Multi-criteria optimisation in the design of modular homes

from theory to practice

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Multi-criteria optimisation searches by a genetic algorithm define a Pareto optimal front, a state in which one objective can only be improved at the expense of another. But optimisation is not a search for the best but for better - the goal is to improve performance by trading-off conflicting criteria or objectives. A live case study is the focus of this search with parameters behaving as genes and objectives as the environmental shapers of the phenotype. The genetic algorithm is an effective and powerful tool in the computational design tool box, one which can improve the design process and the fitness of its outcomes.

Keywords: multi-criteria optimisation, genetic algorithm, parametric modelling, modular homes

INTRODUCTION

The subject of this paper is multi-criteria optimisation using a genetic algorithm (GA) applied to a live case study (Figures 1 & 2). GAs are seldom used by architectural practices for optimisation searches to inform their workflow and improve outputs and the reasons for such reticence might include: methods and potential benefits are not well understood; searches can be complex, taking time to understand and set-up; and lastly, authorship of the design is less distinct or individual than with the traditional design process.

This paper will review existing literature on the subject of GAs before outlining the case study and the outcomes of an application of this method. The application of GAs has often been demonstrated for the early stages of design optimisation, however the focus here is on the intermediate stages, how they influence and inform developed outputs, and how they can feed back solutions for further iteration. The GA

can deal with the quantifiable complexity of artificial evolutionary processes and offers the architect a design tool with significant power:

"Through the use of intricate algorithms, complex computations, and advanced computer systems, designers are able to extend their thoughts into a once unknown and unimaginable world of complexity." (Narahara & Terzidis 2006)





Figure 1 Left to right: Type 1 module series (BVN Donovan Hill), Type 2 module series (Owen & Vokes). Photos: Happy Haus

MULTI-CRITERIA OPTIMISATION

Large or small, design problems are 'wicked problems' in that they are ill-defined rather than the usual 'tame' or 'benign' problems scientists and engineers have to deal with (Rittel & Webber 1973). Design problems may also be described as 'organised complex systems' and, if embarking on an optimisation process, it is important to carefully investigate those areas of design where prediction using simulation is actually possible (Hanna 2010). Such ill-definition and complexity suggest that the design problem may not be an optimisation problem in itself, nevertheless some of its tasks may be subject to the logical procedures of optimisation searches:

"The art of architecture always engages, at some level, the search for an optimal formal, spatial, constructional answer to diverse aesthetic and performance measures, or a knowing compromise among the above." (Burry & Burry 2010)

This also reminds us that whilst the goal of optimisation is to improve performance toward some optimal state it is more accurately defined as the search for a 'satisficing' solution, an optimal state which is better relative to others (Simon 1969). Therefore, rather than defining a solution to the problem, the GA searches for trade-offs between interacting performance criteria.

GAs originated from studies of cellular automata by John Holland and colleagues at the University of Michigan (Holland 1992). 'An Evolutionary Architecture' (Frazer 1995) was inspired by Holland's research and proposed the genetic model of nature as a generating force, considering form, space and structure as the outward expression of architecture.

But more specifically a GA is a method for solving constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution. The algorithm repeatedly modifies a population of individual solutions and at each step the GA randomly selects individuals from the current population and uses them as parents to produce the children for the next generation. Over successive generations the population 'evolves' towards

an optimal solution.

If well directed GA's are suited to the organised complexity of design tasks and will search multiple criteria to find optimal states within models until the search stops when termination criteria are met (Deb 2011). The optimal state achieved following this process may be defined by a Pareto optimal frontier and the optimal, also known as 'non-dominated', solutions are found here. It is then the task of the designer to further evaluate this representative sample (Horn et al. 1994).



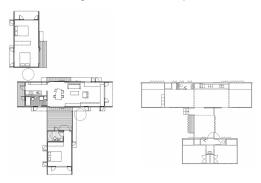
Studies of commercial and housing developments have used GAs to generate optimal solutions in the early stages of theoretical design problems. In the office context a GA was used to optimise the thermal and lighting performance of buildings in Phoenix and Chicago, and parameters allowed placing and sizing of windows to vary based on trade-offs; a 'micro GA' strategy began the search with a population of only 5 individuals (Caldas & Norford 1999).

A GA search used for a 200 unit housing project with multiple environmental, functional and economic constraints traded-off better views achieved at higher levels against the increased cost of constructing additional floor levels (Narahara & Terzidis 2006). Similarly, an evaluation procedure, using a distributed execution environment (DEXEN) and cloud computing, followed Frazer's (1995) methodology to generate point-block housing configurations for a hypothetical site in Singapore: in this study the trade-off objectives included the maximisation of saleable value of flat type versus a score based on the desirability of the view (Janssen & Kaushik 2013).

