SHAPE GENERATION USING PARETO GENETIC ALGORITHMS

Integrating Conflicting Design Objectives in Low-Energy Architecture

LUISA G. CALDAS
Instituto Superior Técnico
Department of Civil Engineering and Architecture
Technical University of Lisbon
Av. Rovisco Pais, 1049-001 Lisbon, Portugal
Tel: +351 218418346, Fax: +351 218418344
Email: luisa@civil.ist.utl.pt

Abstract. The Generative Design System [GDS] presented in this paper was developed to assist designers in researching low-energy architecture solutions. The GDS has the capability to evolve architectural forms that are energy-efficient, while complying to design intentions expressed by the architect, and responding to conflicting objectives. To achieve this evolutionary development, the system integrates a search and optimization method [Genetic Algorithm], a building energy simulation software [DOE2.1E], and Pareto multicriteria optimization techniques. The GDS adaptively generates populations of alternative solutions, from an initial schematic layout and a set of rules and constraints designed by the architect to encode design intentions. The two conflicting objective functions considered in this paper are maximizing daylighting use, and minimizing energy consumption for conditioning the building. The GDS generated an uniformly sampled, continuous Pareto front, from which six points were visualized in terms of the proposed architectural solutions.

1. Introduction

The use of Artificial Intelligence techniques in the process of architectural design has been a topic of interest in the last years. Practical implementations include structural optimization (Shea, 1998), acoustical optimization (Monks, 1998) and low-energy architectural design (Caldas and Rocha, 2001). One of the most immediately applicable methods in the area is the use of search mechanisms like Simulated Annealing or Genetic Algorithms. However, the search and optimization engine is only one of the components that are necessary to build a Generative Design System. Figure 1 illustrates how a GDS should be able to generate alternative solutions for a given design problem, evaluate their efficacy or adequacy according to some user-defined criteria, and adaptively search for alternatives that present a better pay-off in terms of the desired objective function.

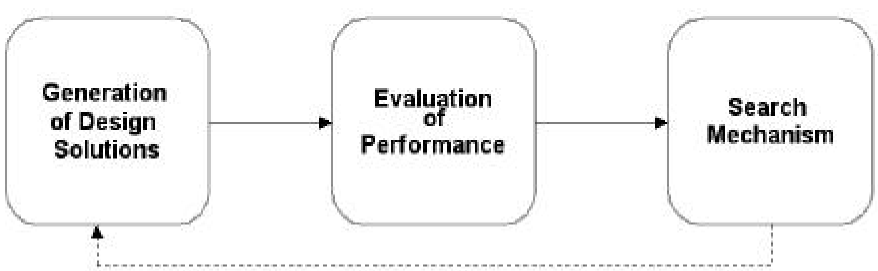


Figure 1. Flow chart of a possible Generative Design Systems used in architecture

Figure 2 represents a diagram of the methods used in this paper in each of the GDS components. In the search mechanism, Pareto Genetic Algorithms are used, which can handle multi-objective optimization problems without resorting to the use of artificial weighting factors, and instead look for the best possible trade-offs between conflicting design objectives.

