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ASSOCIATIVE PARAMETRIC DESIGN AND FINANCIAL OPTIMISATION – CASH BACK 1.0

Parametric design for visualising and optimising return on investment for early stage design decision-making

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Abstract. Cash-Back 1.0 presents research on the development of methodologies and technologies to simulate the cause and effect of early stage geometric design alternatives of buildings and the real time results upon financial pro-forma. Through the encoding of design rules and their associative relationships to financial pro-forma the research illustrates enhanced visualisation of early stage building design decisions and their cumulative impact on financial goals and constraints. The research presents value an associative parametric design process affords often-disparate domains through correlation and visualisation. The paper describes incorporation of a feedback loop between pro-forma and geometric models in conjunction with an optimisation method. Given the level of uncertainty in early stage design decision making the research contributes partial solutions to the domain problems of design decision uncertainty and design cycle latency and is further argumentation for increased use of parametric design methods and automation to support design domain integration.

Keywords. Parametric design; genetic algorithm; design decision support; multi domain optimisation; domain integration.

1. Introduction

Architecture, engineering, construction professionals and owners need to define objectives, propose and iterate on options, analyse these options with respect to the pre-defined goals, and make decisions conventionally with high degrees of uncertainty in early phases. Early stage design decision making is often based on tacit rules of thumb and reflection (Schön 1983), and although given the opportunity to correlate competing objectives, they are rarely visualised and understood as parameter coupling problems (Hirschi and Frey 2002). Design uncertainties are exacerbated by large gaps in the correlation of each of these domain experts' goals; the linking of project geometry to financial drivers and objectives is our case in point. These gaps in part exist as a result of differing tool sets, differing problem definition, differing representation and abstraction methods (Mitchell 1990), and differing ability to visually and analytically communicate the cause and effect of their specific design domain decisions for a project alternative (Akin 2002). Design is by definition an ill-defined problem computationally as there are multiple solutions typically as a result of multiple objectives (Simon 1973). Adding to this complexity, design is a social and technical process where there is a need to coordinate poorly linked processes and data amongst a wide range of team members and stakeholders (Fischer 2006). This lack of linking and correlation is in fact where the research starts.

The research here presents a prototyped enhancement for early stage design and domain integration which is produced in terms of rapid generation of design alternatives that are visualised, qualified and quantified across multiple objectives, design and financial, leading to a higher fidelity understanding of a project's simplified return on investment (ROI).

2. Research motivations

The research is motivated by an interest in proving out the value of parametric design as a core methodology for improving upon domain integration, design cycle latency reduction, and further demonstrating the necessity for design automation and integrated optimisation. More narrowly we enumerate the research motivations through a set of contemporary deficiencies in traditional design and planning process; 1) deficient rapid design alternative generation; 2) deficient domain integration; 3) deficient visualisation of cause and effect; 4) deficient use of sensitivity analysis; and 5) deficient understanding of the complexity inherent in parameter coupling problems. Building designs are based on multiple participants, multiple objectives and attributes which include, but are not limited to, technical, financial, aesthetic, environmental and functional aspects (Smith and Jaggar 2007). The decisions made during the early design stage in relation to these attributes affects the real value of the project (Jaggar 2002). Leveraging design optimisation and domain integration approaches in the early phases offer the greatest influence upon a project's costs and for minimising expenditures associated with the design (Bon 1989). Research of current industry practices indicate a propensity to rush the design and planning stage forfeiting the benefits of paying attention to cost estimation (Smith and Jaggar 2007) arising from the lack of integrating such requirements into the design process (Akin et al. 1998). Furthermore the lack of correlating development economics and objectives into the design process has been under-developed and explored (Ferry et al. 1999, Wong et al. 2005). Architects somewhat uniquely prefer to contemplate more design alternatives than other professionals while searching for a design solution (Akin 2002). Parametric design tools allow designers to generate more design options more rapidly (Aish 1992, Burry and Murray 1997, Gerber 2009). However in doing so the design team also must evaluate performance criteria for each design solution in terms of requirement and constraint satisfaction. Rapid generation of design alternatives coupled with rapid analysis allows designers to minimise the design cycle and improves the quality of the end product (Yi and Malkawi 2009) however this has yet to become the normal practice in the early stage modeling of a financial pro-forma in concert with programming and massing design studies. The absence of automatic integration of discipline specific information is costing AEC professionals valuable time (Flager et al. 2009). The research demonstrates an improvement upon the current level of domain integration, in particular the developers' pro-forma with the concept and massing program models of the architect. The integration of multiple domains leads to the problem of multi-dimensional or multi objective optimisation. As with all 'ill defined' design problems optimality is a trade off. However through integration a design team can better reduce uncertainty and understand the trade-offs through a correlated visualisation and empirical quantification of these trade offs (Gerber and Flager 2011). Another deficiency is of visual clarity of the project's constraints and their impact on geometry and financial models. While current modes of development practice—'go no go' decisions on projects—rely on rules of thumb and quick calculations owner developers are not being given the opportunity to see visualised optimality in terms of overall massing, site coverage, and programmatic mix; geometry and its cause and effect on ROI. A further deficiency is of a design team's ability to understand cause and effect with sensitivity. Sensitivity analysis provides designers a tool to measure the relationships between the multiple domain objectives (Saltelli et al. 2000). While it is widely understood that structural costs and geometric differentiation will have large effect upon project financials, it is not part of current design practice to visualise a sensitivity analysis that can be quantified through generation of many design alternatives. Crucial for multidisciplinary design optimisation is the ability to identify the weighting of design trade-offs, what-ifs and their impacts on the different disciplines (Hardee et al. 1999). Coupling among design tasks is an important measurement of the complexity which in turn severely affects the design cycle completion time and design solution quality (Hirschi and Frey 2002). Design complexity increases rapidly when the interdependencies between design elements, or number of parametric relationships grow (Erhan et al. 2010). Fundamentally the human designer's inability to manage a large number of coupled parameters inherent in a multi-domain problem such as the optimal programmatic and massing and financial model of a building supports the argument for increasing the formalisation of parametric process and the use of automation techniques for linked domains.