Figure 2
Top: Type 1
habitation module
(DH) = 60.8m2
Bottom: Type 2
habitation module
(OV) = 69.03m2
(both 17.9m overall
length). Drawings:
Happy Haus

These experiments demonstrated how useful GAs can be as a method of searching for optimal solutions in the early stages of design. The case study which follows explores the use of a GA for a live project in the intermediate to later stages of design where two architectural solutions for a modular home series are already provided. It examines these solutions in configurations generated by the GA traded-off against environmental performance.

Figure 3 Left to right: Type 1 configuration Right, Type 2 configuration. Drawings: Happy Haus



THE PROBLEM

Happy Haus are a niche developer producing several series of architecturally designed modular homes. The company is based in Brisbane, Australia, but these modules may be sited in Darwin's tropical heat and humidity or Hobart's temperate coolth.

No specific site is examined, however Brisbane is used as the location for the modular homes where only a small amount of energy consumption is needed for heating and cooling. Nevertheless, 50% of homes in Australian warm temperate climates like south-east Queensland are mechanically cooled, mainly due to poor passive solar design strategies [1].

Evaluations were therefore based on passive solar design principles used in conjunction with passive shading devices designed by the architects, and the ideal orientation of a habitation module. For Brisbane, in the southern hemisphere, this requires living spaces to face 20-30° degrees east of solar north, thus maximising winter heat gain and minimising winter heat loss. Only the habitation module's environmental performance was simulated whilst two sleeping modules were also considered for the effect they had on reducing solar gain and affecting annual energy use by over-shadowing. A further consideration is that the Type 1 habitation modules have almost equal sized glazing on both long sides whilst the Type 2 modules have large areas of glazing on one long side only.

Although cooling breezes are from the southeast and the narrow plan of the modules suits crossventilation this was not taken into account in the simulations. Site, micro-climate and customers requirements initially determine the mix and configuration of habitation and ancillary modules, whilst advice, price and further suggestions for configurations are provided by Happy Haus (Figure 3).

In the simulation glazing is fixed, as the interior is assumed to be air conditioned for the purposes of calculating annual energy use figures only, although it is understood that inhabitants may control their home environment by simply opening doors and windows or wearing fewer or more layers of clothing. Otherwise simulation is based on the performance requirements of the National Construction Code/Building Code of Australia 2015 (NCC/BCA) for a single dwelling in Climate Zone 2 and the client's product specification (Figure 4).

Element	
	R-Value
Walls	2.8
Exposed floor	1.0 upwards
Roof	4.1 downwards
Aluminium framed windows:	
U-value	5.5
Solar Heat Gain Coefficient (SHGC)	0.65
Transmittance Value (TVw)	0.65

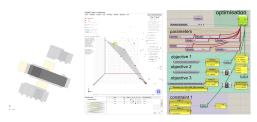
Modules modelled in Rhino/Grasshopper were passed into Ladybug/Honeybee as thermal zones in which air is assumed to be mixed. Habitation modules were single zones for this purpose whilst ancillary modules had low mesh outputs for ease of simulation operations using shading analysis.

Figure 4 NCC/BCA & Specification requirements

CASE STUDY

Objectives (phenotype). Search criteria or objectives defined the purpose and influenced the value of the optimisation process. These were set to:

- Minimise internal solar gain during the cooling months, December to February
- Maximise internal solar gain during the heating months, June to August
- Minimisation of energy use annually (water heating, heating, cooling, lighting, appliances)



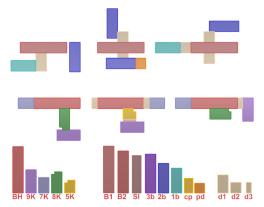
Simulations were carried out using EnergyPlus 8.1, a stand-alone program, whilst data was taken from the 'Brisbane Representative Meteorological Year' (RMY) files developed for the Australia Greenhouse Office for use in complying with the NCC/BCA. Because EnergyPlus reads input and writes output as text files, links are made to the graphical user interfaces of Rhino, Octopus and Grasshopper for visualisation purposes (Figure 5).

In Octopus's attribute space 'optimal' (non-dominated) solutions are shown dark-shaded and for ease of visualisation the three dimensions which represent these solutions are linked by a Delaunay mesh. Octopus is based on SPEA-2, an improved elitist multi-objective evolutionary algorithm, shown to have advantages over NSGA II in multi-dimensional space (Zitzler et al. 2001). Meanwhile, 'elite' (dominated) solutions are shown light-shaded.

