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SYNTHESIZING DESIGN PERFORMANCE:
AN EVOLUTIONARY APPROACH TO MULTIDISCIPLINARY DESIGN SEARCH

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ABSTRACT

Design is a goal-oriented decision-making activity. Design is ill defined and requires synthetic approaches to weighing and understanding tradeoffs amongst soft and hard objectives, and imprecise and/or computationally explicit criteria and goals. In this regard, designers in contemporary practice face a crisis of sorts. How do we achieve performance under large degrees of uncertainty and limited design cycle time? How do we better design for integrating performance? Fundamentally, design teams are typically given neither enough time nor the best tools to design explore, generate design alternatives, and then evolve solution quality to search for best fit through expansive design solution spaces. Given the complex criteria for defining performance in architecture, our research approach experiments upon an evolutionary and integrative computational strategy to expand the solution space of a design problem as well as presort and qualify candidate designs. We present technology and methodology that supports rapid development of design problem solution spaces in which the objectives of three design domains have multidirectional impact on each other. The research describes the use of an evolutionary approach in which a genetic algorithm is used as a means to automate the design alternative population as well as to facilitate multidisciplinary design domain optimization. The paper provides a technical description of the prototype design, one that integrates associative parametric modeling with an energy use intensity evaluation and with a financial pro forma. The initial results of the research are presented and analyzed including impacts on design process; impacts on design uncertainty and design cycle latency; and the affordances for "designing in" performance and managing project complexity. A summary discussion is developed that describes a future cloud implementation and the future extensions into other domains, scales, tectonic, and system detail.

1 INTRODUCTION

The research seeks to contribute to the synthesizing of an integrated design methodology of often poorly coupled and asynchronous design domains and activities. A societal driver of the research can best be understood through the fact that buildings consume nearly half of all energy used by the United States (U.S. Department of Energy 2011). A second driver of the research can be understood through the fact that the overall performance of buildings is greatly impacted by design decisions made during the early stages of the design process. Unfortunately, the early stages are also when design professionals are often unable to adequately explore design alternatives and their impact on energy consumption (Schlueter and Thesseling 2009; Flager et al. 2009). One design solution cannot satisfy optimally all functional and aesthetic requirements and needs, as certain goals come at the expense of others (Kalay 1999). The inherent trade-offs in performance-based design require simultaneous searching for aligned improvement of competing objective criteria such as energy and cost. Computing can support the design process by increasing the generation of design alternatives while providing a trade-off analysis that can be easily assessed, ranked, and filed according to multiple performance criteria—for example, by using efficient and powerful computational methods such as genetic algorithms (Caldas and Norord 2002; Wright, Loosemore, and Farmani 2002).

Performance assessments for architecture are typically made only after the initial design phase, due to the need for specialized knowledge, with simulation software that requires an expert in the field for the task (Holzer, Tengono, and Downing 2007). In addition, the incorporation and translation of parameter coupling into quantitative trade-offs to be balanced against the demands of other interests of a multidisciplinary design team is often too difficult and time consuming to be incorporated at the early stages of design, when there is the greatest opportunity for overall optimization or improvement (Caldas 2008; Fabrizio, Filippi, and Virgone 2009). The few tools that are available often suffer from a technological and methodological disconnect between designer and tool; interoperability issues with other domain expert tool sets; time-intensive analysis; and inefficient feedback methods that do not enable informed decision making (Oxman 2008; Holzer, Tengono, and Downing 2007). This research builds upon associative parametric design methodology and augments it with an evolutionary solution space evaluation approach incorporating multiple design domains and criteria to in part address this deficiency. The research utilizes parametric design and multidisciplinary design optimization (MDO) to influence design at the schematic level in the interest of exploring more energy, cost- and design-efficient design configurations earlier in the design decision-making process.

