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Passive Solar Building Design Using Genetic Programming

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ABSTRACT

Passive solar building design considers the effect that sunlight has on energy usage. The goal is to reduce the need for artificial cooling and heating devices, thereby saving energy costs. A number of competing design objectives can arise. Window heat gain during winter requires large windows. These same windows, however, reduce energy efficiency during nights and summers. Other model requirements add further complications, which creates a challenging optimization problem. We use genetic programming for passive solar building design. The EnergyPlus system is used to evaluate energy consumption. It considers factors ranging from model construction (shape, windows, materials) to location particulars (latitude/longitude, weather, time of day/year). We use a split grammar to build 3D models, and multi-objective fitness to evaluate the multiple design objectives. Experimental results showed that balancing window heat gain and total energy use is challenging, although our multi-objective strategy could find interesting compromises. Many factors (roof shape, material selection) were consistently optimized by evolution. We also found that geographic aspects of the location play a critical role in the final building design.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Experimentation

Keywords

passive solar performance, energy efficiency, evolutionary design, genetic programming, split grammar

1. INTRODUCTION

Evolutionary design is well established in the field of architecture [2, 28]. Genetic algorithms have been used to design external shapes [27, 26, 6], internal floor plans [12, 17, 13], and structurally sound forms [31].

Of particular relevance in today's world of climate change is the application of evolutionary algorithms towards energy-efficient building design. Some examples are as follows. Caldas applies evolutionary design towards a number of energy-related design problems, such as window placement, and building and roof design, in order to minimize energy use [7]. Turrin *et al.* evolve large roof structures that provide thermal and lighting comfort using passive solar techniques [30]. Malkawi *et al.* address the placement of windows and air ducts to maximize ventilation and satisfy thermal criteria [19]. Marin *et al.* create 3D building designs that maximize sunlight explosure during winter [20]. Harrington *et al.* evolve structures that maximize sun exposure in summer, and minimize it in winter [14]. Yu considers human occupancy factors, which helps in efficiently using lighting and mechanical heating and cooling systems [33]. Bouchlaghem designs building envelopes using energy considerations [5]. Wright *et al.* use a genetic algorithm to design the HVAC (heating, ventilating, and a/c) system for a multi-story building [32].

This paper uses genetic programming (GP) to evolve buildings using energy efficiency considerations. A split grammar denotes aspects of the building to be evolved, including model geometry, window definitions, roof shape, and construction materials. Experiments focus on simple cuboid structures with optional roof shapes and open-space floors. The two main energy factors investigated are winter window heat gain and annual energy usage. These factors are usually at odds with each another. Passive solar heating in winter requires windows to collect the mid-day solar radiation. But these same windows are poor insulators at night, and also can cause overheating during warmer weather. One goal is to see how well evolution balances these competing factors in the solutions produced. We introduce other model requirements into fitness measurements, which pertain to model shape and window usage. We use multi-objective analysis to evaluate these multiple, often conflicting, requirements.

Another goal is to explore the effects of location geography on the model designs. Fitness evaluation uses the EnergyPlus simulation software to perform energy simulations. This comprehensive system considers a wealth of factors, such as model shape and size, windows, and materials used. It also considers environmental information about the location, for example, weather conditions, latitude/longitude, time of year and day, and many others. This results in a very detailed and precise analysis of energy usage.

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The paper is organized as follows. Section 2 reviews the EnergyPlus system, and discusses basic issues regarding energy analyses and evolutionary design. Our system's split grammar and sum of ranks multi-objective technique are described in Section 3. Section 4 presents results for two experiments. The first examines a single-story building designed for 5 diverse world locations. The second case investigates a multi-story building, evolved using 5 fitness objectives pertaining to shape and energy factors. Comparisons with related work are made in Section 5. Concluding remarks end the paper in Section 6.

2. ENERGY EFFICIENCY AND EVOLUTIONARY DESIGN

2.1 EnergyPlus

A green building is a sustainable resource-efficient building, that minimizes negative impact on the environment [16]. According to a report published in 2006 [1], over 70% of green building research was focused on energy and atmosphere research. Therefore, in most cases when designing a green building, architects and engineers try to minimize fossil fuel energy and electricity usage. One way to do this is by using passive and active solar techniques for heating during the winter, and not overheating in the summer.

