Three-Dimensional Shape Generation of Low-Energy Architectural Solutions using Pareto Genetic Algorithms

Luisa G. Caldas[1]
[1]Instituto Superior Técnico, Technical University of Lisbon, Portugal
Email: luisa@civil.ist.utl.pt

Abstract. *This paper extends on a previous work on the application of a Generative Design System [GDS] to the evolution, in a computational environment, of three-dimensional architectural solutions that are energy-efficient and adapted to the climatic environment where they are located. The GDS combines a well-known building energy simulation software [DOE2.1E] with search procedures based on Genetic Algorithms and on Pareto optimization techniques, successfully allowing to tackle complex multi-objective problems. In the experiments described, architectural solutions based on a simplified layout were generated in response to two often-conflicting requirements: improving the use of daylighting in the space, while controlling the amount of energy loss through the building fabric. The choice of a cold climate like Chicago provided an adequate framework for studying the role of these opposing forces in architectural form generation. Analysis of results shows that building characteristics that originate successful solutions extend further than the building envelope. Issues of massing, aspect ratio, surface-to-volume ratio, orientation, and others, emerge from the analysis of solutions generated by the GDS, playing a significant role in dictating whether a given architectural form will prove adapted to its climatic and energy requirements. Results suggest that the questions raised by the exploration of form generation driven by environmental concerns are complex, deserving the pursuit of further experiments, in order to better understand the interaction of variables that the evolutionary process congregates.*

Keywords. *Generative Design System, Genetic Algorithms, Evolutionary Architecture, Artificial Intelligence in Design, Building Energy Simulation, Bioclimatic Architecture, Environmental Design.*

Introduction

This paper presents a Generative Design System [GDS] that is able to generate full three-dimensional architectural solutions that are energy efficient and respond to conflicting design criteria. The system combines a Genetic Algorithm, a detailed building energy simulation software [DOE2.1E], and Pareto optimization techniques, to evolve architectural designs within a given domain. The GDS adaptively generates populations of alternative solutions from an initial schematic design containing topological information, and a set of rules and constraints defined by the architect as a way to encode his main architectural intentions, which may leave to the system various degrees of freedom towards the generation of different solutions.

The flexibility embed into the GDS permits different types of use by the architect: having a predefined geometry and using the system just for the generation of façade design and window sizing; using the GDS simply for determining what materials should be used in an external wall, considering initial costs, energy performance, and embedded energy in the materials themselves; or using the GDS to suggest the overall geometry and spatial layout of the building, within given constraints and requirements. In this paper, we focus mostly in the latter, demonstrating an application of the system to the generation of a two-storey building with eight rooms, for a cold climate like Chicago.

The problem setting has been described elsewhere (Caldas, 2004), including the schematic layout used. In plan, it consists of four adjacent spaces, sharing the same internal corner (see figure 1). While the relative locations and adjacencies of the spaces are fixed, their exact dimensions are a variable to the GDS. The dimension of the façade elements is also variable, knowing that windows are only allowed in the two external walls of each space as drawn in the schematic design in figure 1, even in the event of new external walls being created during the evolutionary process. Window width is always equal to wall width, but its height can vary. This simplified design problem has nonetheless 44 independent variables and generates about 350 dependent variables. Each solution's gene is composed of 120 alleles. This gene is then manipulated to search for the most energy-efficient spatial configurations and façade solutions.

In the 1st floor, rooms 1, 2, 3 and 4 can vary in their length and width, but are constrained to have the same height. In the 2nd floor, rooms 5, 6, 7, and 8 are allowed to have different heights as well. Roof tilts can range from a flat, horizontal roof to a maximum of 45º. The azimuth of the tilt can vary, as shown by the arrows in figure 1. Whenever there is a tilted roof, a roof monitor is generated, with length equal to the corresponding wall and with the maximum possible height allowed by the roof geometry.