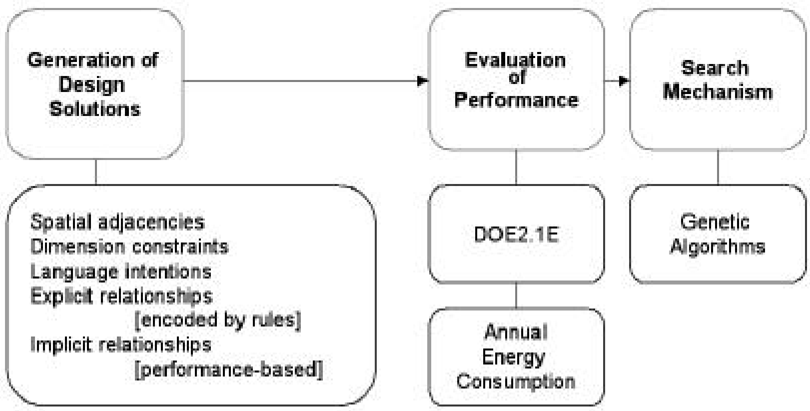


Figure 2. Flow chart of the Generative Design System presented

2. Previous work

While the ‘Evaluation of Performance’ and ‘Search Mechanism’ steps have been documented elsewhere (Caldas and Rocha, 2001; Caldas and Norford, 2002), the ‘Generation of Design Solutions’ step may be more complex to describe. The designer starts the system with a basic layout that defines the number of spaces, their adjacencies and constraints, but does not provide exact geometry, which will be determined by the GDS. The system is thus provided with topological information, instead of geometrical one.

The schematic layout used for generating alternative design solutions is similar to the one used in a previous paper (Caldas, 2002). In plan, it consists of four adjacent spaces, sharing the same internal corner [figure 3]. 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 3, even in the event of new external walls being created during the evolutionary process. 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 3. 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.

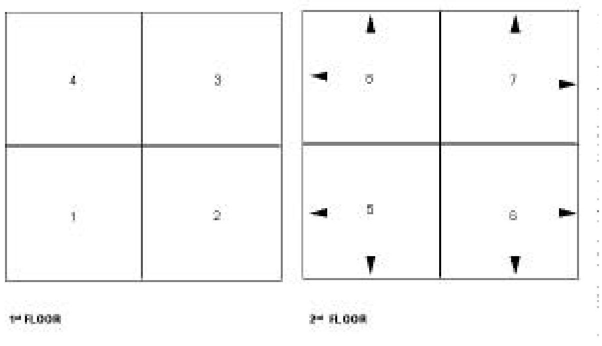


Figure 3. Basic layout for 1st and 2nd floors. Arrows show possible roof tilt directions.

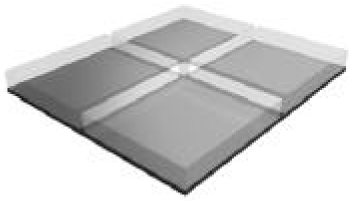


Figure 4. Graphical representation of 1st floor room constraints. Each room could have at most 15 x 15 m, with minimum dimensions of 3m.

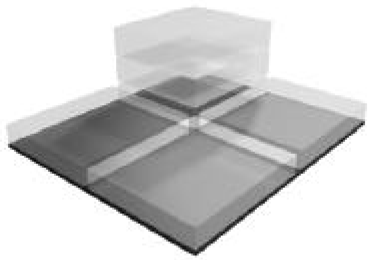


Figure 5. Graphical representation of 2nd floor room constraints. Space height can vary between 3 and 6 m. The topmost volume indicates maximum roof height.

When dealing with variable building shapes, a number of issues emerge regarding window size and positioning. For fixed building shapes, it is possible to determine upper bounds for window size, which are limited by the dimensions of the window wall. However, if wall size is not known in advance, since it is a variable itself, it becomes impossible to do so. This represents a drawback in terms of standard genetic algorithm functioning. In common GA implantations, the constraints for each variable are determined prior to running the program. To deal with this situation in a thorough way would require a dynamic constraints GA, which had not yet been implemented. It thus became necessary to find a simplified solution for the experiments presented here. Window width was made equal to wall width minus external walls thickness, thus becoming a dependent variable. In terms of height, 1st floor windows posed no problems, as wall height was fixed and constraints could be determined in advance. For the 2nd floor, the maximum window height was set equal to the minimum wall height, to ensure windows would always fit into the respective wall, regardless of their height.

These simplified rules have the disadvantage of allowing little variation in façade design. Windows always stretch from wall to wall, and vary in height only. This led to a certain standardization of generated facade solutions, which is nevertheless counteracted by the great variety of shapes produced by the GS. To introduce more diversity into the experiments, and also as an useful environmental analysis strategy, window height could be driven to 0, meaning that if the GS found that excluding a window was beneficial in terms of overall building performance, it was allowed to do so.

