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DESIGNING-IN PERFORMANCE THROUGH PARAMETERISATION, AUTOMATION, AND EVOLUTIONARY ALGORITHMS

'H.D.S. BEAGLE 1.0'

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Abstract. Design is both a goal oriented and decision making activity. It is ill-defined by nature as designing includes weighing and understanding trade-offs amongst soft and hard objectives or in other words vague or imprecise and computationally definable criteria and goals. In this regard designers in most contemporary practices face a crisis of sorts. How do we achieve performance or sustainability under these large degrees of uncertainty or with limited design cycle times? Fundamentally design collaborations, teams of domain experts, are not typically given enough time to design-explore, generate design alternatives in order to find or evolve solution quality through expansive design search spaces. Given these limitations of time and the ever more complex criteria for 'designing-in' performance our research approach provides a computational strategy to expand the solution space as well as pre-sort and qualify candidate designs. The research presents a novel methodology and technology framework and an initial implementation that was developed to enhance the human activity of design exploration, domain integration, and further evolve design process for performance goals. The research does so through generating and optimising a highly correlated solution space in conjunction with a near simultaneous evaluation of design alternative fitness.

Keywords. Parametric design; multi-disciplinary design optimisation (MDO); evolutionary algorithms; performative design process.

1. Introduction

The early design stage of any project can be considered the least constrained phase where design decision-making has the most significant impact on a project's ability to maximise its design objectives. Of particular importance to our research are the objectives for performance; aesthetic, energy and financial. In current practice, domain specific knowledge necessary to meet the requirements of individual objectives has been poorly integrated into an overall design process. Simulated performance feedback is often performed in an asynchronous fashion. This issue expands once coordination of different disciplines is taken into account and limitations of time and resource are considered. In this paper the development of a framework and technology that allows for rapid development of multi objective design problem solution spaces is presented. The use of an evolutionary approach is described, in which a genetic algorithm is used to both automate the design alternative population while facilitating multidisciplinary domain optimisation. This methodology specifically enables a generative process where performance criteria are integrated into the early stage model to improve upon design cycle latency and design uncertainty through visualised and analysed convergence of multiple design criteria. The paper provides a technical description of the performance based design methodology and platform design that integrates associative parametric models with an energy use intensity calculator and a financial pro forma. The initial results of the research are presented and analysed including noted impacts on the design process regarding design cycle latency and the affordances for designing in performance and managing design complexity. A summary discussion proceeds to explore the future of *design optioneering* based on our continuing development of the technology for a cloud-based implementation.

2. Precedents and background research

In contemporary practice, designers focus mostly on meeting the functional and programmatic performance criteria to satisfy the design requirements in early stages, while other performance criteria are deferred until a later phase (Turrin et al. 2011). Dealing only with narrow ranges of performance without quantitative criteria in the early phase decreases the quality of the final design solution (Chong et al. 2009). Generating expansive design solution spaces in early design stage is also absent from the typical architectural design process as designers mostly focus on small sets of alternative solutions (Turrin et al. 2011). However, repeatedly generating and evaluating design alternatives in the conceptual stage provides most satisfactory design solutions (Liu et al.

2003, Yi and Malkawi 2009). Generating alternative geometric configurations is a significant affordance of parametric modelling, and the number of tools and methods that support architectural design are increasing (Burry and Murray 1997, Hesselgren et al. 2007, Gerber 2009). Although generation of multiple design alternatives is a major advantage, the requirement of evaluating each alternative individually according to pre-set performance criteria arises. Furthermore the number of performance objectives increases both complexity and time necessary for the evaluation process (Flager et al. 2009). Integrating a set of performance criteria or parameters in early design process allows for multi-disciplinary design collaboration due to generation and performance evaluation being done simultaneously (Holzer et al. 2007). However, this also requires domain specific feedback from experts and their simulation tools in order to drive the design evolution. Traditional design entails manual adjustments to the design at hand after performance evaluation have been carried out by domain experts with no linking between geometry and engineering parameters (Sanguinetti et al. 2010). Researchers have identified this lack of dynamically linking simulation data to design models as an obstacle for performance based design (Oxman 2009). Automated generation and evaluation of design alternatives shortens the design cycle and enables design exploration (Grobman et al. 2009). In addition as satisfying design objectives is often an intrinsic trade-off between competing objectives, genetic algorithms (Frazer 1995) have been seen to offer potential solutions by facilitating search and ranking through expansive possible scenario sets (Wright et al. 2002).