Objective Functions

The two conflicting objective functions considered are maximizing daylighting, and minimizing energy consumption for space heating. In a cold climate, it might be predicted that, for energy conservation purposes, the generated shapes would be as compact as possible, to minimize heat losses around the perimeter of the building. However, the presence of daylighting requirements would introduce an opposing force in the shape generating process, as the best shapes for harvesting daylighting are slim, narrow shapes with a higher surface to volume ratio. This classifies as a multi-

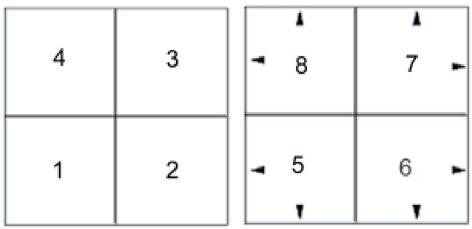


Figure 1. Problem layout for Floor 1 (left) and Floor 2 (right)

criteria problem, where typically there is no single solution that is optimal, in the sense that it responds best to all objectives simultaneously, but instead different solutions will represent different degrees of compromise between the conflicting criteria. In this type of context, it is the decision maker who will have to decide where he wants to situate the final solution, in terms of favoring certain criteria in detriment of others.

One of the particularities of using a Generative Design System like this one is that, because each room dimensions are variables between certain limits, there is no apriori control over the area of the building. In an energy-saving context, an immediately emergent strategy in the first generations of solutions is reducing the size of the building, since a smaller building will always tend to consume less than a large one. To contradict this tendency, two methods can be applied in evaluating solutions: penalty functions or normalization of objective functions. The penalty function will depend on the discrepancy between a desirable building size and the solution proposed. The problem with applying penalty functions in this case is that tey tend to confuse the search, since the GA is getting feedback through objective function values that are degraded according to a degree of violation of other constraints that do not necessarily correspond to the quality of the solution itself, in terms of the environmental variables under study. This study thus resorted to normalizing energy consumption for heating and lighting per unit area, which should allow results to be comparable throughout buildings of different dimensions.

Pareto Genetic Algorithms

This research avoided the application of plain aggregating approaches, like the use of weighting factors, as they require from the decision maker that preference between the different criteria is determined prior to performing the search, by preattributing different weighting factors. Instead, our search relies on Pareto optimization techniques, which provide a frontier of solutions representing the best possible trade-offs between the conflicting targets, providing the decision maker with that information prior to determine which objectives to favor. The generation of this trade-off information comes in the shape of a Pareto front, and it is the role of the Pareto Genetic Algorithm to locate it. Many Pareto GAs tend to cluster their search around particular areas of the search front, giving scarce information about other possible areas of interest, a process called genetic drift. Our experiments were able generated well-defined, uniformly sampled Pareto fronts, by using appropriate ranking and niching strategies, which force the search to spread all over the Pareto front. This is achieved by exerting a pressure against the formation of cluttered niches, in a process where each element of the same niche will degrade the fitness of its neighbors, thus preventing the generation of solutions that are too similar among themselves.

Results

In terms of the architectural solutions generated, the frontier of Pareto solutions range from long and narrow buildings, representing the best shapes for harvesting natural light but inefficient in terms of energy consumption, to compact shapes with minimum heat transfer problems, but which are poor daylighting collectors. Between these extremes, the Pareto front presents a large variety of compromise solutions, representing the best trade-offs in terms of the two objective functions.

Comparative Analysis of Results

A comparative analysis of the heating loads and lighting levels of the solutions generated by the GDS is performed, in order to further desegregate the information and have a deeper insight into the quality of the solutions generated by the system.

As previously explained, Energy Intensity (energy per unit area, in KWh/m2) was used as the objective function instead of the absolute amount of energy spent in each building, as a way to normalize simulation output despite differences in building size. However, when analyzing the solutions generated by the GDS, the emergent pattern is that buildings that are situated in the area of the Pareto front where minimum use of heating energy dominates, are typically much larger than those in the area where minimum artificial lighting use prevails (see figure 4 and table 1).