A constraint was introduced with each evaluation to check thermal comfort levels; the individual is to be within the range -1.0 to +1.0 of the Predicted Mean Vote (PMV) for the year. Thermal comfort takes account of: dry bulb temperature; mean

radiant temperature; relative humidity; internal air speed of 0.5m/s; metabolic rate of 1 met i.e. occupants are seated; clothing level set at 0.5 clos for summer, 1.5 clos for winter. Other factors not considered included internal heat gain (lights, people etc.) and occupant's use of fans. The PMV was adjusted by a factor of 0.9 to account for a non-conditioned, warm climate, internal environment (Fanger & Toftum 2002).

Parameters (genes). Parameters take values from Grasshopper's sliders and, whilst a limitation of this particular method, nevertheless a wide range of values could be explored by Octopus. Based on 7 dimension parameters defining various translations and rotations, there were 768 possible configurations for Type 1 and 144 possible configurations for Type 2. Configurations which were generated respected relationship adjacencies and the internal layouts of the modules (Figures 6 & 7). Fixed parameters included the habitation module's main dimensions and its glazed window and door dimensions.



Choice of parameters significantly influenced the value of the optimisation process. For example, the principles of passive solar design could have been tested by allowing free orientation of all modules from 0 to 360 degrees however, it would only really be necessary to take the cardinal points to verify these principles. Instead the decision was made

Figure 5 Typical graphical user interface for each evaluation (dh1): left to right -Rhino, Octopus, Grasshopper

Figure 6 Top to bottom: Type 1, Type 2, module variations

Figure 7 Type 1: translation / rotation, 6 of 768 variations



to parameterise the position of each sleeping module and fix orientation of the habitation module to the ideal 20 degrees east of north. Thus the effects of shading could be understood and comparisons of energy use and internal solar gain could be easily made between series Types 1 and 2 for the configurations generated.

Figure 8
Optimisation results

MIN. MAX. MIN.	40	5 @	ion	Internal solar gain	Internal solar gain	Energy use/yr.	Carbon emissions/
Type 1	Solutions	Orientation (0° = north)	3A populat	kWh/m²	kWh/m²	kWh/m²/yr.	
6h1 4.43 3.04 211.33 171.17 dh2 4.51 3.09 212.05 171.76 dh3 4.48 3.14 212.15 171.84 dh4 4.51 3.16 212.41 172.49 dh5 4.59 3.20 213.04 172.57 dh6 4.61 3.28 213.62 173.09 dh8 4.63 3.29 213.77 173.15 dh9 4.64 3.30 213.77 173.15 dh10 4.80 3.18 214.62 173.84 dh11 4.56 2.91 211.97 171.70 dh13 4.87 3.20 215.04 172.61 dh13 4.87 3.20 215.04 174.18 dh13 4.87 3.20 215.04 174.18 ov1 3.31 1.64 194.40 157.46 ov2 3.23 1.67 194.71 157.72 ov3 3.26			•	MIN.	MAX.	MIN.	MIN.
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	ov10			3.42	1.92	196.31	159.01

Figure 9
Existing Brisbane
dwellings (Branz &
Environment 2010)

Type	Area m²		NatHERS Stars	Energy use/yr. MJ/m²/yr.	Energy use/yr. kWh/m²/yr.	Carbon emissions/yr Kg CO ₂ - e/m ² /yr.
Dwellings		Average				40.00
Dwellings		Range		200 - 1400	56 - 389	
1 bed	81	Best	9.5 - 9.75			13.00
2 bed	65	Worst	0.5 - 2.5			120.00

Optimisation. As the total possible number of variations of each type was quite low the population size and generation numbers were restricted. Type 1 with an initial population of 50, reproduced to make

100 individuals and yielded 14 for further evaluation, whilst Type 2 with an initial population of 25, reproduced to make 50 individuals and yielded 10 for further evaluation (Figure 8). Cross-over and mutation terminated after 1 generation in both cases.

Solar gain and energy use metrics were normalised by floor area to facilitate comparison of results, whilst the energy use of the modules was converted into carbon emissions rates based on Queensland, Australia electricity emissions levels of 0.81 KgCO2-e/m2/yr. (Australian Government, 2014). The overall results could be compared with standards for existing dwellings in Brisbane (Figure 9), but whilst the modular homes are designed to achieve a National Home Energy Rating (NatHERS, scale 1-10) of 6 Stars, in 2003 less than one per cent of Australian houses achieved this rating (Branz & Environment 2010).