3. 'H.D.S. BEAGLE 1.0'

In order to acquire and provide efficient feedback to support early design stage decision making, the development of a method and tool the *H.D.S. Beagle 1.0* was structured through three major activities: parameterisation, automation, and evolutionary algorithm.

3.1. H.D.S. BEAGLE 1.0: PARAMETERISATION METHOD

In order to automatically generate a solution space, it is necessary to first formally define the design problem regarding design objectives, variables, and constraints (Marks 1997). With regards to this research, design objectives are defined as the goals of the optimisation exercise. Constraints are defined as the criteria that a design option must satisfy in order to be considered a feasible design solution. Variables are defined as parameters of the design that can be manipulated for a defined range to achieve objectives and satisfy constraints. These definitions were then used to generate an associative parametric digital model – in this case using Autodesk® Revit™ – that was driven by the design variables specified. The purpose was to provide designers a visual means of observing direct cause and effect of modifying variables on the resulting design configuration to ensure consistency with design intent. In accordance with the interest of the project, all necessary parameters were divided into three primary categories: design, energy settings, and financial pro forma.

Design Parameters: Design parameters are specified by the designer and are the driving factors of form and building massing. The geometric parameterisation process takes into consideration 1) Form driving parameters for design intent, 2) Site constraints parameters, and 3) Level setting parameters to vary level-to-level heights and assign space usage accordingly. Level setting parameters were discovered to be particularly critical as they enabled automated exploration of design program configurations.

Energy Setting Parameters: As the project utilises Autodesk® Revit™ to form the energy model, energy related parameters can be varied into two categories: 1) global energy settings (or project-wide setting); 2) individual energy settings associated with mass zones and mass surfaces. To form the energy model, Autodesk® Revit™ transforms a defined mass into an energy model with the following elements: Mass Exterior Wall, Mass Floor, Mass Glazing, Mass Interior Wall, Mass Opening, Mass Roof, Mass Skylight, Mass zone and Mass Shade. Each mass element provides properties that are related directly to expected energy consumption. Settings within the energy setting dialog box, or global energy settings, are applied to all the mass elements. Currently, *H.D.S. Beagle 1.0* utilises 13 global energy settings, along with enabling individual surface energy settings.

Financial Parameters: Parameters of the financial pro forma are based on a simplified financial calculation model that determines the net present value (NPV) of the design in question. The financial model and parameters used in *H.D.S. Beagle 1.0* can be separated into 4 sets: construction cost, operation cost, revenue and financing. With regards to the construction cost, 10 items were taken into account. The construction costs are designed to correlate the geometric model with its conceptual construction type. Conceptual operation costs are calculated based off of program areas combined with schematic energy costs provided by the energy analysis results from Autodesk® Green Building Studio. In terms of revenue, this is determined according to space usage and space program type. Relevant financial parameters were generated in a worksheet as part of the Excel template within *H.D.S. Beagle 1.0*. The values and NPV worksheet provides flexibility needed in order to calibrate the financial model to reflect market values and project specifics accordingly.

3.2. H.D.S. BEAGLE 1.0: AUTOMATION

After designers have defined the problem and objectives of a design project, a solution space is be automatically generated. To solve the current interoperability issues and automate the process, *H.D.S. Beagle 1.0* was developed using C# to be a plug-in for Autodesk® Revit™ to integrate three domains: design, energy and financial. The platforms integrated by this research include Autodesk® Revit™, Autodesk® Green Building Studio™ (GBS), and Microsoft® Excel™. Autodesk® Revit™ was used to provide the parametric modelling platform and geometric configuration engine. Autodesk® Green Building Studio™ is a web-based energy analysis service that served as the energy simulation engine. Microsoft® Excel™ provided not only a means of containing necessary financial parameters but also an interface to hold design parameter ranges, constraints, and formulas needed to calculate design scores. The automation loop of *H.D.S Beagle 1.0* was enabled by custom coding of the Revit and Excel API's and GBS SDK.

