sets of design alternatives. We offer examples of built-in evaluation methods within design optioneering tools. We argue that a tool's ability to automatically evaluate design solutions against users' predefined fitness criteria, greatly filtering a large set of alternatives generated, may be the most relevant and effective evaluation of creativity support for this class of tool.

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evaluation, innovation, design, creativity support tools

ACM Classification Keywords
I.5.2 Design Methodology

General Terms
Human Factors, Design, Theory

INTRODUCTION
Design optioneering tools are creation tools that use parametric modeling, performance simulation and design optimization to systematically generate and evaluate design alternatives [7,8]. Design optioneering is a departure from customary architecture and engineering practice. Customarily, architects design a relatively small set of design alternatives which represent specific points in a multi-dimensional design space [5]. In architecture, this small set of design alternatives may be communicated in the form of two or three laser cut scale models or a few dozen photo-realistic visualizations. Even with the support of state-of-the-art computer-aided design tools, individual designs are iterated relatively slowly and with considerable design effort.

Conversely, architects and engineers using design optioneering practices generate orders of magnitude more design alternatives by specifying design objectives in the form of design parameters and parameter ranges. They use genetic algorithms to automatically and iteratively generate large sets of design alternatives [7]. The designs that best fit the architects or engineer's predefined parameters "survive" multiple "generations," i.e. iterations, and mutate to spawn successive generations of uniquely new designs.

Contrasting with traditional design practice, *optioneered* designs are computed parametrically and bred algorithmically. The numerous design alternatives that are produced are often represented by a multi-dimensional plot of the solution set and might be coupled with a matrix of thumbnails of rendered designs, as in Figure 1. Researchers investigating the approach argue that design optioneering is unique in that it "enables designers to more efficiently and with more certainty explore more complex and tightly coupled design solution spaces." [ibid]

DESIGN OPTIMIZATION AS A CSE
Design optioneering tool sets are an under-researched class of Creativity Support Environments (CSEs). To the extent that design optioneering tools empower users to be "not only more productive but also more innovative" [10] they satisfy the broad definition of CSEs (a.k.a. CSTs) put forth by Shneiderman et al in their 2006 NSF workshop report. As a tool for creative thinking, optioneering tools support exploration, experimentation, and by definition they generate numerous combinations of multiple design parameters. Gerber [7] articulates the following six features of the design optioneering approach:

1. rapid design exploration
2. increased integration between disparate design and engineering domains
3. rapid visualization of the cause and effect of design decisions
4. quantified understanding of multi-objective tradeoffs
5. reduced design decision latency
6. transparency and automation of the generation and evaluation of the design solution spaces.

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Gerber's features map closely to the design principles for CSEs in [10]. The overlapping goals include those of maximizing exploration, increasing collaboration, emphasizing iteration, and supporting evaluation.

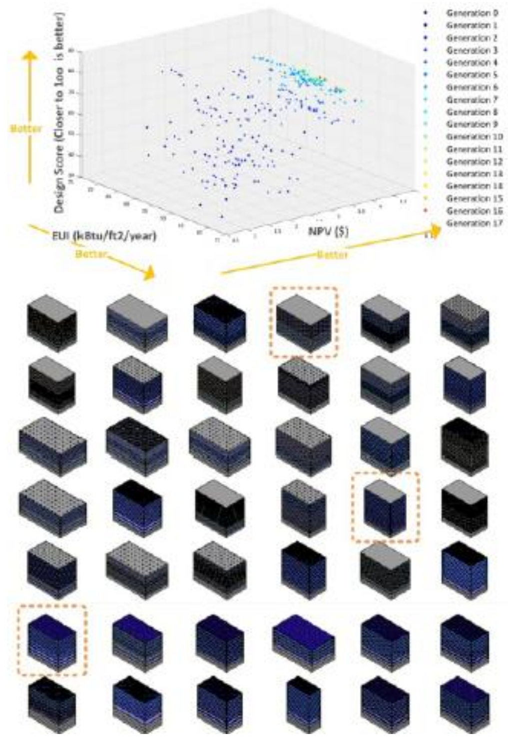

Figure 1. Sample Design Optioneering Results from [7]

DESIGN OPTIMIZATION AND EVALUATION

Evaluation of CSEs is an active area of research, motivated in part by the dearth of qualitative and quantitative models describing creativity. Carroll et al. [2] have developed, and statistically validated, six orthogonal factors to describe CSEs. These include *Results worth Effort*, *Expressiveness*, *Exploration*, *Immersion*, *Enjoyment* and *Collaboration*. The factors of creativity that are most relevant to design optioneering tools are *collaboration* and *exploration*.