2 RELATED RESEARCH AND MOTIVATIONS

Parametric modeling is understood to decrease the time and effort needed to modify designs, while yielding improved form-finding processes (Aish and Woodbury 2005). Exploring parametric alternatives while assessing structural impact in real time is an example of a performance-based design integration (Shea, Aish, and Gourtovaia 2005). Motivated by increasing integration of design domains for alternative generation with integrated performance evaluation may be accomplished by designing parametrically (Gerber and Flager 2011; Malkawi 2005).

2.1 Multidisciplinary Design Optimization

Multidisciplinary design optimization (MDO) (or multi-objective optimization) refers to optimization methods for solving design problems that have several objective functions from multiple disciplines (Coello Coello, Lamont, and Van Veldhuisen 2007). Critical to our discussion of optimization in architectural design is Prof. Carlo Poloni's definition of MDO as "the art of finding the best compromise" (Poloni and Pediroda 1997). Although integrating parametric design tools with simulation tools is a relatively new research topic, building energy simulation tools have been in use for over 50 years (Oxman 2008; Crawley et al. 2008). Yet problematically these tools require specialized familiarity and models of sufficient level of detail in order to yield relevant results (Aish and Marsh 2011). Building performance optimization is always a multidisciplinary problem requiring multiple experts (Flager et al. 2009; Keough and Benjamin 2010). Poor technological interoperability used by different domain experts is considered a significant obstacle for MDO (Holzer, Tengono, and Downing 2007). Furthermore, a lack of real-time analysis between architecture and engineering parameters is another deficiency in current architecture, engineering, and construction (AEC) multidisciplinary design (Sanguinetti et al. 2010). To these ends there have been numerous solutions that use parametric modeling to support the MDO approach for generating integrated design alternatives more rapidly (Holzer, Hough, and Burry 2007; Shea, Aish, and Gourtovaia 2005; Keough and Benjamin 2010).

2.2 Heuristic Search and Evolutionary Algorithm

The genetic algorithm (GA) was first introduced in the 1970s as a heuristic search method inspired by the evolution processes (Holland 1975). The applications of GAs in multidisciplinary design optimization are generally understood to be suitable for managing large numbers of variables and for providing lists of optimum solutions—a Pareto front—rather than a single solution (Haupt and Haupt 2004). Our evolutionary approach is largely instigated by the work of numerous researchers who have brought to the field of design and computation the use of GAs, and by their interest in optimizing multiple performance criteria (Frazer 1995; Wang, Zmeureanu, and Rivard 2005). In design, a multicriteria GA method was applied to optimize the trade-off relationship between building energy costs and the occupant's thermal comfort (Wright, Loosemore, and Farmani 2002). GA has also been used to both shape a building's envelope according to simulated energy performance and to size and place glazing elements with regard to expected thermal and lighting performance (Tuhus-Dubrow and Krarti 2010; Caldas and Norford 2002); and for geometric form optimization and for taking into account construction cost and real-estate valuations (Rüdenauer and Dohmen 2007; Alfaris and Merello 2008). Another precedent employed GA to optimize structural design and was able to identify the optimum solution out of approximately 30,000 possible designs (Flager et al. 2009). Furthermore, recent works have combined parameterization and GA in pursuit of performance optimization (Yi and Malkawi 2009; Turrin, von Buelow, and Stouffs 2011). In this context GAs are considered a more efficient means for handling complex design problems where a Pareto front of candidates can be evolved and trade-offs can be design explored.

3 TOOL DEVELOPMENT METHOD

The objective of our prototypical technology, the H.D.S. Beagle 1.0 (the Beagle), is to provide multidisciplinary design teams with a large number of systematically explored design options more rapidly than current conventional methods. To accomplish this, the Beagle provides an integrated conceptual design and conceptual energy use with development economics in an automation and optimization routine. There are three major components comprising the tool development: parameterization, domain integration, and multidiscipline search and evolutionary optimization.