3. Precedent solutions and background research

Associative parametric design methods and tools have been used as an answer to many deficiencies listed above (Mitchell 1990, Burry and Murray 1997, Motta 1999, Aish and Woodbury 2005, Kilian 2006, Gerber 2009) including for; form generation and structural optimisation of a high-rise tower considering cost and value relationships (Chok and Donofrio 2010); rapid design and structural geometry alternative generation (Rolvink et al. 2010); improving collaboration of design team linking with other design disciplines (Hladik and Lewis 2010); and for sharing domain knowledge by providing rapid design performance feedback (Shea et al. 2005, Holzer et al. 2007, Flager et al. 2009) for examples. Another precedent was developed to assist architects with understanding the cost of construction projects in the initial design stages (Jrade and Alkass 2007). Another, ViSA (Visual Sensitivity Analysis) method was proposed to help in decreasing the complexity related to interdependencies between design elements by visualisation of sensitivity of parametric design models (Erhan et al. 2010). Furthermore, with the advent of Building Information Modeling (BIM) the software providers have begun to further offer cost estimating features to assist multidisciplinary team an ability to forecast their ROI (Azhar et al. 2008). Building volume optimisation (BVO) is suggested in early design stages for finding cost efficient building-volume designs by pointing out the dependencies between geometry and cost (Schoch et al. 2011). However, there still remains a gap in tool and method development to specifically more tightly couple the developer's financial modeling and objectives to that of early stage design modeling.

The research method used for the development of the prototype tool named 'Cash Back 1.0' is based on three primary activities: problem formulation, process integration, and design exploration and optimisation. The first step is to formally define the design problem including the design objective, variables and constraints. The design objective of the research is to visualise and optimise return on investment ROI. The constraints are the criteria—bounding box for example—that a design option must satisfy to be considered feasible. Finally, the variables are the parameters—program mix for example—of the design that can be manipulated within defined ranges to achieve the objectives and satisfy the constraints from which we build an associative parametric digital model. The second step and goal of the process integration activity is to link the design model to the financial model in the form of excel tables and then to the automation and optimisation mechanism. Next, the data flow between the tools is automated to reduce design cycle latency that is pervasive in current design practice. Once the design problem is formalised and an integrated process model has been created, the designer can then design explore (Kilian 2006). However, exploring the design space using manual trial and error methods is still impractical due to the large number of possible alternatives. In this case, an optimisation technique using a genetic algorithm is applied to systematically breed, evaluate and rank the design space in an automated fashion. By generating plots of the alternatives along constraint ranges, trade offs and competing parameters can be discerned and decided upon.