There are many building analysis systems available for thermal simulation and energy usage analysis. One popular free system is EnergyPlus [24]. EnergyPlus uses a sophisticated and detailed simulation that considers load calculation, building and energy performance, heat and mass balance, water use, energy flow, and other factors. To analyze a building model, EnergyPlus will consider the structure's geometry and construction (eg. materials, windows, doors, roof shape), and environmental information about the location (latitude and longitude, weather, time of year, time of day, and many others). The result is a precise and comprehensive analysis, useful for performing detailed investigations about many aspects of energy use of the building. More than 2000 international weather files are available.

We use EnergyPlus to perform energy analysis during fitness evaluation. Our GP system (written in ECJ) communicates with EnergyPlus via multi-threaded spawned processes. GP generates an input file for EnergyPlus, containing all evolved aspects of the building to analyze, including model geometry, location of windows and doors, and material information for all components. A weather file will supply the relevant geographic and environmental information for the building's location. Results of EnergyPlus's analysis will then be used to establish energy performance. Final results of analyses, including 3D model views, are readable with Sketchup[1], a free 3D design and visualization tool. All the 3D images in this paper are rendered with Sketchup.

2.2 Preliminary Insights

Preliminary experiments gave useful insights into the nature of energy evaluation and evolutionary design. We quickly learned that the most energy-efficient buildings may also be undesirable ones. For example, we did some runs using a single fitness criteria: minimize annual energy usage in winter. Figure 1 shows the inevitable result – a tiny insulated shack with no windows, and small or missing door. Small buildings with no windows and doors are most efficient to heat and cool.

[1]http://www.sketchup.com/

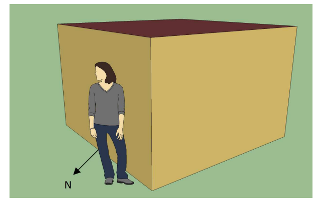
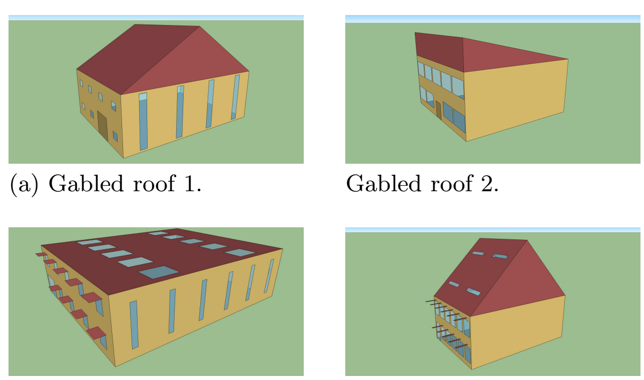


Figure 1: Evolved result using only winter heating energy usage, and not considering solar heat gain via windows.

Practical designs require balancing energy efficiency and functional necessities. With respect to the window creation, there are two strategies that can be used. One approach is to enforce window creation with the split grammar, to guarantee window generation via the genotype itself. However, enforcing too many design constraints this way can discourage innovation, which is a recognized strength of evolutionary design. Another strategy is to use evolutionary pressure to encourage windows. For example, one can introduce a window heat gain measurement, which EnergyPlus readily calculates. This encourages passive solar heating during winter daytimes, which should promote lower energy consumption during winter. However, these windows also result in heat leakage during winter nights, and higher air conditioning costs in the summer, both of which increase energy consumption. It will be a task for GP to balance these competing factors.

Early experiments showed that using winter window heat gain alone was often unsatisfactory. Although it would indeed encourage window creation, especially in the direction of the noon Sun, other sides of the building could still have minimal window areas, or none at all. A combination of window heat gain and other window area evaluations (eg. area %) seems to be an approach to consider.

Other design trends were seen. Skylights are energy leakers, and GP always discards them. Similarly, flat roofs were always preferred. Because we did not incorporate insulated attics, any non-flat roof would needlessly enlarge the building's interior, adding to energy use. These insights not withstanding, gabled roof shapes and skylights were always available for use, although we expected evolution to ignore them.



(a) Gabled roof 1. Gabled roof 2.

(c) Overhangs and skylights. (d) Gabled Skylight roof.

Figure 2: Roof, overhangs, skylights.

The architectures examined are based on basic cuboid structures, with roof variations (Fig. 2). We do not consider room layouts (floorplans), but instead treat each floor as an open space. EnergyPlus can handle either case, and both affect its energy simulations. Note that, in the case of open areas, EnergyPlus will not accurately simulate floor levels whose footprints have concavities.

