Shape Generation Using Pareto Genetic Algorithms: Integrating Conflicting Design Objectives in Low-Energy Architecture

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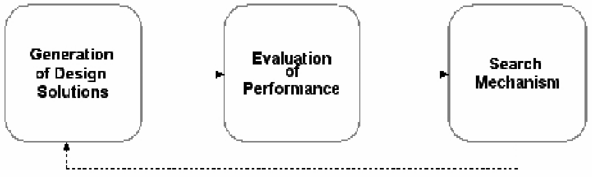
The Generative Design System [GDS] presented in this paper was developed to assist designers in researching low-energy architecture solutions. The GDS has the capability to evolve architectural forms that are energy-efficient, while complying to design intentions expressed by the architect and responding to conflicting objectives. To achieve this evolutionary development, the system integrates a search and optimization method [Genetic Algorithm], 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.

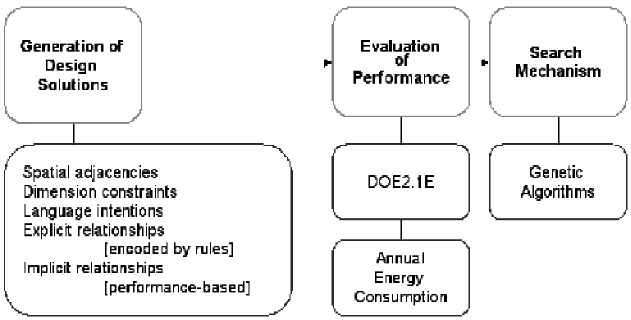
1. Introduction

The use of Artificial Intelligence techniques in the process of architectural design has been a topic of interest in the last years, where recent practical implementations include structural optimization [1, 2], acoustical optimization [3], and low-energy architectural design [4, 5, 6]. One of the most immediately applicable methods in the area is the use of search mechanisms like Genetic Algorithms and Simulated Annealing. Nevertheless, the search and optimization engine is only one of the components that are necessary to configure 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 user-defined criteria, and adaptively search for alternatives that present a better pay-off in terms of the desired objective functions.



► Figure 1. Possible flow chart of a Generative Design Systems applied to Architecture

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

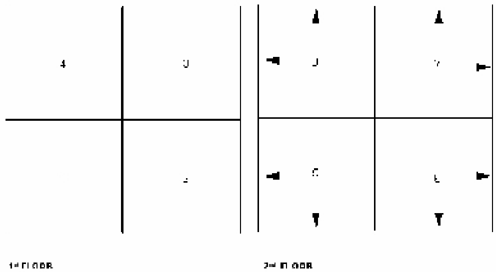


► Figure 2. Flow chart of the Generative Design System presented

2. Previous work

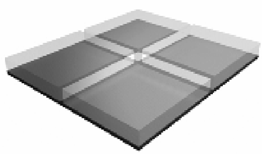
As the strategies used for 'Evaluation of Performance' and 'Search Mechanism' have been documented elsewhere [4, 5], this paper will focus mostly on the 'Generation of Design Solutions' module. The designer starts the process by giving the system a basic layout for the solution, defining the number of spaces, their adjacencies and constraints, but not providing the building's exact geometry. The system is fed with topological instead of geometrical information, because the latter will be determined by the GDS. The schematic layout used in this paper for generating alternative design solutions is similar to the one used in a previous paper [5]. In plan, it consists of four adjacent spaces, sharing the same internal corner (see figure 3). While the relative locations and adjacencies of the spaces are fixed, their exact dimensions are a variable to the GDS. Dimensions of the façade elements are also variable, with the constraint 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 that new external walls are created during the evolutionary process.

Despite its apparent simplicity, this simplified design problem has 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.