Evaluation - Type 1 series. Equal amounts of glazing to both long sides of the habitation module provided greater internal solar gain and energy use year round compared with the Type 2 module. It would however be more pleasant internally in the heating months as almost double the amount of solar gain occurred in the Type 1 module compared with Type 2. Energy use and carbon emissions appeared high compared to existing Brisbane dwellings, but they included electrical use for appliances which could account for 20-30% of this total.

A cluster of optimal individuals illustrated by dh6 indicated that the sleeping modules located to the south west and east of the habitation module provided beneficial shading in the cooling months, especially from low angled late afternoon summer sun, whilst allowing unobstructed heat gain from the

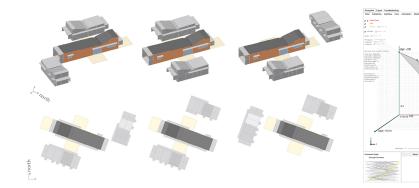


Figure 10 Left to right: dh6 (optimal, cluster), dh1 (optimal), dh11 (elite), dh6 (optimal, cluster)

north in the heating months (Figure 10).

The lowest annual energy use in this sample was dh1 where the sleeping modules were more evenly spaced away from the long glazed sides, again providing beneficial shading in the cooling months whilst allowing heat gain in the heating months.

Evaluation - Type 2 series. Internal solar gain and energy use were about 10% lower than the Type 1 module. For the optimal configurations this is about 16kWh/m2/yr. or 950kWh/yr. more for Type 1, which represents about \$265.00/yr. at Standard rates and \$323/yr. at Peak rates [2]. The simulation assumed that mechanical cooling and heating would be used by the owners, however this might not be the case. Energy use and carbon emissions appeared high compared to existing Brisbane dwellings, but as with Type 1, they included electrical use for appli-

ances which could account for 20-30% of this total.

A cluster of individuals illustrated by ov2 indicated a configuration that allows low angle winter sun to penetrate adequately whilst obstructing low angle early and late afternoon sun in summer (Figure 11). The least internal solar gain in summer and energy use annually was achieved by ov1 which allowed even more penetration of northern winter sun, however it achieved the least internal solar gain in winter of all the optimal solutions evaluated. A surprise is ov8 which gave very low energy use and low heat gain in summer, but also low heat gain in winter, an option a customer might be happy with. Such an evaluation confirms that this is a process of finding trade-offs rather than the best of all options.

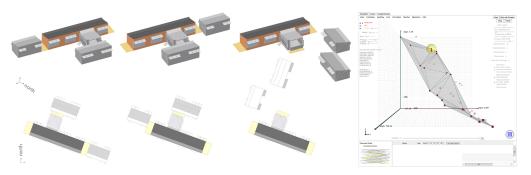


Figure 11 Left to right: ov1 (optimal), ov2 (optimal, cluster), ov7 (optimal), ov2 (optimal, cluster)

DISCUSSION

Effectiveness and utility. Optimisation provided informed design solutions at the intermediate stage which could be fed back into further design generation or adaptation of existing solutions. For example it highlighted the performance characteristics of particular configurations of modules oriented to the ideal for maximising passive solar design benefits. It also enabled ease of comparison of environmental performance between series Types and with existing Brisbane dwellings.

By refining the parameters and objectives for optimisation a reasonable number of solutions were generated to facilitate further evaluation by the architect. Thus the GA's optimal solutions not only informed and influenced the design process but also suggested alternatives for further consideration.

Work flow in real-time. Evaluations processed in the cloud using Amazon EC2's various compute or memory optimised instances were generally faster per evaluation compared to a standard PC set-up for CAD. At this intermediate stage the optimisation therefore provided timely and useful feedback into the workflow. Perhaps such methods could be a step towards satisfying the architect's desire for, "... far greater computer power to allow the multiparameter decision-making to take place in real-time" (Burry 2011).

Three views of each application (Rhino, Grasshopper, Octopus) were needed to follow evaluations in real-time and view data and changes propagating through the model. This process generally occurs in the background in the cloud, however being able to easily view this process helped understanding and facilitated decision making.

Complexity and cognitive stress. Architects who are familiar with these tools have rarely examined methods of working with multiple criteria relevant to optimisation searches, as noted by Jabi (2013). One reason might be the cognitive stress factor involved with making complex parametric models linked to evolutionary algorithms. These factors have been recorded for Visual Dataflow Modelling (VDM) tools

like Grasshopper (Figure 12) where iterative tasks in particular are noted as causing high cognitive stress, whereas node-based procedural modelling software, as used in the gaming sector, incurs lower cognitive stress (Janssen & Chen 2011).