4. Tool design

'Cash Back 1.0' was designed through use of Rhino, Grasshopper, Galapagos, and Excel. The tool was conceived of as a prototype with placeholders and variables for future incorporating of additional constraints and pro forma requirements. The Grasshopper algorithm definition is divided into 8 parts named according to their functions:

1. *Site constraints*: defines the allowable dimensions of the site including the boundaries, setbacks, and maximum allowable building height, which derive a bounding box for maximum geometric envelope. All parameters in this part are constant throughout the entire optimisation process, and defined by the designer.
2. *Program ratio*: divides program into 3 varying ratios of retail, office and residential areas; the sum of all ratios should not exceed 1.
3. *Program geometry*: defines the length and width of each program's base, and height portion of the building that accommodates it. This parameter is used as a genome (variable) for the Galapagos optimisation process, through the generation of massing configurations of each program.
4. *Continuous geometry*: defines the upper surface plane of each program mass from which the next mass is parented and generated. This part of the algorithm is necessary to ensure that the upper mass length and width change as a variable, and are dependent on the upper surface dimensions of the mass below; whenever the lower mass changes, the upper mass automatically optimises

itself to accommodate changes, maintaining an overall programs ratio of 1.

5. *Cost and revenue*: defines a series of simplified mathematical functions for cost and revenue calculation based on varying surface floor areas and number of floors. This component is structured to be extensible and to accommodate real world cost complexity.
6. *Profit calculation*: defines a series of simplified mathematical functions of the concept of net profit calculations, through subtracting total cost from total revenue.
   Floor surface area × no. of floors = overall program surface area
   Selling price per sq. ft. × program overall area = total revenue
   Cost per sq. ft. × program overall area = total cost
   Total revenue – total cost = estimated profit (fitness value)
   This component is structured to be extensible and to accommodate real world profit calculation methods such as net present value and internal rate of return equations.
7. *Galapagos*: is an evolutionary algorithm component that, in our case study, works off independently driven parameters and is based on one calculated fitness value. The single-numerical fitness value is defined as the subtraction of two hypothetical calculated market values: overall construction costs and total sales revenue, with profit maximisation as Galapagos' optimisation objective (Rutten 2010).
8. *Excel exporter*: defines an excel exporter that has been incorporated into the algorithm to export the values of floor plate areas, heights, and dimensions to the developers' excel spreadsheet for their further use and investigation.

4.1. CONTROL GENES AND FITNESS VALUE

The genetic algorithm component, Galapagos, breeds designs though generations and offspring by altering the parameters i.e. control gene values. These genes include (Figure 1):

9. *Residential Program ratio:* one ratio composed of three values, each defining the number of floors of each program, whose sum is equal to 1. Within this context, only the residential value is altered by Galapagos. The other two values are determined by changing the parameters mentioned below.
10. *Base length of one side of the volume (side X or Y):* changes the length of one of the sides of the program mass. The other side is determined by altering overall floor plate area.
11. *Floor-to-floor height:* altering the height of each floor, which consequently changes the number of floors of each program within the bounding box defined by the constraints.
12. *Program overall area*: changes the overall area of each program which impacts the number of floors and the size of floor plates.

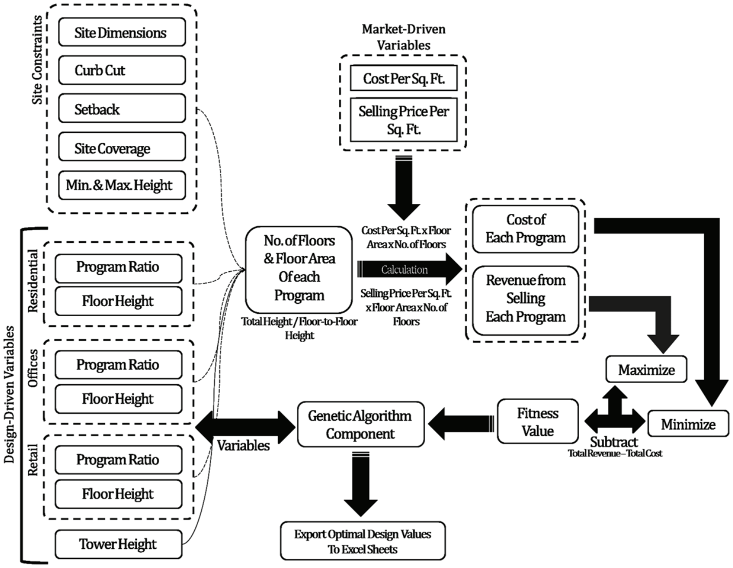

Figure 1. Optimisation workflow showing the design-driven and market-driven variables as well as the sequence of optimising the form.