A possible explanation for this pattern is that in smaller buildings, where side-lighting from windows may be an efficient option, it is worth to invest in daylight by creating narrow, slim shapes. In larger buildings, where it may be difficult anyway to avoid deep plan situations, since there are limits set in the program to the length of the spaces, the GDS adopts the strategy of creating bulky shapes to prevent heat loss, and gain in that respect an advantage that it does not have in relation to daylighting.

By analyzing the relative sizes of the first and second floors, it is also possible to see that solutions that behave better in terms of heating typically have a top floor that is smaller than the ground floor. It is well that roofs and houses covers in general are particularly susceptible to heat loss, as hot air goes up due to buoyancy. The GDS thus adopts the strategy of reducing its relative size. On the other hand, the best solutions in terms of daylighting have top floors that are larger than the ground ones, as they are probably less prone to be obscured by upper level construction elements.

A deeper analysis was carried out for solutions 1 (best in terms of heating, worst in terms of lighting), and solution 7 (best in terms of lighting, worst in terms of heating), in an attempt to identify the strategies used by the GDS to reach those solutions. The analysis was done in a room-by-room basis. The best solution in terms of heating is basically constituted by compact, large spaces facing

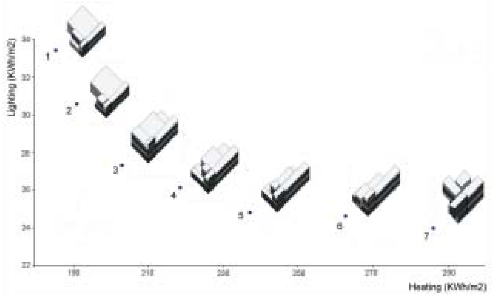


Figure 2. Pareto Front solutions

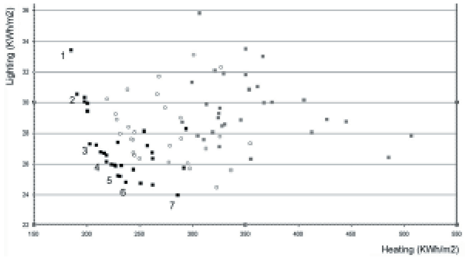


Figure 3. Progression of GDS search for solutions, from random Generation 1 to Generation 400, when the experiment stopped. Solutions depicted in figure 2 were chosen from the Pareto front.

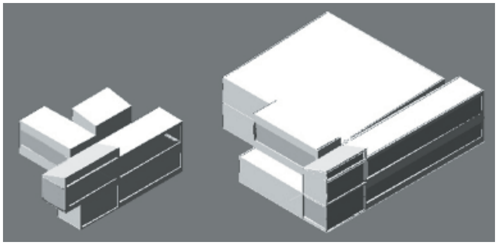


Figure 4. Solution 1 (right) and Solution 7 (left), shown at the same scale.

Solution	Heating (KWh/m2)	Lighting (KWh/m2)	Area (m2)	Floor 1 Area(m2)	Floor 2 Area(m2)
1	185	33	605	322	283
2	190	30	595	314	281
3	202	27	397	220	177
4	218	26	314	194	120
5	237	25	236	144	92
6	262	24	214	112	102
7	286	23	147	70	77

Table 1. Pareto Front Solutions: Energy Intensity for heating and lighting, and building area.

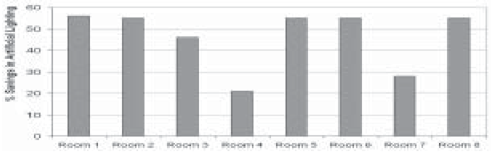


Figure 13. Solution 1: Annual percentage savings in artificial lighting, per room

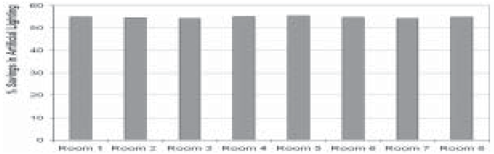


Figure 14. Solution 7: Annual percentage savings in artificial lighting, per room

northeast, enveloped by thin, all-glazed south sunspaces (figures 5-8). The best solution in terms of lighting is formed by small, narrow spaces, where daylight can easily penetrate. The south-facing large glazing areas also exist in this case, forming long sunspaces (figures 9-12).