3. SYSTEM DETAILS

3.1 Split Grammar

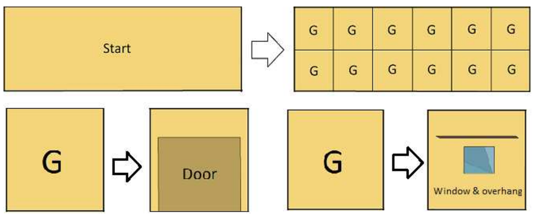


Figure 3: An example of rules for a split grammar. The split rule at the top splits a wall into 12 sub-walls. The bottom-left rule converts a sub-wall to wall and door. The bottom-right rule converts a sub-wall to window, overhang, and wall.

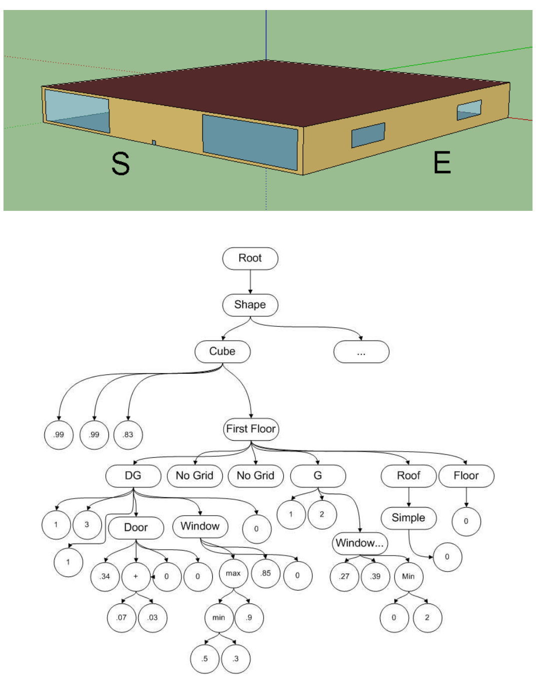


Figure 4: View of a building model, and its split grammar tree.

Stiny proposed shape grammars for constructing 2D and 3D designs [29]. A shape grammar is a context-sensitive grammar that rewrites configurations of shape components into new configurations, visaviz rewriting rules. A split grammar is a restricted shape grammar that uses iterative sub-division rules instead of general rewrite rules (see Figure 3). Although of weaker expressivity, split grammars are more easily implemented in computer software, and are also practical in applications for 3D architecture [15, 23, 10].

Our GP design grammar takes the form of a split grammar. We implement the split grammar in the style of one used in McDermott *et al.* [21]. Explicit mappings are made between the GP tree expressions and models being designed. Figure 4 shows a GP tree, along with the corresponding building structure. Each modeling requirement (cubic model with 3 walls, 1 wall with a door, floor, roof,...) is encoded directly in the tree. Other GP functions likewise refine the requirements of walls, doors, windows, skylights, and so on.

We use the ECJ GP system [18]. The grammar is implemented using strong typing [22], where 11 data types are defined. These range from basic numeric types, to specialized types for different components (window, door, roof, ...). Specialized functions define specific architectural components. For example,

$$Add\ Door\ Grid(I_1, I_2, I_3, D, W, I_4)$$

is a function of type *DoorGrid*. It creates a subdivided wall into an $I_1 \times I_2$ grid, locates the door at position I_3, uses expression D to define the door, W to define the windows, and I_4 to define the wall material. D and W are subtrees of type *Door* and $Wall$ respectively. Other design functions include $Add\ Window$, $Add\ Gabled\ Roof$, and others.

Name	Material	U-Factor
Wall_1	wood, fiberglass, plaster board	0.516
Wall_2	wood, plywood, insulation, gypsum	0.384
Wall_3	gypsum, air (0.157 TR), gypsum	1.978
Wall_4	gypsum, air (0.153 TR), gypsum	1.994
Wall_5	brick, insulation, concrete, gypsum plaster	0.558

Name	Material	U-F.	SHGC
Win_1	3mm glass, 13mm air, 3mm glass	2.720	0.764
Win_2	3mm glass, 13mm argon, 3mm glass	2.556	0.764
Win_3	6mm glass, 6mm air, 6mm glass	3.058	0.700
Win_4	6mm LG, 6mm air, 6mm LG	2.371	0.569
Win_5	3mm glass	5.894	0.898
Win_6	6mm glass	5.778	0.819

Table 1: Wall and window materials. LG=low emissivity glass.