3.3. H.D.S. BEAGLE 1.0: EVOLUTIONARY ALGORITHM

One brute-force solution to parametric design is to traverse all possible combinations of all possible design variables in order to isolate optimal design solutions. However, such an approach is time prohibitive as design solutions exponentially increase with the number of variables explored. For example, 5 design parameters for an orthogonal building with 13 energy parameters, where each parameter only has a choice of 2 values has a potential number of $2^{(5+13)}$ = 262,144 solutions. If each solution takes 1 minute to analyse, a full analysis of all solutions would require approximately 182 days to generate. Real design problems typically possess more than just 5 design parameters, and each parameter has larger ranges than 2. The use of Genetic Algorithm (GA) was employed as a means of providing a more efficient manner to intelligently search through and locate optimal results. Our GA optimises an initial set of individuals using three steps: 1) evaluation, 2) selection, and 3) population. During initialisation, quantities of dissimilar individual solutions are produced. The solutions are then evaluated based on a series of "fitness criteria" and selections are made by the programmed fitness function, which evaluate the rate how close the solution is to the optimal solution. The more "fit" a solution is, the higher the probability that the solution will be selected to "survive". The next step serves to propagate the population through a recombination of genes and mutation. This three-step process is then repeated, with each cycle representing one step of the evolutionary process, i.e., a new generation. The process is cyclical and therefore continuous until an optimal solution is generated or other stopping criteria are reached. In order to provide practical feasibility of GA within *H.D.S. Beagle 1.0*, the method and definition of some key components were defined as described below:

Encoding In GA, individual genotypes are often represented by binary strings. Each binary bit is considered as a gene, with the binary string being named a chromosome. However, this approach allows for "mutations" to occur which might allow the design to exceed previously defined constraints. Therefore, in order to ensure compliance with design constraints, the actual parameter value is used directly for each design variable instead of binary strings to represent the genes on the chromosome in GA. Such an encoding method is widely used to solve practical problems.

Fitness Criteria & Fitness Function In our research cases, three objective functions are used to evaluate offspring and determine "fitness" levels of individual offspring.

Objective Functions of *H.D.S. Beagle 1.0:*

D_{obj} = Max. DRCP

F_{obj} = Max. NPV

E_{obj} = Min. EUI

Where

D_{obj} = Design Objective Function

F_{obj} = Financial Objective Function

E_{obj} = Energy Objective Function

DRCP =Design Requirement Compliance Percentage

NPV = Net Present Value

EUI = Energy Use Intensity

Evaluation As design problems are a multi-objective optimisation problem (MOP) including multiple objective functions, the optimum becomes defined as locating solutions which compromise (trade-offs) rather than a single optimal (Coello Coello et al. 2007). Therefore, the Pareto optimum was selected as the optimisation method for this project. A specific Pareto front Ranking Method was adopted for our research.

Selection Our initial selection method was based on the fitness proportionate selection. In this selection method, the probability that each individual is selected is proportional to its perceived fitness in that generation, i.e. the individuals ranked highest are most likely to be selected than those ranked lower. However, this method may lead to early convergence by premature super individuals. To avoid this drawback, the tournament selection method was chosen instead (Miller and Goldberg 1995).

Population method Currently, the population method, crossover ratio, mutation rate, selection size, and maximum iteration number are set by the user manually in H.D.S. Beagle 1.0 in order to accommodate for user preference and due to varying complexity and scale of design problems.

Convergent criteria In the current version of the *H.D.S. Beagle 1.0*, there are two mechanisms that will stop the GA; the first is defined by the user as the maximum iteration number when initialising the GA; the second is defined when the GA reaches three generations that have the same optimal result i.e. there no longer is a quantifiable improvement or difference. At this point the GA will determine that the design has reached the optimal solution.

4. Case study

In order to test the capabilities of *H.D.S. Beagle 1.0*, both real world design problems and hypothetical design scenarios were utilised. The case presented here was an example of a real world design problem adapted to *H.D.S. Beagle 1.0* and used to demonstrate the capabilities of the tool. The project used for this case study was provided by a design team, who is developing a high-performance K–12 school prototype building design with approximately 25,000 to 30,000 square feet of usable program space. The intention of this design was to generate a flexible and efficient prototype design that could be replicated and adapted to multiple sites. The design intent provided by the designer of this project expanded upon the requirements set forth by the client to achieve a net zero energy building configuration for each site using a flexible module created by the designer.

Original design Process – in house In the original design process a configuration of the adaptable module was generated for a specific site in an attempt to maximise the expected efficiency of the design. Once a design was generated then the configuration was analysed by creating an energy model in Autodesk® Revit®, and exporting the model into a gbXML format for Autodesk® Ecotect® and eQuest, for analysis. Once the analysis was obtained then the design was manually altered according to designer experience and another analysis was run in order to determine any measurable difference between the designs. However, this trial and error process was not efficient enough to provide relevant feedback in a timely manner. This is in part due to interoperability issues between the software used. This is also in part due to that even after the analysis was generated using the tools previously mentioned, there was not the ability to isolate direct cause and effect of design changes to the expected performance of each design.