The location of daylighting reference points has to be calculated by the program for each new solution generated. The rules for placing the sensors were: one sensor in the center of the space, and the other 2 meters away from the innermost walls. This strategy tries to ensure that natural light is used throughout the space, and that it penetrates into the deeper areas of the rooms. The sensors are placed 0.75m high, approximately desktop height. Figure … shows an example of lighting sensors automatic placement by the GA (the dark dots in the figure are sensors for the 2nd floor room).

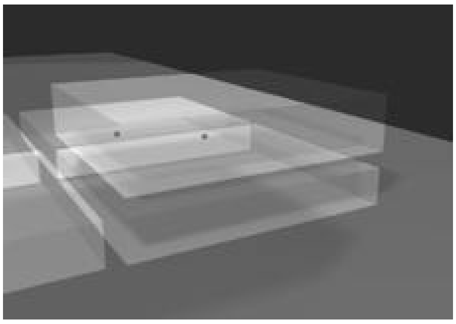


Figure 6. The two dark dots represent daylighting sensors automatically placed by the GA inside a 2nd floor room

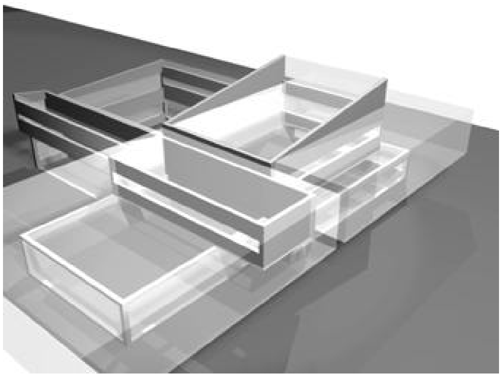


Figure 7. Spaces being generated within the given rules and constraints.

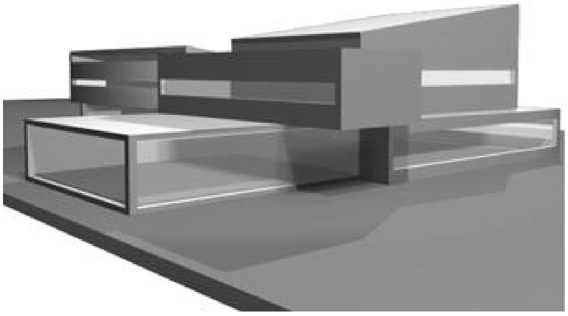


Figure 8. View of one solution generated by the GA

3. Method

Pareto shape generation experiments were done using Chicago climatic data. This climate was chosen because it represented an interesting challenge for the Generative System, since the requirements for heating and daylighting are quite conflicting. The problem the GS had to solve was to find the best trade-offs between solutions that provided adequate daylighting and minimized the need for heating. The objective of finding a good Pareto front is not to achieve solutions that perform well either in terms of heating or lighting, but to find the solutions that, while having a good performance in terms of heating, also have the best possible performance in terms of lighting given the priority given to heating, and vice-versa. Middling solutions that perform reasonably well in terms of the two conflicting criteria are usually located towards the center of the front.

A Pareto run was performed having as the two objective functions both minimizing energy spent in lighting [corresponding to maximizing use of daylighting], and minimizing energy for heating. The progression of the search is shown in figure 9. Because the problem was quite complex, due to the large number of variables in the problem [44 independent variables] and the use of two objective functions, the GS was run for 400 generations. The population size was 30 individuals.