Different construction materials with varying energy efficiency properties are available to the grammar. Wall and window materials are shown in Table 1. U-factor is the overall heat transfer coefficient. Lower U-factors means better insulation. SHGC (Sun heat gain coefficient) measures the solar energy transmittance of glass. A high SHGC means solar energy (heat) is more easily transferred through the glass. The total number of materials were 5 walls , 3 roofs, 2 floors, 6 windows, and 3 doors.

3.2 Multi-objective Fitness Evaluation

Table 2: Example different rankings for a minimization problem. Best in each ordering labelled *.

Fitness	Wt-Sum	Pareto Rank	Ranks	NRS
(33,0,125,39)	197	1*	(3,1,6,3)	2.27
(30,24,38,18)	110	1*	(2,3,3,2)	1.4
(0,47,43,18)	108*	1*	(1,4,4,2)	1.73
(78,62,2,0)	142	1*	(6,6,1,1)	1.37*
(43,19,20,79)	161	1*	(4,2,2,4)	1.47
(55,55,89,80)	279	2	(5,5,5,5)	2.67

Given the multiple, heterogeneous factors used in fitness evaluation, we treat this as a multi-objective problem (MOP) [9]. This avoids the complexities and biases involved with a single-objective, weighted sum approach. We use the sum of ranks (average rank) scoring strategy. It was originally used for high-dimensional MOP [3, 11], since Pareto ranks is increasingly ineffective with 4 or more objectives. Unlike Pareto, sum of ranks does not commonly result in outlier solutions that are strong in a minority of objectives [4].

Sum of ranks is computed as follows. Given a minimization problem in k objectives, a population member i has a raw objective vector $(o_1^i, ..., o_k^i)$. Next, each objective 1 through k is assigned a rank relative to the rest of the population, resulting in a rank vector $(r_1^i, ..., r_k^i)$. The normalized sum of ranks is then:

$$Fitness_i = \sum_{j=1}^{k} \frac{r_j^i}{max_j}$$

where max_j is the maximum rank value for objective j. Lower fitness scores are preferred.

Table 2 shows example rankings for a minimization problem of 4 objectives. The weighted sum tallies the raw scores using a weight of 1 for all. This is followed by the Pareto rank. Finally, the normalized sum of ranks is shown, using the above procedure.

To promote diversity, when 2 individuals have identical raw fitness vectors, a penalty value is added to their ranks. This discourages copies of the same individual.

4. EXPERIMENTS AND RESULTS

4.1 Experiment: Geography

Table 3: Average daily temperature (C) for 5 cities.

Location	Description	Jan.	July
Anchorage, USA	northern subarctic	-2	14
Eldoret, KE	equatorial, tropical	17	17
Las Vegas, USA	subtropical, hot desert	9	32
Melbourne, AU	southern hemisphere, temperate	18	8.5
Toronto, CA	humid continental	-6	21

A single-story building suitable as a public facility (pool, library) or small business (offices, store) is to be designed. Table 3 lists 5 cities to be separately considered. The goal is to see how their geographic locations and weather affects the resulting designs. Files containing weather data and other geographic information for the cities were obtained from [25], and used by EnergyPlus.

Functions	Add Root, Add Cube, First Floor, Add Door Grid, Add Grid, Add Door, Add Window, Add Window Overhang, Add Empty Grid, Add Simple Roof, Add Skylight, Add Gabled Roof, Add Gabled Roof2
Flt/Int math	avg, max, min, *, /, IfElse, float:(half, half2), int: (inc, dec)
Terminals	ERC, Int_ERC

Table 4: Design language.

Parameter	Value
Number of runs per city	10
Generations	100
Population size	300
Initialization	ramped half&half
Grow tree depth range	2-6
Full tree depth range	5-12
Max tree depth	17
Tournament size	3
Crossover/mutation rates	90%/10%
Probability of function node selection	90%
Elitism	2
Diversity penalty	2

Table 5: GP Parameters

The split grammar is summarized in Table 4. Only single floor models are considered. A variety of roof shapes are possible, as well as skylights and window overhangs. Walls, windows, doors and floors are constructed from materials, as described in Section 3. Reasonable size ranges for floors, walls, doors, and roofs are specified. For example, floors are between 10 to 20 meters in length and width.