While the control genes are independently driven numerical sliders, the fitness value is a dependent number calculated using a series of simplified mathematical functions that operate based on the control genes, and site and program constraints and requirements. In this working context, the series of generations were generated from an initial genome (parent) with the following parameter values:

Residential program ratio = 0.60
Floor-to-floor height: Retail 4.50 m, Office 4.20 m and Residential 3.5 m
Base length of one side: Retail 102 m, Office 65 m and Residential 132 m
Total Program Area: 400,000 m^2

These values represent a basic scenario of a mixed-use tower for experimental purposes where optimising programmatic mix for profitability is the driving fitness criteria. Within this framework, Galapagos breeds the fittest genomes a product of parent and mutation factors to populate another generation, and so on. This process results in eliminating parameters that performs worst and breeding parameters that are most fit until Galapagos hones in on a generation with the most-fit offspring. In our case study, the selected offspring showing the highest hypothetical profit value is a tower with overall residential volume of 280,000 m^3, offices area of 430,000 m^3, and retail area of 1,900,000 m^3.

5. Results and analysis

With the linking of the four components; the parametric model, the automation algorithm, the spreadsheet and the genetic optimisation algorithm, the designer is able to more efficiently integrate into a project workflow the ability to rapidly design optioneer with return on investment (ROI) incorporated a-priori. ‘Cash-Back 1.0’ offers a way to efficiently create a parametric model with capabilities to calculate and visualise (ROI) during the schematic design phase. The system provides for multi-objective optimisation of building geometry in search of an optimal programmatic configuration that provides maximum revenue and minimum expenditure associated with the design and construction. For this experimental study, ’Cash-Back 1.0’ generated 56 generations. A pareto optimal front is noticeable from the plotting of the data set as the solution space curve flattens and illustrates smaller and smaller variations evidencing of honing in on a program mix and increase in profitability. The optimal solution for our initial experimental mixed-use case can be seen in (Figure 2) Generation 12.

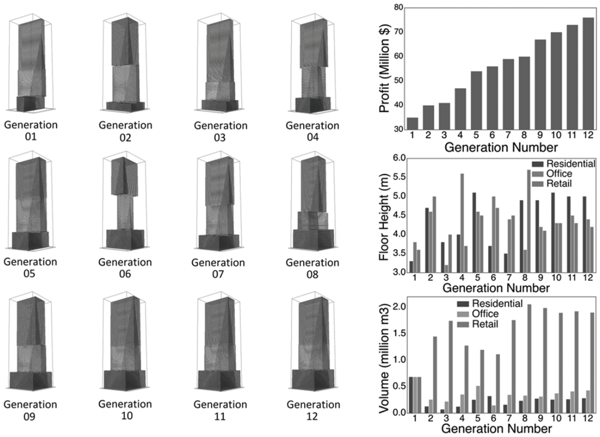

Figure 2. Illustration of a sub-set of single offspring from 12 generations illustrating an optimisation of project profitability as functions of design parameters. The hypothetical profit value of our mixed-use building goes from 35 to 76 million seen top right, while Floor Height and Volume values are changed accordingly.

6. Conclusion

The paper presents a prototype that integrates disparate design models from different expert domains, their often differing and competing goals, in order to rapidly communicate trade-offs and maximise project value. The integration minimises errors based on uncertainty and minimises latency in the generating and evaluating of large multi-objective solution spaces (design alternatives). The research builds upon parametric design technology and methods, automation and optimisation technologies and methods, and creates a multi-disciplinary design and analyses processes to optimise for project value, here initially and purposefully limited to simplified project financial pro-forma. It presents a partial solution for the problem of deciphering cause and effect where the understanding of the weighting of factors can be near impossible without computation. 'Cash-Back' is being continued through the research and development of more robust implementations on multiple platforms including Gehry Technologies Digital Project tied into a commercial risk analysis package and a custom implementation using Autodesk's Revit and Green Building Studio as an energy use intensity calculator. These tools are being applied to both hypothetical and real world projects to amass a data set to statistically analyse the improvement on the quality of solutions. In conjunction the research looks to continue to develop metrics that look at design process map improvements, design cycle latency for example by virtue of implementing these tools into early stage design decision making.

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