Design optioneering is a creative task, with the task being how to generate and explore a set of designs that optimize against multiple, competing constraints. In building design it is commonly necessary to simultaneously consider multiple complex objectives including site utilization, structural design, building form, energy use, and construction and operation costs. The design task draws on expertise in multiple domains including structural engineering, energy simulation, architecture and finance. Improving the integration of multiple expert domains – i.e. improving collaboration – is an explicit goal of optioneering [4,6,7]. Although no quantitative measures of collaboration exist, design optioneering researchers consistently cite increased collaboration among design disciplines as a primary benefit to the approach.

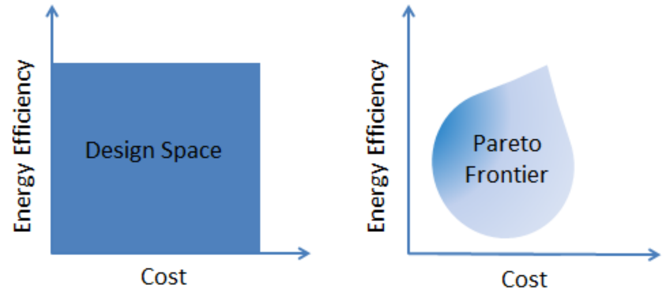

Figure 2. Design Space and Pareto Frontier (stylized)

The set of design permutations for any given design task is vast. Flager et al calculate that for the simplistic one room, steel-frame building used in their energy and structural optimization study there were $55x10^6$ possible solutions [6]. Cognitive limitations prevent users from discerning meaningful differences across solutions in sets of this size. Furthermore, time constraints prevent users from exhaustively exploring the set for top performing solutions. To address these limitations, Pareto analysis is used to winnow the set of all solutions down to a subset that is reasonably efficient across multiple objectives [7]. Figure 2 shows a stylized plot of all possible design alternatives in a design space (left) and the reduced set of optimized alternatives as computed by a Pareto analysis (right). The Pareto set identifies a subset of equally good solutions from the set of all solutions. For each member of the Pareto set there exists no other solution that is equal or better with respect to all other parameters. As an evaluation tool for creativity, the Pareto set delineates the most interesting and optimized solutions from the set of all possible solutions [9]. Calculating the Pareto set allows users to focus their design exploration among the most promising solutions.

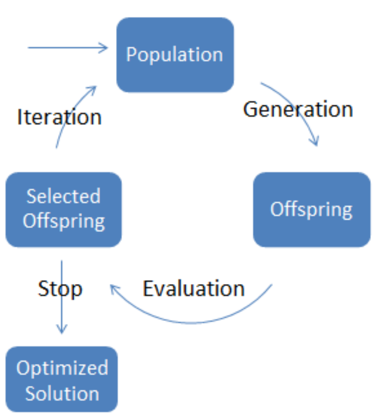

Figure 3. Typical Architecture of a Genetic Algorithm

In addition to Pareto analysis, genetic algorithms are also used to evaluate designs in design optioneering. These algorithms generate, select and breed the solution space. Users control variables such as the population size, number of iterations, probability of mutation, and stopping criteria. Figure 3 shows the typical architecture of a genetic algorithm. Genetic algorithms mimic natural selection by introducing random variation into the design process. Design researchers deliberately choose genetic algorithms over alternative optimization algorithms for their ability to evaluate discontinuous and "noisy" design spaces [6]. Analogous to natural selection, designs produced by genetic algorithms are systematically evaluated against constraints in the design environment. The most adaptive designs, i.e. the most creative designs, survive.

CONCLUSION

Pareto analysis and genetic algorithms are two built-in evaluation techniques guiding the creative output of optioneering tools. It can be argued that these evaluation techniques increase the creative capacity of the designer by generating a large number of informed guesses at desirable designs. Using design optioneering methods researchers have computationally generated and analyzed over 5,000 design alternatives in 32 hours [6] where conventional methods require 12 weeks to produce three alternatives [5]. A large set of analytically tested designs is preferable to the small set of solutions produced in the typical design project. Design theory indicates that the exploration of a large number of design alternatives is essential to successful design [3]. Software features that automatically evaluate the fitness of designs produced by the software support the creative process by focusing designers' attention on the most relevant and potentially innovative designs.

We propose that evaluation methods might best be *designed in* to CSE tools themselves. Since the creative space of design alternatives is conceptually infinite, CSEs in engineering and architecture must include evaluation support within the software that is used to generate designs. Continuous evaluation both narrows focus and expands creativity; Pareto analysis focuses the set of design alternatives to the most optimal solutions, while stochastic methods like genetic algorithms introduce randomness to expand the space.

Admittedly, this method of evaluation is lacking external validity. Shneiderman and Plaisant [11] compel us to consider that one of the most convincing measures of creativity support is a tool's ability to enable expert users to achieve their professional goals. It may be the case that the best evaluation of design optioneering tools is done by the professional consuming the designs – she is the final arbiter of the creativeness of the solution, relative to the design problem. The degree of support that a design optioneering tool provides for the creative process may be best judged by the designer's willingness to anoint one design, among many, as the most creative.

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