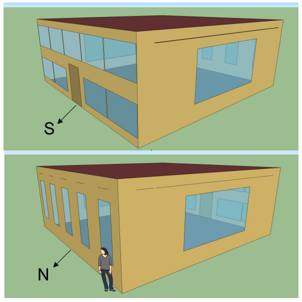
The fitness objectives are: (i) Window heat gain in winter (maximize); (ii) Annual energy consumption (minimize); (iii) At least 25% window area per wall. The first two objectives are measured by EnergyPlus. Temperatures below 20C invoke heating, and those above 24C activate air conditioning. Window area is evaluated by proportionally penalizing wall window areas below 25%. Other GP parameters are shown in Table 5.

4.1.1 Results

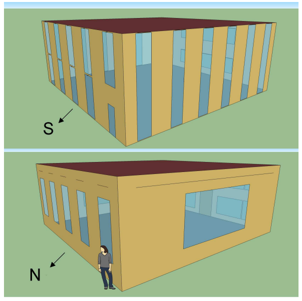
Location	South	West	North	East
Toronto	94	27.5	24	35
Las Vegas	87	28	25	28
Eldoret	45	52.5	27.5	55
Anchorage	89	26	22.5	28
Melbourne	25	29	81.5	38

Table 6: Window area of top solutions.

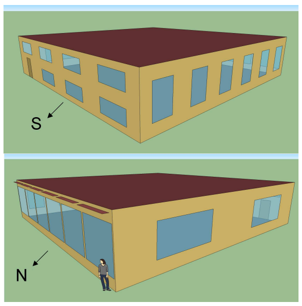
Figure 5 (a-e) shows the top ranked solution for each city's 10 runs, and an additional Toronto solution (f). They were selected by collecting the top ranked solution of each of the 10 runs per city, and re-ranking using the sum of ranks. The resulting top score is designated the top-ranked solu-



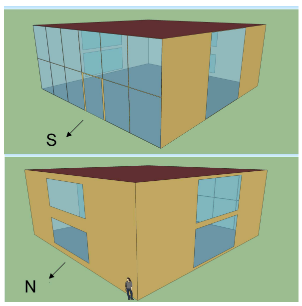
(a) Anchorage, USA



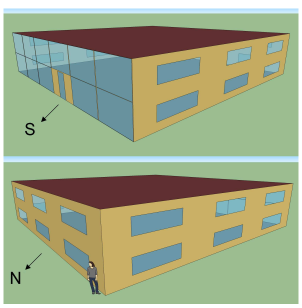
(b) Eldoret, Kenya



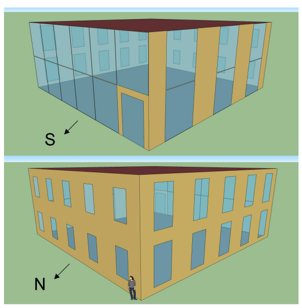
(c) Melbourne, Australia



(d) Las Vegas, USA



(e) Toronto, Canada



(f) Least efficient Toronto solution ("a")

Figure 5: Top ranked solution for each location.

tion (which does not necessarily mean they have the minimal energy efficiency, since energy usage is but one of the 3 objectives considered).

Some design trends can be seen. Energy considerations meant that all models have flat roofs. Alternate roof shapes do not contribute to window heat gain, and so the greater volumes they introduce are detrimental. Skylights never appear, as they reduce energy efficiency (they are poor insulators). Window awnings are missing or very small. Larger awnings reduce heat gain, and so they are discarded.

All northern cities (a, d, e, f) have a wall of windows facing south for solar heat gain, while Melbourne's (c) is facing north. Eldoret's equatorial location means that window heat gain is omnidirectional. Windows on the other walls are often minimally over the desired 25% target. Many Eldoret, Melbourne, and Toronto models tended to have larger window areas on the east compared to the west. Perhaps this warms the building in the morning, after a cold night. Table 6 summarizes the window areas for the top solutions.

Most building footprints expanded to the maximum area. The exception to this was Anchorage, whose models were

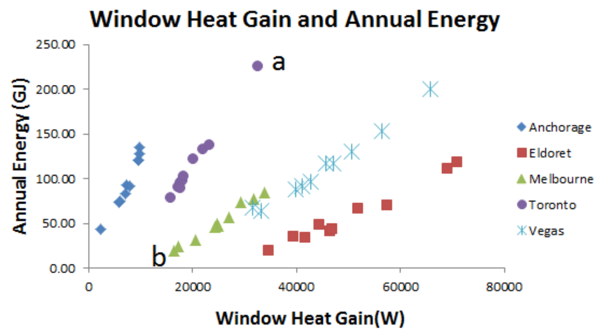


Figure 6: Energy usage scatter plot of top-ranked solutions. Each point is top scoring solution from one run.