Figures 13 and 14 show the results for each room in terms of percentage artificial lighting savings throughout the year, due to daylighting use. These numbers assume that dimmable lighting controls would be installed, linked to photoelectric sensors, and that maximum savings achievable are 70%, as there are always people turning on lights, even if unnecessary, days when the sky is too covered, and spaces as service areas where artificial lighting will keep being used.

While in solution 7 the percentage of savings is close to the maximum for every room, in solution 1 there are three spaces that show degraded performance. An analysis of these spaces reveals that Room 4, despite having the worst performance, is a relatively small space of 38 m2, with reduced impact over final results. Room 3, on the contrary, is the largest space, with about 225m2 (15x15m),

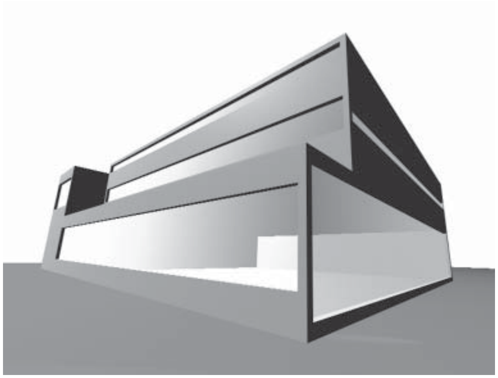


Figure 5. Solution 1: view from the Northeast, showing Room 3 in the ground floor, and Room 7 on top

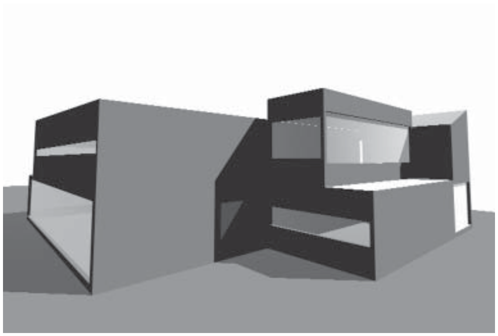


Figure 6: Northwest view, with Rooms 3 and 7 in the left

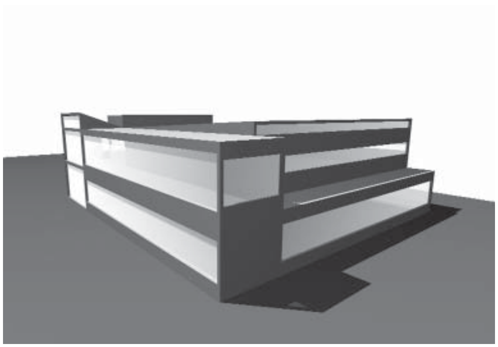


Figure 7. Solution 1: view from the Southeast, showing the large south-facing areas surrounding the core spaces of Room 3 and Room 7 on top

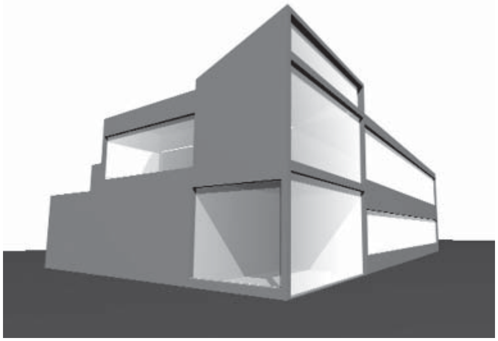


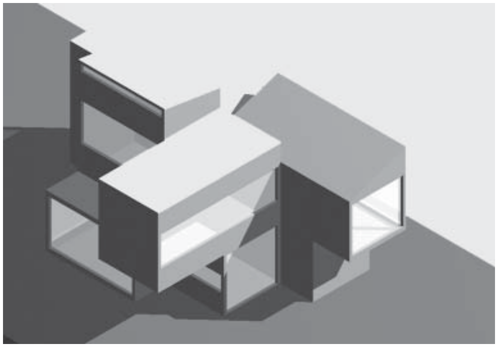
Figure 8: Southwest view, with south-facing sunspaces