It can be seen that from the initial random population [hollow squares in figure 9], the points moved towards the regions of lower objective function values and by generation 100 [grey squares] the points were starting to define an initial boundary. By generation 400 [small dark squares], that boundary was much more clearly defined, and been further pushed towards the lower regions of the solution space. It might be the case that running the GS for more generations would further increase the definition of this boundary, since some of the points of the final generation are not yet at the Pareto front, but for the demonstration purposes of this exercise that definition level is close satisfactory. Some of the most significant points of the front were visualized, which are highlighted by the larger shaded squares in figure 9. The three remaining squares towards the top left of the graph highlight the poor-performance solutions also visualized, for comparison purposes. Figure 10 illustrates the Pareto-front points, and the building shapes they represent.

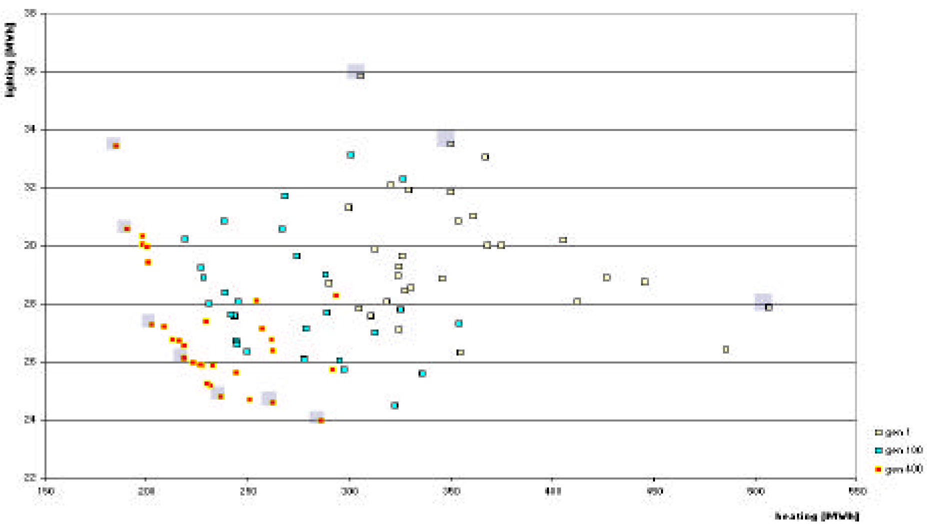


Figure 9. Progression of Pareto front search, from generation 1 to 400. The shaded squares indicate points visualized in figures 11 and 12.

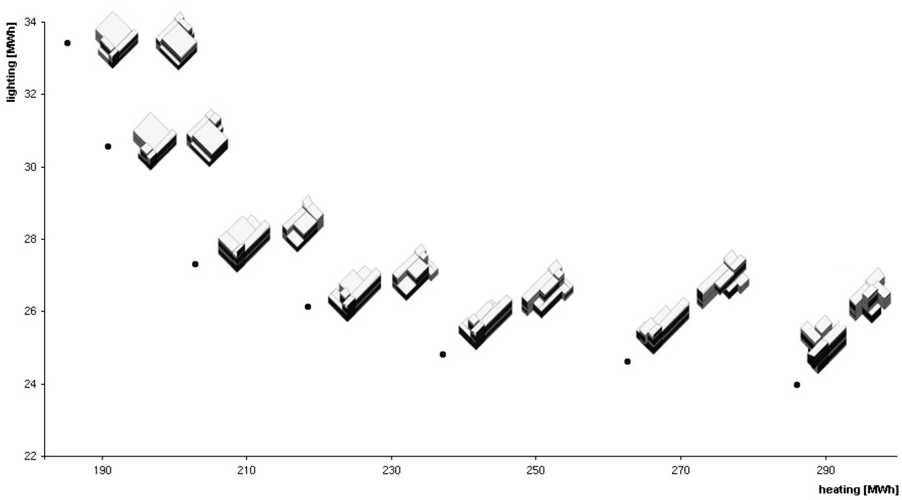
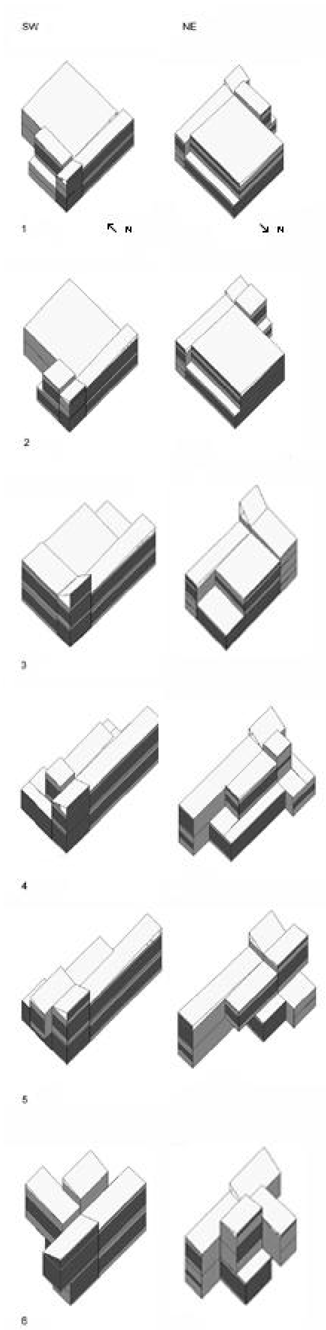