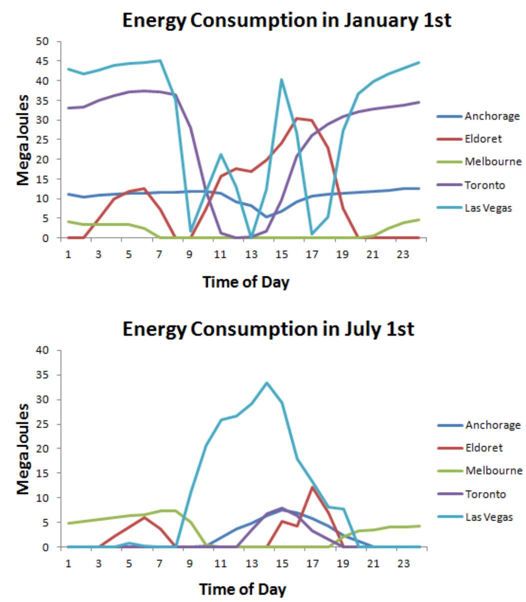


Figure 7: Energy consumption of the top-ranked model for each city, January 1 and July 1.

smaller than the others. Because of the weak sub-arctic Sun, window heat gain has less impact, and so smaller building sizes are preferred for heating.

Figure 6 is an energy vs window heat gain scatter plot of the solutions. Each city's set of solutions occupies a distinct niche, with only Melbourne and and Las Vegas partially coinciding. Note that heat gain is proportional to annual energy usage: greater sun exposure for heat gain requires increased window area. But these windows are poor insulators during winter nights, and also increase cooling costs during the summer. Anchorage models have the least window heat gain. Conversely, the intense sunlight at Eldoret (equator) and Las Vegas give them the highest heat gain. The most efficient model was a Melbourne model (**b**), while an outlying Toronto solution (**a**) was the least efficient. Curiously, the plotted solutions appear to reside on Pareto fronts. An analysis shows that 8 solutions for Eldoret, Toronto and Las Vegas sets are Pareto undominated, as are 9 for Anchorage and Melbourne.

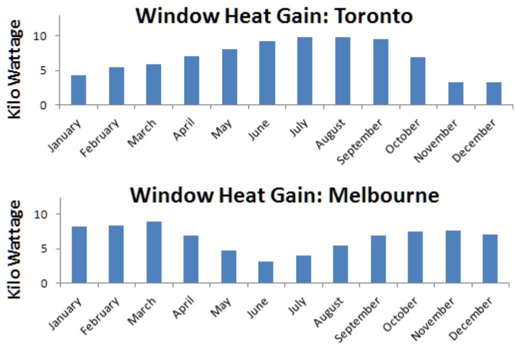


Figure 8: Annual window heat gain: Toronto and Melbourne

The annual energy usage in Figure 6 spans a significant range. The average home energy usage in Canada ranges between 94-129 GJ[2], and so our energy range is reasonable. Note that domestic houses are much smaller than the buildings in Fig. 5, and do not have empty, open floor plans as our models have. In the GP runs, energy efficiency competed equally with window heat gain and minimum window area, and the solutions indicate varying degrees to which these criteria were satisfied. Besides factors in material selection (discussed below), the main criteria for comparing and selecting between solutions for each city is to determine the preferred balance between heat gain and energy use. The top-ranked Toronto solution in Figure 5(e), also happens to be the most energy efficient of the Toronto models. An alternative Toronto solution shown in Figure 5(f) is the least energy efficient Toronto solution ("a" in Figure 6) The difference between these solutions' scores – and most solutions for all cities – is due to this classic trade-off between energy use and window heat gain. The model in (f) has the largest roof height, and hence largest southern window area. This optimizes window heat gain, but also increases energy use on the whole. The model in (e) has the smallest height of all the Toronto models. Hence it has lower heat gain, and uses less energy.

Figure 7 shows the hourly energy consumption of the top-ranked models for each city, during January 1 and July 1. Melbourne has consistently low energy use. Las Vegas, however, is an energy hog during winter nights and summer days. Toronto also requires heating energy during winter nights.

The effect of latitude is illustrated in Figure 8. Toronto's heat gain peaks in August, while Melbourne's peaks in March.