with Room 7 following at 200m2 (aprox. 15x13m). Despite the fact that these large dimensions are detrimental in terms of daylighting performance, creating a compact, massive form is part of the strategy for reduced heating energy. As can be seen in figure 5, Room 3 has large windows to bring daylight into the space. However, its heating load does not become excessively high because it doe not have an exposed roof. Contrarily, Room 7 is more exposed to heat loss due to its large roof area, thus counteracting that effect with reduced fenestration, causing poor performance in terms of daylighting.

The analysis of solution 7 reveals that all spaces, except for Room 3, have one of its dimensions as 3m only. These thin, elongated forms immediately assure that daylighting use will be highly successful. Room 3 is the only one that is slightly deeper (5x5m), but the choice of large floor-to-ceiling windows insures natural light availability.

Energy Use and Energy Intensity

One final analysis will distinguish between the consideration of total energy use in the building, and energy intensity (energy per unit area). Figure 15 plots, for solution 1, the performance of each room, in every month of the year, both in terms of amount of heating energy used and of artificial lighting savings. Each point represents a month, and trendlines illustrate performance throughout the year. All lines tend to zero in the summer months. It can be seen that most rooms achieve a good balance, being located in the graph area that combines high lighting savings with low heat input. The three outliers are: Room 4, with very low



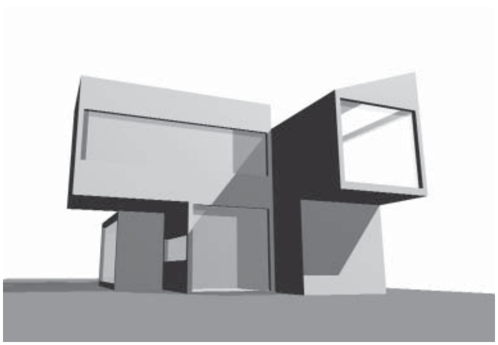


Figure 9. Solution 7: Northwest aerial view, showing the fragmented, narrow rooms generated, and their layout according to different orientations

Figure 10: view from the West

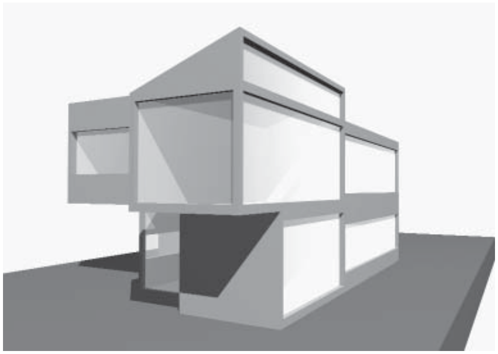


Figure 11. Solution 7: view from the Southeast, showing south-facing rooms

Figure 12: Southwest view, with Room 1 (ground floor) and Room 5 (top floor) in the foreground

Figure 15 . Solution 1 - Heat Addition Energy (KWh) versus Savings in Artificial Lighting, plotted for every room and month

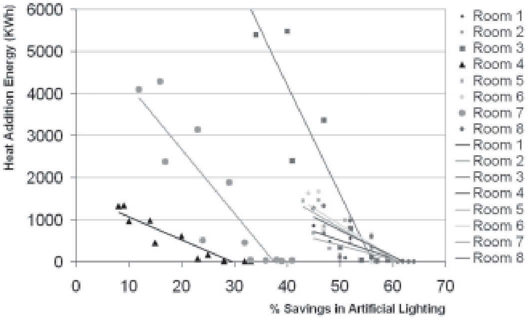


Figure 16. Identical, but showing Heat Addition Energy Intensity (KWh/m2).