3.1 Parameterization

In order to automatically generate a solution space it is necessary to first formally define the design problem, including the design objectives, variables, and constraints. These definitions are then used to generate an associative parametric digital model. There are three domains: design parameters, energy setting parameters, and financial pro forma parameters. Design parameters are treated as design problem–specific geometry parameters to be specified by the designer. Energy-setting parameters are determined by location, system, and material variables available through Autodesk® Revit® for schematic energy analysis. Financial pro forma parameters are based on a financial calculation model to determine the net present value (NPV). Once the design problem has been formalized, the next step is to utilize these parameters as integral to each other to generate a set of possible design alternatives.

figure 1

System architecture diagram of the H.D.S. Beagle, illustrating the tool component and domain integrations, the designer-driven actions, and the automation and search operations.

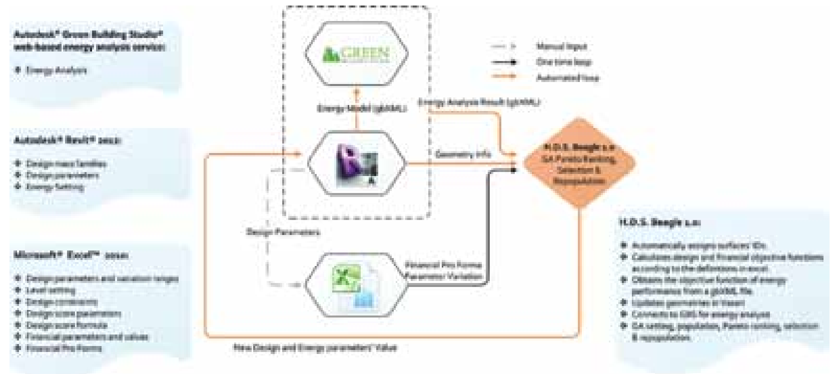

figure 1

3.2 Domain Integration

The platforms integrated in this research include Autodesk® Revit® and Autodesk® Green Building Studio® (GBS) with a Microsoft® Excel™-based financial model custom coded into an automation and optimization routine. The overall system architecture is illustrated in Figure 1.

Autodesk® Revit® is used by the designers to define a series of parameters that drive the variable geometric configurations. It also serves as an insertion point for the energy settings necessary for driving a schematic energy analysis through GBS. GBS is a web-based energy analysis service that we integrated and automated as the energy simulation engine. The Beagle also integrates Microsoft® Excel® 2010 to provide not only a means of containing the financial parameters and formula but also a platform in which designers set up design parameter ranges, constraints, space programming requirements, and the design score calculation formula. The template has been prototyped to provide extensibility to accommodate the broadest range of early stage design decision-making problems.

In order to integrate these three expert domains, the Beagle was developed in C# as a plug-in for Autodesk® Revit® through the Revit API, the GBS SDK, and the Excel® API. Our technology enables the generation of design alternatives according to user-defined parameter ranges; automatically gathers the energy analysis result of each design alternative; automatically calculates three objective functions; and uses a GA to search, rank, select, and breed an improving population and plot a Pareto front of these design alternatives.