Figure 10. Pareto front points. Larger versions of the images can be seen in figure 11



The building shapes can be better visualized at a larger scale in figure 11. The best solution in terms of heating (#1) is basically constituted by a single, compact, large space facing northeast, with thin, all glazed south and west elements surrounding it in a sunspace type of configuration. This happens both in the 1st and 2nd floors. The best solution in terms of lighting (#6) is formed by small spaces, where daylight can easily penetrate. The south-facing large glazing areas still exist in this solution, in long and thin rooms facing south. The intermediate solutions show basically a progressive transformation from one solution to the other. Solutions #4 and #5 are interesting ones, showing long and thin south-facing elements, and a number of smaller, north-facing spaces.

Finally, figure 12 illustrates some of the poor examples also identified in figure 9. Solution W1 performs quite poorly in terms of lighting because many of the spaces have small or nonexistent windows. This might have lead to a good performance in terms of heating, but the fragmented distribution of spaces creates many external surfaces that represent high wall-to-area ratios, and many exposed roofs and floors too, what reduces the solutions efficacy in terms of heating too. Solution W3 is reasonably good in terms of lighting, but quite poor for heating, mainly due to large roof tilts and glazing surfaces, and to the use of large overhangs and small volumes.

Figure 11. Pareto front points. Solution #1 represents the best building shape in terms of heating. Solution #6 is the best building shape in terms of lighting. Other images represent intermediate solutions [see figure 10 for comparison]

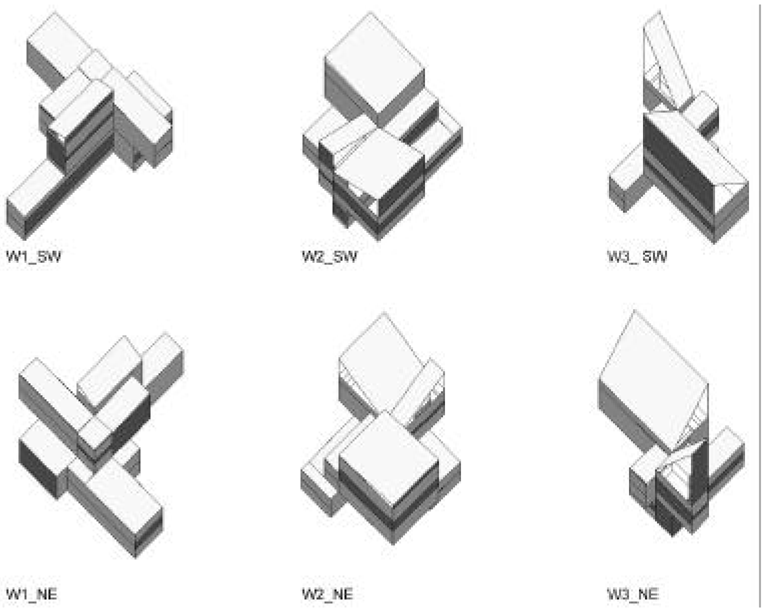


Figure 12. Some poor performance solutions from the initial random generation.