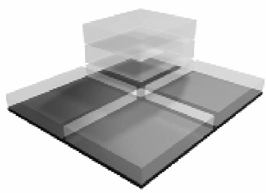


◀ Figure 3. Basic layout for 1st and 2nd floors. Arrows show possible roof tilt directions

In the 1st floor, rooms 1, 2, 3 and 4 can vary in 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. Roof tilts can range from a flat, horizontal roof to a maximum of 45°. 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 4. Graphical representation of 1st floor rooms maximum constraints. Each room could have at most 15 x 15 m, with minimum dimensions of 3m

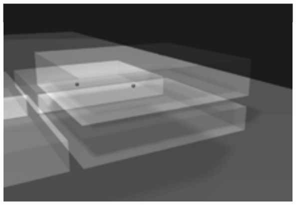


▲ Figure 5. Graphical representation of 2nd floor rooms maximum constraints. Space height can vary between 3 and 6 m. The topmost volume indicates maximum roof height

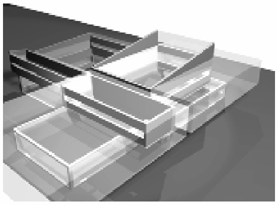
When dealing with variable building shapes, a number of issues emerge regarding window size and positioning. For fixed building shapes, it is possible to determine upper bounds for window size, which are limited by the dimensions of the window wall. However, this method becomes unfeasible if wall size is not known in advance, since it is a variable itself. This represents a drawback for the typical implementation of genetic algorithms, in which 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, where the constraints for some variables would depend on the values assigned to the genetic algorithm to another variable, and would thus only be determined during the execution of the program. Because a dynamic constraints GA has not yet been implemented for this application, it became necessary to find a simplified solution for the experiments performed. Window width was made equal to wall width minus the thickness of external walls, 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 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 a useful environmental analysis strategy, window height could be driven to 0, meaning that the GDS was allowed to completely exclude windows if it found it was beneficial in terms of overall building performance.

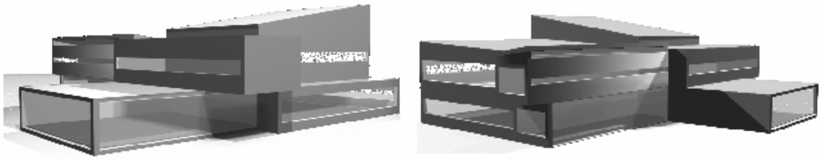
The location of daylighting reference points has to be calculated by the program for each new solution generated. The rules for placing the sensors were: one sensor in the center of the space, and the other two meters away from the innermost walls. This strategy tries to ensure that natural light is used throughout the space, . The sensors are placed at a height of 0.75m,



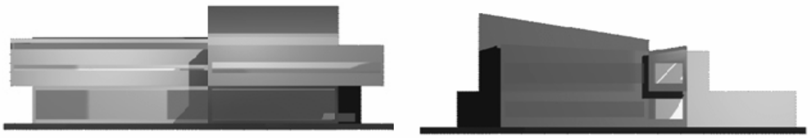
▲ Figure 6. The two dark dots represent daylighting sensors automatically placed by the GA inside a 2nd floor room



▲ Figure 7. Spaces being generated within the given rules and constraints. Translucent boxes represent upper bound constraints for each space, while opaque planes represent the spaces generated by the GDS approximately desktop height. Figure 6 shows an example of automatic placement of daylighting sensors by the GA (the dark dots in the figure are sensors for the 2nd floor room).



◀ Figure 8. Left: SE view of a solution generated by the GA for Oporto climate, Portugal. Right: SW view