Original design process with MEP consultant During the design process an MEP engineer was employed to assist in generating a more efficient design configuration using the adaptable module previously mentioned. The intent was that the MEP engineer would be able to provide a more efficient starting point for the design and be able to aid in providing suggestions for optimising the design configuration's system efficiency. However, the result was that the MEP engineer was able to provide suggestions for optimising systems within a single design configuration and was unable to aid in the optimising of the design configuration itself. In addition, the analysis cycle for each design configuration required 1 week, thereby minimising the results of the analysis on the design configuration due to time constraints. This is in part due to the level of detail of the analysis provided by the MEP engineer for each configuration. While the in house analysis provided by Autodesk® Ecotect® and eQuest was a preliminary schematic analysis, the MEP engineer analysis was provided at the level necessary for generating final construction documents. Therefore, while the MEP analysis provided was more complete for each configuration, it was not efficient enough to provide relevant feedback in a timely manner to support decision making at the schematic design phase of this project.

H.D.S. Beagle 1.0 application The introduction of the Beagle here was used as a test to emulate the design process and determine if a notable improvement in the efficiency feedback loop could be observed. In order to utilise Beagle for this project the objective of the design and desired variables required explicit definition at the beginning of the process. At this point the designers defined maximised energy efficiency as the overall objective. The base geometry in this case is fixed, however, the glazing ratio, sill height of glazing, and depth of shading devices is variable for optimising for different sites. Figure 1 summarises the design parameters and the results of south facing wall. The Beagle ran 5 times with different site orientations of: 0, 22.5, 45, 67.5 and 90 degrees. *H.D.S. Beagle 1.0* successfully presented the optimal configurations for each orientation within 11 generations. The total time spent for each run was around 6 hours with 500 configurations analysed each time.

TABLE 1. Process Comparison.

	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

5. Results and conclusions

In our *H.D.S. Beagle 1.0* research we observed findings that so far demonstrate an improvement in the performance of generated design solutions within the context of this and other case studies. There has also been a significant observed reduction in design latency. *H.D.S. Beagle 1.0* allowed the designer to go from analysing one design per day to over 800 per day (see Table 1).

Given the exponential complexity of design problems the benefits from utilising this type of methodology are substantial. Comparing the three processes used during the case study, *H.D.S. Beagle 1.0* was able to provide relevant feedback in a timely manner in order to influence the schematic design phase of this project. Future work needed is to further investigate how to acclimate this process to accommodate early stage design. Of interest is the design process of translating design problems into formulaic parameters that can then be explored by *H.D.S. Beagle 1.0*. As a there are elements of design which are resistant such a translation, a full investigation of these elements is underway in order to maximise potential benefits or to more accurately gauge the relevance of *H.D.S. Beagle 1.0* to the design process. A second continuation of the research includes further development of the optimisation algorithm, data visualisation and designer interfaces.

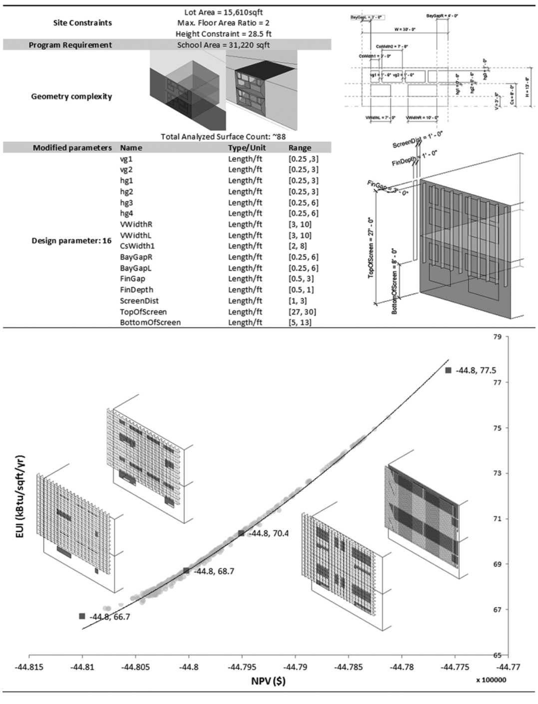

Figure 1. Analysis result summary.

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