3.3 Evolutionary Optimization

A GA was selected as the heuristic search method for this project. Terms and processes such as genes, generations, chromosomes, mutations, crossover, offspring, and inheritance are defined. Encoding was necessary to convert design intent into a language recognizable by GA. In the Beagle, genes are equal to modifiable parameters, and chromosomes correspond to individuals that are composed of these genes. The GA then optimizes an initialized set of individuals (population) using three main steps: 1) evaluation, 2) selection, and 3) population. These solutions are evaluated based on a series of fitness criteria - the objective functions of the design solution. The closer a design solution is to fulfilling all fitness criteria, the more fit it is considered, and the higher the probability that the solution will be selected to survive to the next generation, using a tournament design GA in order to avoid early convergence (Miller and Goldberg 1995). Through recombination and mutation, the population is able to generate diversified offspring. This three-step process is then repeated, with each cycle representing one step of the evolution, i.e., a new generation. The process is cyclical and continuous until an optimal solution space is generated or other stopping criteria are reached. Currently, the population method, crossover ratio, mutation rate, selection size, etc., are set by the user in the Beagle manually in order to accommodate for user preference and due to varying complexity of design problems. The fitness criteria are determined by the Beagle based on compliance with defined objectives from the three domains—design compliance, energy performance, and financial performance—and ranked. Determination of design compliance is constrained to meeting specified design program requirements. In order to determine energy performance, the energy use intensity formula (EUI) internal to GBS is chosen as the objective for finding the lowest calculated EUI, i.e., minimized energy usage. The financial performance's primary goal is to measure net present value formula (NPV) to provide estimates regarding the cost of construction, operation costs, and expected generated revenue values where maximization of NPV is desired.

4 RESULTS AND ANALYSIS

Based on the approach and tool development described above, the research team began testing and analyzing a series of practice, experimental, and pedagogical experiments. Scenario 12 (Figure 2) is representative of our most complex mixed-use tall building, intentionally a twisting double tower on a shared plinth where the interaction of one tower with the other could not be easily understood in terms of NPV, EUI, and the maximizing of design score. The results are presented through three categories: 1) impact on design process; 2) impact on design uncertainty and design cycle latency; and 3) qualitative description of the observed affordances for integrating design domains and for managing project complexity.

Table 1

Methodology	Initial Model #	Energy Result	Feedback Time
Original: In-House	1 for each analysis	1 result per run	1 day per analysis
Original: MEP consultant	1 for each analysis	1 result per run	1 week per analysis
H.D.S. Beagle 1.0	1 for all analysis	>800 results per run	800 per 8 hours

Practice-based case study of energy simulation feedback process data (design cycle latency).

4.1 Scenario Data and Results

In terms of impacting process the research has yet to acquire a statistically valid data set to say much conclusively. One previous but very different case did suggest some hurdles to surmount in order to implement in practice; these are described in part in the limitations and future work portion

figure 2

Scenario 12 parametric model design, illustrating design score criteria, constraints, modifiable parameters (genes), results, and average run times.

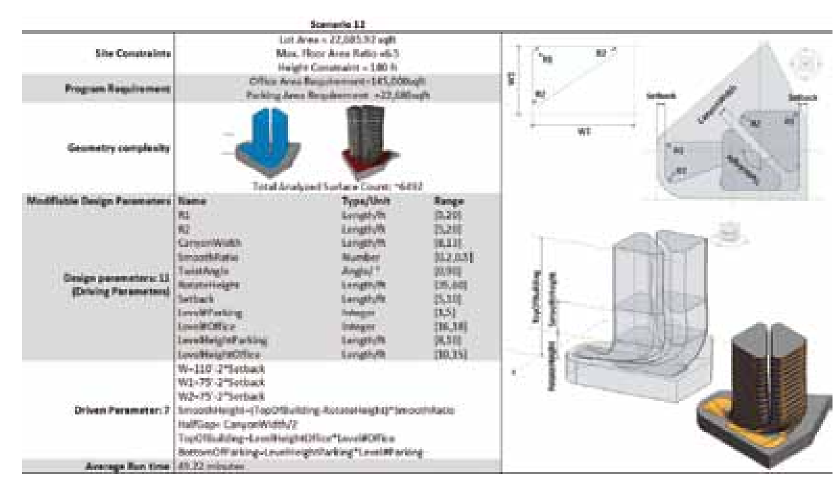

figure 2

figure 3

Parallel geometric and analytical data visualization illustrating three 2D plots of data set for three offspring of scenario 12.