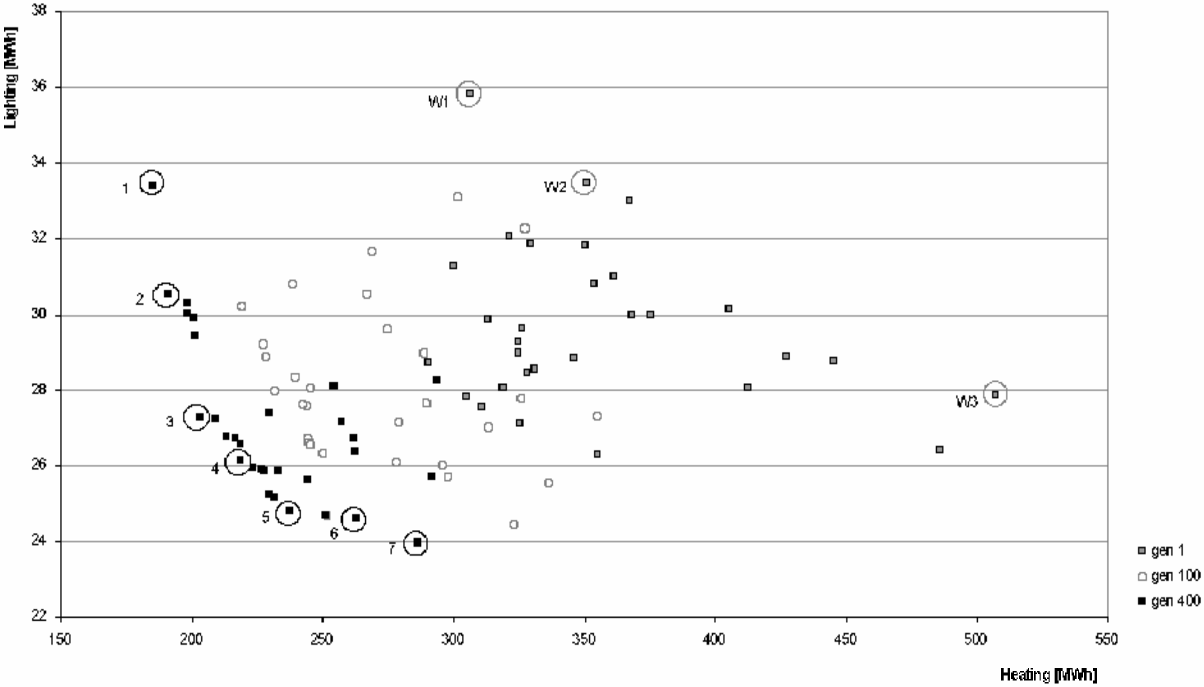
◀ Figure 9. Left: South elevation. Right: West elevation

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 Design System, as requirements for heating and daylighting are in conflict: larger openings provide adequate daylighting and useful solar gains, but are a significant source of heat loss in a severe winter climate. The problem the GDS had to solve was to find the best trade-offs between solutions that provided adequate daylighting and minimized the need for heating. Pareto-optimal search methods [7] were applied to locate the frontiers of best compromises between the conflicting objectives. Appropriate niching and ranking strategies [8] were used to spread the front through a large are of the solution space, so that formal variation would emerge and solutions would not be too similar to each other. 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 with two objective functions: minimizing energy spent in lighting (corresponding to an adequate use of daylighting), and minimizing energy for heating. The progression of the search is shown in figure 10. The problem under study was complex, due to the large number of variables in the problem (44 independent variables) and to the use of two objective functions, so the GS was run for 400 generations. The population size was 30 individuals.

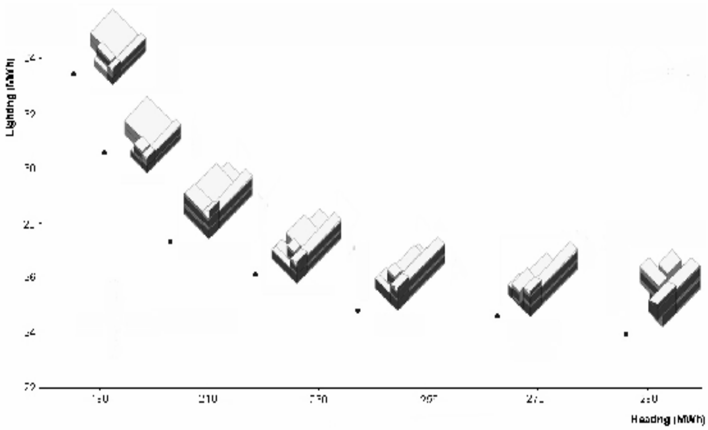
It can be seen that from the initial random population [grey squares in figure 10], the points moved towards the regions of lower objective function values and by generation 100 [hollow circles] the points were



▲ Figure 10. Progression of Pareto front search, from generation 1 to 400. Numbered circles indicate points visualized in figures 11 and 13

starting to define a frontier. By generation 400 [black squares], that boundary was more clearly defined, and had been further pushed down towards the lower regions of the solution space. It is possible that running the GS for more generations might further increase the definition of this frontier, since some of the points of the final generation are not yet at the Pareto front, but the definition level achieved is satisfactory for demonstration purposes. Seven of the most significant points of the front, highlighted by the circles in figure 10, were visualized. The three remaining circles towards the top of the graph highlight the poor-performance solutions also visualized, for comparison purposes. Figure 11 illustrates the Pareto-front points, and the building shapes they represent.