4. Daylighting Analysis

The last step involves ‘zooming’ into solution #1 from figure 11. This building configuration has the best heating performance found. However, it shows some non-evident features, like very large north- and east-facing windows in some of the spaces, what might not be expected in such a cold climate. Our hypothesis was that the configuration of having a very compact space, with a small wall-to-surface area ratio, could make the use of very large openings not too detrimental in terms of heating, while allowing for adequate daylighting of the space. Using DOE2-generated lighting reports, the percentage of artificial lighting savings due to daylighting use was plotted for both room 3 [the large, bulky space in the ground floor] and for room 7 [the similar space located above it, in the 2^{nd} floor]. Results are shown in figures 13 and 14.

From figure 13 it is possible to conclude that by using large north facing windows, room 3 achieves a 70% artificial lighting reduction for most of the year, except for months like January and February [70% reduction is the maximum allowed, since it is assumed that there will always be some lights turned on, like task lighting at individual workplaces]. So, even though the space is quite deep, the combination of east- and north-facing windows is very successful in providing good daylighting to the space.

Room 7, on the contrary, uses mostly east-facing openings [both a window and a clerestory type of opening, due to the slightly tilted roof], with a very reduced north-facing window. This causes a substantial change in the profile for artificial lighting savings, as can be observed in figure14. In this room, savings are more reduced, happen mostly during the morning hours, and only reach the 70% level in the peak summer months.

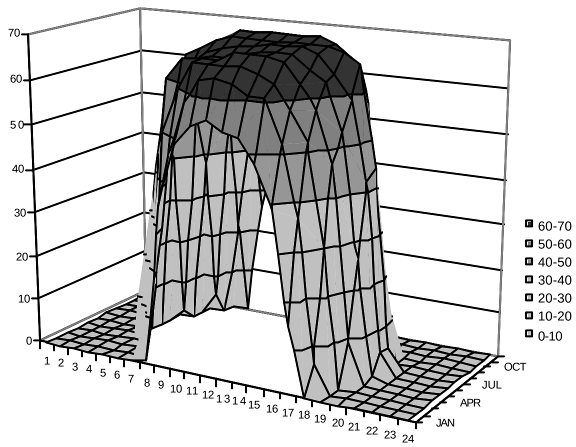


Figure 13. Plotting percentage of artificial lighting savings due to daylighting use for Room 3 of solution #1

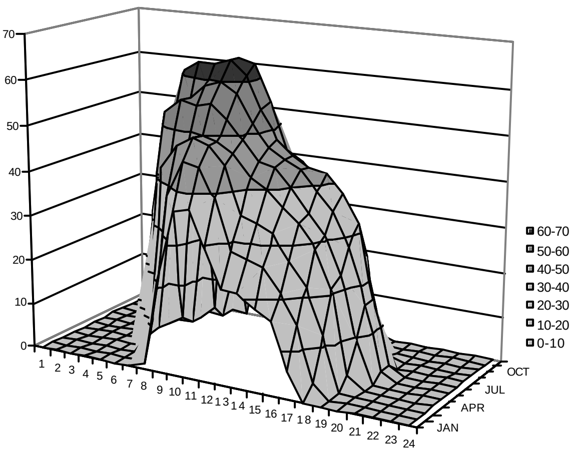


Figure 14. Plotting percentage of artificial lighting savings due to daylighting use for Room 7 of solution #1