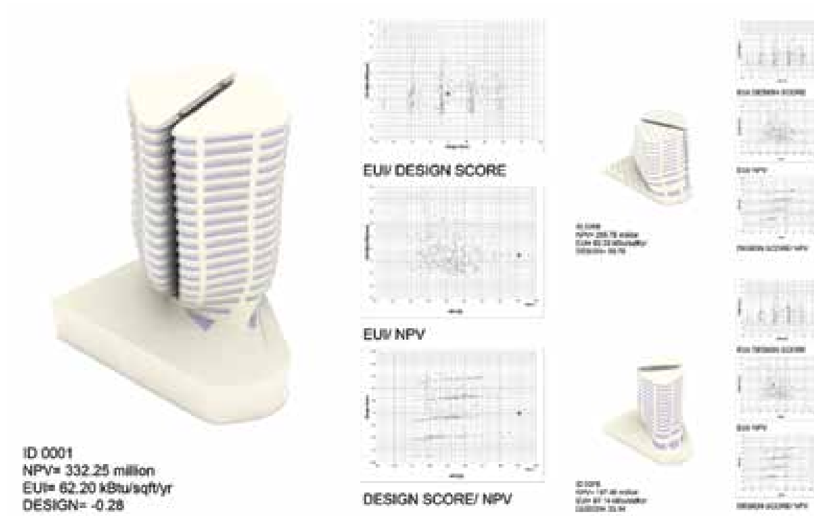

figure 3

of this paper (Section 4.2). By way of comparison, the case was developed to search for envelope configuration on a box school typology emphasizing louver patterning as opposed to complex form finding (Gerber and Lin 2012). The designers of the project had two original approaches to utilize energy performance feedback in supporting their design decision process. One was to collaborate with MEP consultants; the other was to conduct in-house analysis. However, both approaches failed to provide analysis results before the design decision had to be made. In contrast, H.D.S. Beagle 1.0 allowed the designer to go from analyzing one design per day to over 800 per day.

In terms of design cycle latency, the number of models generated after initial setup was, on average, .63 minutes per cycle and a total of 841 models over 8.8 hours, as shown in Table 1. In terms of the heuristic success for the two primary domains—NPV and EUI—the initial values were -73.46 million dollars for NPV and 57.24 kBtu/sqft/yr for EUI. While we did not reach a plateau or convergence criteria for the approximately 800 data points generated, we did begin to see a Pareto front formed on two axes and across a surface for all three criteria. We measured the following improvements for each of the two respective criteria: the best NPV value improved by 1.63 million dollars, with the Pareto solutions ranging from -72.83 to -73.46 million dollars; EUI improved by 1.08 kBtu/sqft/yr, with the Pareto solutions ranging from 56.16 to 68.37 kBtu/sqft/yr.

In terms of uncertainty and in attempting to value the generative aspect of the Beagle, there were a number of non-obvious discoveries in reading the data in conjunction with the geometric results. First, the two explored driving parameters, CanyonWidth and TwistAngle, show less impact on EUI values compared to TargetGlazingPercentage; second, Design score has a noticeable sensitivity to the value of FloorNumber in this specific scenario. This indicates that each modifiable parameter has an uncoupled but significant effect on each objective. As a result, the research suggests that the uncertainty can be decreased by providing sensitivity analysis of each parameter. Another finding is that offspring that have a better EUI value exhibit glazing area ratios of around 10–20 percent. Currently the research only explores uniform percentage opening throughout all exterior walls. Whether enabling individual opening variation will yield better EUI values within the same range is a question of interest for later research. Lastly, the range of the resultant solution space is very broad for all three objectives: NPV from 15.02 to 29.23 million dollars, EUI from 50.91 to 88.37 kBtu/sqft/yr, and Design Score from -105.80 to 90.28. This shows that the Beagle provides the opportunity for designers to explore a much broader range of alternatives with data and performative feedback

support. It is important to note that tacit rules of thumb normally employed by an experienced designer can be easily refuted as a project's geometric complexity increases, as is evident in the canyon parameter example.