Consistent use of energy-efficient materials could be seen in the solutions. Walls always used an energy-efficient material definition composed of brick, insulation, concrete, and gypsum plaster ($Wall_5$ in Table 1). A window glass (Win_2) having a balance of good U-factor and high SHGC was used in almost all cities. Anchorage results, however, sometimes used Win_4, which sacrifices SHGC efficiency for higher insulating properties.

4.2 Experiment: Multi-floor Building

Here, we create a 5-floor office building to be built in Toronto, Canada. Five fitness objectives measuring energy efficiency and model design are defined: (i) Window heat gain in winter (maximize). (ii) Annual energy usage (minimize). (iii) Each wall should have 35% window area. (iv) Each floor should have 15% smaller area than the floor below it. (v) The sum of floor level volumes should be 10000 m^3. Items (i) and (ii) use the evaluations as used in Section 4.1. Sum of errors squared is used for (iii) and (iv), and the absolute volume error is used in (v). The GP language in Table 4 is used, except that *Add Root* permits 5 floors. The parameters in Table 5 are used, although the maximum generations is increased to 80.

4.2.1 Results

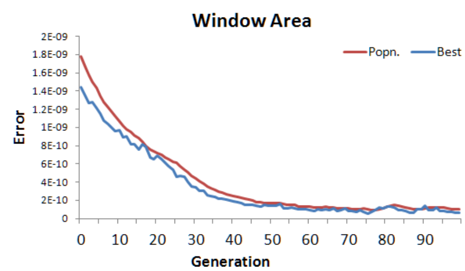


Figure 9: Window sum of errors. Average 10 runs.

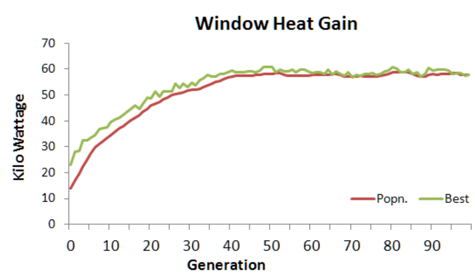


Figure 10: Window heat gain. Average of 10 runs.

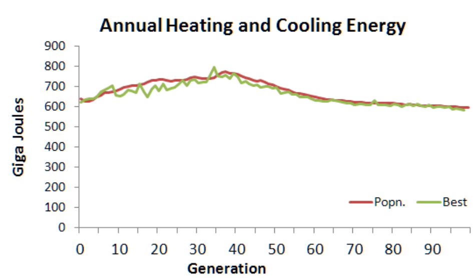


Figure 11: Annual energy. Average of 10 runs.

Figure 9 shows the performance of the 10 runs for the window objective (volume and floor area graphs are similar). The plots of the energy objectives are in Figures 11 and 10. Due to the stringent geometry criteria used, energy improvements were more difficult to optimize. Window heat gain steadily improves, until it plateaus at generation 45. This concides with the time when window areas have reached their 35% goal (Fig. 9). Thus, window heat gain

[2] http://www.statcan.gc.ca/pub/11-526-s/2010001/part-partie1-eng.htm

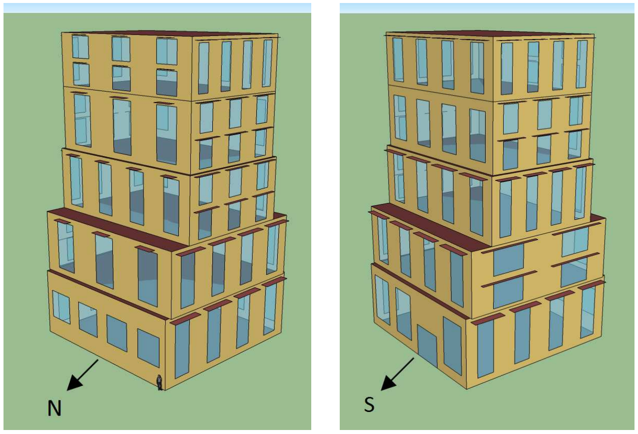


Figure 12: Best model of 10 runs for multi-floor experiment

can only improve by reducing the window objective score. Hence, a balance has been reached between them.

Looking at the annual energy plot, a slow increase in energy consumption occurs up to generation 40. At that point, there is a gradual improvement to the score until the end of the run. This phenomenon often arises with sum of ranks scoring. Improvements to one objective can be delayed, to allow for improvements in other objectives. It is a democratic distribution of benefits to the population as a whole.