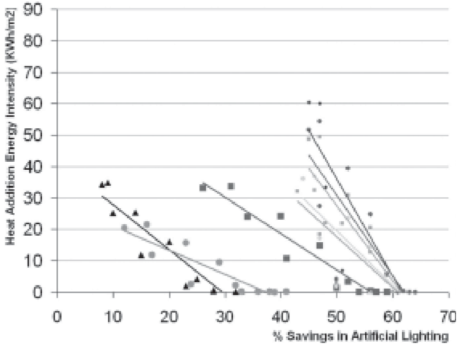


Figure 17 . Solution 7 - Heat Addition Energy (KWh) versus Savings in Artificial Lighting, plotted for every roomand month

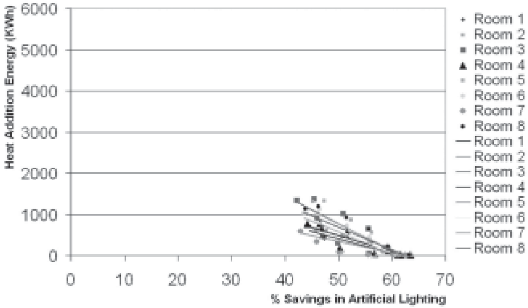
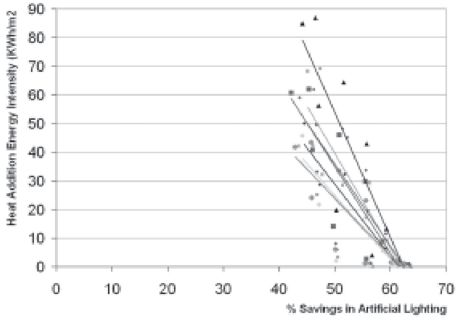


Figure 18. Identical, but showing Heat Addition Energy Intensity (KWh/m2).



savings, but reduced heat input; Room 3, which, despite the fact of achieving relatively high lighting savings, can have high heat inputs in certain months of the year, due to its large dimensions; and Room 7, in an intermediate position between the former two.

If energy per unit area is considered (figure 16), the situation changes considerably. Energy input into Room 3 is not the highest anymore, being surpassed by Rooms 1 and 8, for example. The large size of the space justifies the heat input into it. On the contrary, Room 4 seems to have a worst performance than Room 7 for part of the year, since its reduced size doe not justify the amount of heat it consumes, even if it is not much in absolute terms.

Figure 17 refers to Solution 7, and is plotted in the same scale as fig. 15, for comparison purposes. Looking at total energy input, it might seem that solution 7 does not consume much energy. However, the plotting of energy intensity shows that, in fact, its performance in terms of heating consumption per unit area is poor, quite worse than solution 1, thus pushing it to the area of the Pareto front that corresponds to the worst performance for heating, despite being the best for lighting.

Conclusions

The analysis of results considering Energy Use Intensity, or energy consumption per unit area, provided useful insights into the strategies used by the GDS towards locating the Pareto front between the given conflicting objectives. Those strategies are global and emerge in parallel, including issues of building massing, aspect ratio, surface-to-volume ratio, orientation, façade design, and others, all playing a significant role in dictating if a given architectural form will be energy efficient.

The analysis showed that the massing and aspect ratio of the building play a crucial role in its performance. The question of scale thus arises as a prominent one. To what extent may a design like that of solution 7 be scaled up until its performance degrades extensively? In case it is scaled to have an area similar to solution 1, how will both heating and lighting consumption comparatively behave? Further research is necessary to investigate the combined impact of scale and aspect ratios.

Results suggest that the questions raised by the exploration of form generation driven by environmental concerns are complex, deserving the pursuit of further experiments, to better understand the interaction of the large number of variables that the evolutionary process supports.

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