At the moment, the affordances include primarily the automation of both visual geometric data, i.e., the models, in parallel to the plotted numeric analysis, i.e., the 2D graphs (see Figure 3)—a reduction in latency. What is not afforded nor necessarily expected is the solving for a single optimal result. As is evident in comparing Figure 4 to Figure 5—the final results of scenario 12—the experiment is still inclusive of designer-driven choice, where the three highlighted (i.e., chosen) versions exhibit some improved scoring, they are not necessarily the aggregate best scores as form and implicit architectural constraints come into play and become major factors for consideration in the design decision making. However, in reflecting upon the normative modes of practice, the affordance of rapid design alternative generation with an automated improving heuristic search enables complex geometries to be better understood beyond their aesthetics. Finally, this process provides significant enhancement for design exploring and synthesizing the relationship between geometry and performance.

5 CONCLUSIONS

The work presents a portion of our research into the question of how to more effectively synthesize and "design in" performance criteria in early stage design decision making. The research questions include issues of synthesizing design domains and their disparate models and competing objectives; issues of generative design alternative creation and design exploring; and, finally, issues of design evaluation and the visualization of trade-offs. While the research has progressed through 14 different practice experimental and pedagogical scenarios, numerous questions remain unanswered. While we can document empirically the generation of more design alternatives and the near-simultaneous ranking and improvement of solutions through an evolutionary optimization approach, issues of integration into practice-based design workflows and competition with many tacit rules of thumb have yet to be validated as an improvement. Future work is being designed to further investigate how to acclimate this process into early design stages in practice. A continuation of the research includes further development of domain integrations such as structural design, more in-depth environmental design criteria, and improvement of the optimization algorithms, data visualization, and designer interfaces (Figure 5).

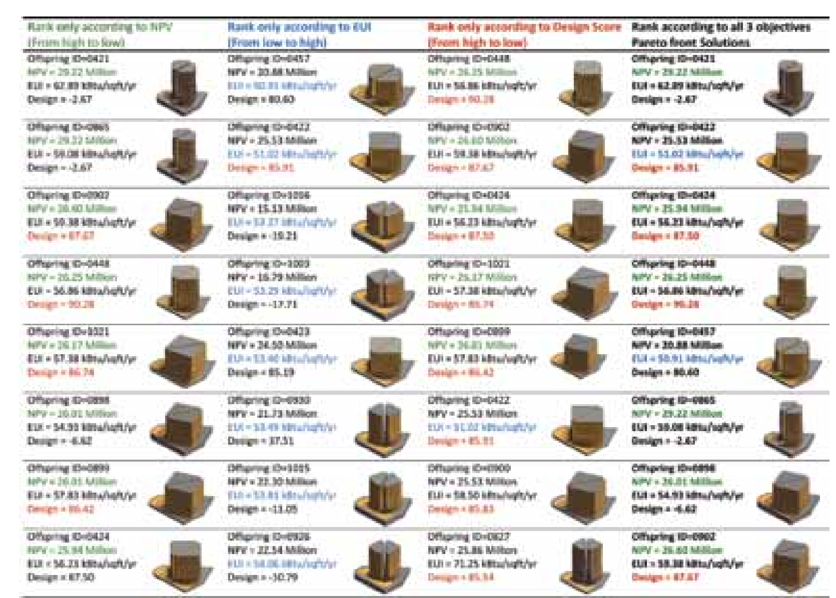

figure 4

figure 4

Subset of Scenario 12 data illustrating the highest-ranking design alternatives for each objective from the overall solution space. The first column shows the eight design alternatives that have the highest NPV values; the second, those with the lowest EUI values; the third, those with the best design scores; the last column shows the design alternatives that have the best ranking when considering all three objectives according to the Pareto ranking method.

figure 5

This figure illustrates a subset of 60 design alternatives providing a designer with feedback via a parallel view of geometric and analytical visualization.

figure 5

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