The analysis of these graphs helped to clarify the reasons behind the use of such large north facing windows in a climate like Chicago, what could not be initially obvious. Even though solution #1 is not the best one for lighting, for it to be in the Pareto frontier it should be able to perform reasonably well in terms of lighting too. However, in the same building, other spaces exist that have very poor daylighting use, such as room 4 [in the northwest corner, 1st floor], whose graph is plotted in figure 15

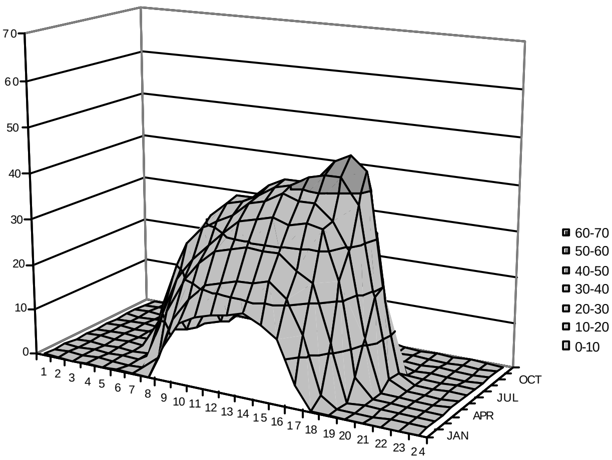


Figure 15. Plotting percentage of artificial lighting savings due to daylighting use for Room 4 of solution #1

Room 4 has only a north-facing window, of relatively reduced dimensions, and has no openings to the west. This causes that the daylighting use profile is quite poor, with percentage of artificial lighting savings being quite low for most of the year, and only reaching the 40-50% range in July and August. However, since this is a rather small space, its impact on overall daylighting use on the building is not too significant.

Many other types of reports can be requested to the Generative Design System, which allow the user to look in detail at physical phenomena happening in each particular space of the building [at the limit, hourly reports can be generated, showing the variables' evolution for each hour of the year]. This includes not only lighting information, of which only one type was shown here, but also information about cooling and heating loads in each space, construction elements [walls, roofs, underground floors, windows, etc.] are causing more energy loss / gain during that time of the year, etc.

This detailed analysis stage demonstrates that the designer does not have to rely on a single objective function, like building annual energy consumption, to assess the relative quality of a solution in environmental terms. Pareto fronts consider multiple criteria simultaneously, and the GDS can also provide detailed information about what is happening in each of the spaces individually. In most situations users may only be interested in high-level, general information, but in cases where detailed information is required, it can easily be made available. For research in shape generation with the GDS, this type of detailed report can help to understand with more depth the complex interaction of variables happening in a particular architectural design.

5. Conclusions

Departing from a simplified schematic layout, the Generative Design System, coupled with Pareto-optimal methods, was able to create a variety of architectural shapes that respond to the different design objectives, both in terms of daylighting use and control of energy required for heating, leading to low-energy design solutions that differed among the type of objectives they respected most. Results from the Pareto based studies proved in general to valuable in understanding how the trade-offs between conflicting objectives influence design solutions located by the Generative Design System.

This GS is not to be regarded as an optimization tool, but instead as a generative mechanism whose goals are not only to reduce energy consumption in buildings, but also to suggest alternative building configurations and work as an augmented design aid. The particular shapes generated in these experiments are a result of the initial layout, rules and constraints applie d. Different initial conditions would lead to the emergence of other design solutions, suggesting this Generative System can be a powerful tool for architects to quickly study alternative low-energy designs and understand which architectural features are more decisive towards achieving desired performance targets.

The GDS did successfully locate spread-out, well-defined Pareto fronts, what provided enough confidence on the results obtained. Future work will address the issue of incorporating dynamic constraints into the system, so that an extra degree of flexibility is added to design elements like windows, roof monitors and other light sources. Finally, the expansion of the method to include more than two objective functions could lead to other interesting results, and remains as future work to be developed.

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