More research needs to be done in this area to examine how CAD might learn from other design sectors to reduce cognitive stress factors.

Simulation. As has been noted, the choice of which parameters, objectives and constraints to enter into the search process is a key task of the designer which determines the value of the optimisation outputs to the design process by revealing areas of convergence and therefore greater likelihood of predictability.

In this study convergence could be seen where individuals clustered on the Pareto optimal front suggested data and configurations for the designer to take to the next step. This could be further iteration and synthesis of promising solutions or discussion with engineers or other stakeholders.

Optimisation and design. Lawson (2004) compares the architect's with the computer's modes of thought and doubts they can be useful equal partners. In response it may be stated that computational design tools are already part of a social and cultural phenomenon that cannot be ignored by architects. For example it has been noted that the present state of digital design and technology could be a return to an age when differentiation was the norm and when collaboration negated the idea of the 'author' of a piece of work (Carpo 2011): the latter point is of concern to architects keen to maintain their sense of individuality in the design process.

It can also be argued that optimisation using a GA is comparable to other innovative or creative human processes because it achieves its results in the process of evaluating individual solutions by combining direction and chance, building new solutions from the best partial solutions of previous trials (Goldberg 1989). Employing 'notions' of what is important or relevant to the task and associations that have worked well in the past is comparable to the early and intermediate stages of the design process.

It has been demonstrated in this paper that multi-criteria optimisation with a GA is appropriate to the architect's workflow in the intermediate stage as it searches for and generates new ideas and tests existing ones, confirming hunches or taking design in new directions. Furthermore the GA can evaluate with ease many more solutions than are possible by an architect, leaving final selection of a reasonable number of fit individuals to the architect, or for later discussion with engineer, client or customer.

By contributing to a better informed process it should also facilitate discourse between designers and engineers, helping each venture further into the 'common ground' (Simon 1969). Although a different kind of thinking is needed, there are clearly parts of the design problem which are suited to such logical processes leading to optimal solutions (Lawson 2005).

Modular homes and optimisation. It is also noted here that prefabrication in the construction industry interfaces well with the tools of computational design. Happy Haus's modular homes share similarities with manufactured products and as the sophistication of its prefabricated process increases, simulation and optimisation may be built-in to the production process.

Also, it is in the nature of prefabrication that its need for up-front design precipitates the production of quantifiable data, distinguishing it from traditional design - data which is food for simulation and optimisation. Both of these features make prefabrication, and single or multi-level modular homes in particular, suitable subjects for further study and research of simulation and optimisation processes.

CONCLUSION

Optimisation tools are not a quick-fix, neither do they supplant the architect's judgement and experience.

Firstly, careful choice of which objectives and parameters to evaluate is essential to avoid wasted efforts. It should also be noted that simulation and analysis precede optimisation thus helping with this refinement, whilst local knowledge and experience further inform the process.

Secondly, it is important to realise that individuals evaluated by the optimisation algorithm are not solutions to the problem, and neither is this the intended outcome. Instead, a selection of optimal solutions enables the designer to make choices based on trade-offs between competing criteria, as is normal in reaching resolution to most design problems.

Thirdly, with current CAD tools, setting-up the parametric model and algorithm is a lengthy and complex task, and once complete, it may not be transferable to other team members. However, there is a synergy between parametric modelling and optimisation methods which may be improved with better CAD tools. Studies have confirmed this interconnectedness and its benefits: reduced time per design option evaluated (increased set-up time noted); im-

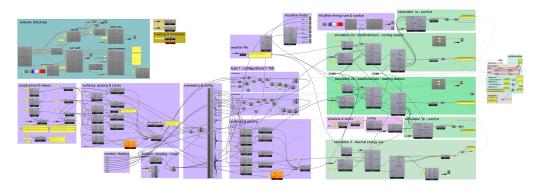


Figure 12 Type 1 series VDM graph: Grasshopper/Ladybug/Honeybee/Octopus, linked to EnergyPlus

provements in performance for complex problems; and increased diligence in the design process (Evins et al. 2012). This synergy between these systems is another area identified for further research.

This live project has demonstrated that optimisation using a GA usefully informs the design process during the intermediate stage such that solutions and data generated could be meaningfully traded-off and fed back for reflection and further iteration. The complexities of such tools should not be ignored and methods for improving cognitive stress levels involved with their set-up are noted for further research. However, for architects faced with increasingly complex projects, large or small, such tools promise a means of resolving quantifiable complexities beyond their own capabilities.

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