Figure 12 shows the top ranked solution of the 10 runs (again determined by using sum of ranks on the 10 top-scoring solutions). Its window areas are 32.3% (N), 33.5% (E), 36.4% (W), and 36.4% (S). The total volume is 9950 m^3. The same wall and window materials were selected as used in the majority of cities in Section 4.1. Some very small window awnings appeared in the model. Larger awnings reduce solar heat gain during the winter.

5. RELATED WORK

Caldas's research using evolutionary computation towards energy efficient building design (reviewed in [7]) is the most related to ours in many respects. In [8], she uses multi-objective Pareto ranking to reconcile two objectives: maximize daylight use and minimize energy consumption. She examines Pareto-undominated solutions to show trade-offs between these conflicting objectives. Whereas a single run with Pareto ranking can produce multiple candidate solutions, we obtain a similar effect in Section 4.1.1 with multiple runs using the sum of ranks. (We did not examine multiple solutions from a single run.) An advantage of sum of ranks over Pareto is that its solutions tend to perform well in multiple objectives, whereas Pareto solutions can often be outliers, with a good score in only one objective. For evolutionary design problems [4], including those examined here, such solutions are often of little value. Furthermore, Pareto ranking becomes ineffective with 5 or more objectives, as found in our multi-floor building experiment. Sum of ranks was originally suggested for high-dimensional multi-objective problems [3, 11], and is quite suitable for the size of problems examined here.

Caldas uses the DOE2 simulation software to evaluate energy usage. DOE2 is a forerunner of EnergyPlus, and uses many of the same factors we use (material, model shape, windows, etc.). Since she uses a genetic algorithm, her chromosome has fixed fields for denoting the evolved model parameters required in DOE2 simulations. Our split grammar is more flexible for denoting variable-sized, complex structures. Although we did not exploit split grammars to explore complex building shapes, we were easily able to denote varying forms of roof structures, skylights, and multiple floors.

Whereas our GP system was entirely automated, many researchers use semi-automated methods for energy-efficient building design. Turrin *et al.* evolve roofs using an interactive GA [30]. The user will consider the roof aesthetics, along with energy simulation results, to interactively evaluate results. Similarly, Malkawi *et al.* use a GA to evolve energy efficient rooms using a combination of energy simulation and user interaction [19]. Marin *et al.* also incorporate results of energy evaluation with human judgements to evolve building envelopes (shapes) [20]. We feel that user interaction is the next natural direction for our system, as it would permit aesthetic judgements to be included. Although we did not examine complex building envelopes, aesthetics would definitely be useful for that, as well as for evaluating the window design and placement that arose in our models

Our split grammar is a simplified version of one presented by Muller *et al.* [23], and later used by Coia *et al.* with GP [10]. Our implementation of the split grammar is inspired by the grammar used in McDermott *et al.* [21].

6. CONCLUSIONS

This paper applied GP towards the energy-oriented design of building architectures. By using the sum of ranks analysis, multiple diverse and conflicting design objectives were considered. Results show that solutions from different runs present trade-offs of the design goals. In particular, because we treated annual energy use and winter heat gain with equal priority, solutions usually indicate a trade-off of these two factors: winter heat gain improvements come at the expense of annual energy usage. In future work, it would be worth examining different preferential targets for energy use and heat gain. One intriguing idea is to consider seasonally-adaptable window awnings. Furthermore, EnergyPlus is capable of accounting for an enormous range of factors besides those that we examined, including ventilation models, various HVAC design factors, floor plans, human factors (clothing), staged zone thermostats, and a host of others. All these factors can be considered in evolutionary design.

We found the split grammar implementation to be very practical for the problems examined. Any aspect of the building architecture (size, shape, material, window placement,...) was quickly incorporated into the grammar. Furthermore, candidate structures were usually sensible. This would not be the case if a more general design grammar (L-system, shape grammar) were to be used. Although we focussed exclusively on simple cuboid structures with different roof choices, the split grammar formalism can denote many complex building layouts and envelopes, which future research should examine. However, in order for EnergyPlus simulations to be accurate, complex footprints will require floor plan definitions. Automated floor plan design is itself a significant complex problem [12, 17, 13].

Our experiments never considered the aesthetic merits of the evolved structures. Although the cuboid structures permit little design variation, window placement could be evaluated with respect to aesthetics. For this purpose, a symmetry analysis might be included. Alternatively, permitting user interaction with the system, as done by other researchers (Section 5), is worth considering.

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