The building shapes can be better visualized at the larger scale of figure 12. 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 type of sunspace configuration. This happens both in the 1st and 2nd floors. The best solution in terms of lighting (#6) is formed by small, shallow spaces where daylight can easily penetrate. The large south-facing glazing areas still exist in this solution, materialized in long, thin rooms. Intermediate solutions show basically a progressive transformation from one solution to the other, in a morphing process. Solutions #5 and #6 are interesting in as much as they show hybrid solutions combining long and thin south-facing elements together with a number of smaller north-facing spaces.



◀ Figure 11. Pareto front points. Larger versions of the images can be seen in figure 12.

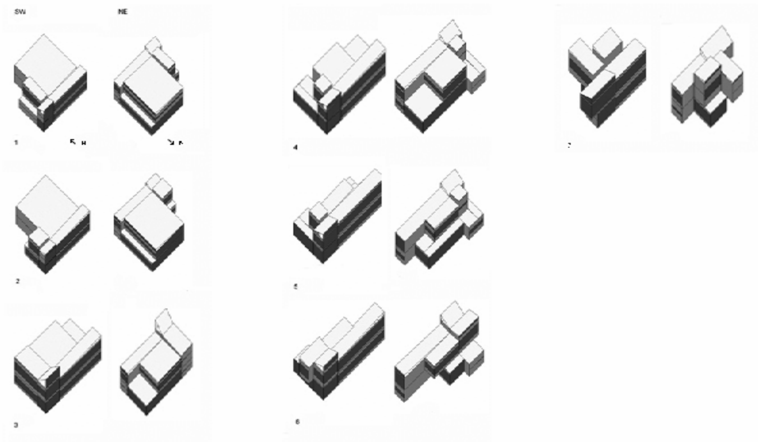
Finally, figure 13 illustrates some of the poor examples also identified in figure 10. Solution W1 performs quite poorly in terms of lighting because many of the spaces have small or nonexistent windows. This might have lead to a good performance in terms of heating, but the fragmented distribution of 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.

4. Daylighting analysis

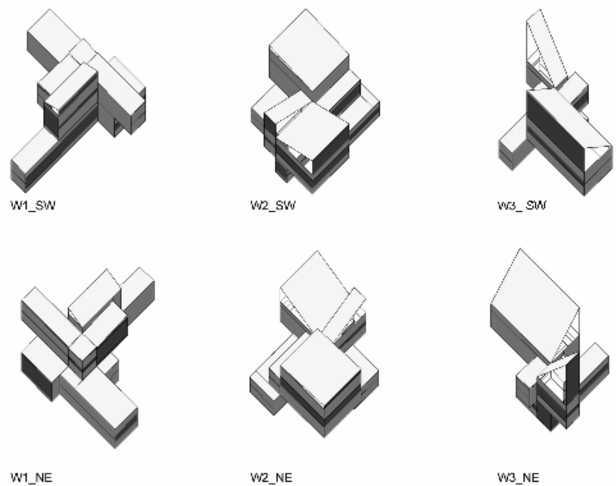
This section involves a closer look into solution #1 from figure 12, whose building configuration has the best heating performance found by the GDS in this set of experiments. However, the building design displays some features, such as very large north- and east-facing windows in some of the spaces, which might not be expected in such a cold climate. Our hypothesis was that the compact space configuration that was generated, presenting 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 NE corner of the ground floor, and for room 7, the similar space located above it in the 2nd floor (fig. 14).

Results are shown in figure 15. From the graph in the left side 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 such months as 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 successful in providing good daylighting to the space.

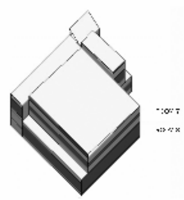
► Figure 12. Pareto front points. Solution #1 represents the best shape in terms of heating. Solution #7 is the best shape in terms of lighting. Other images represent intermediate solutions



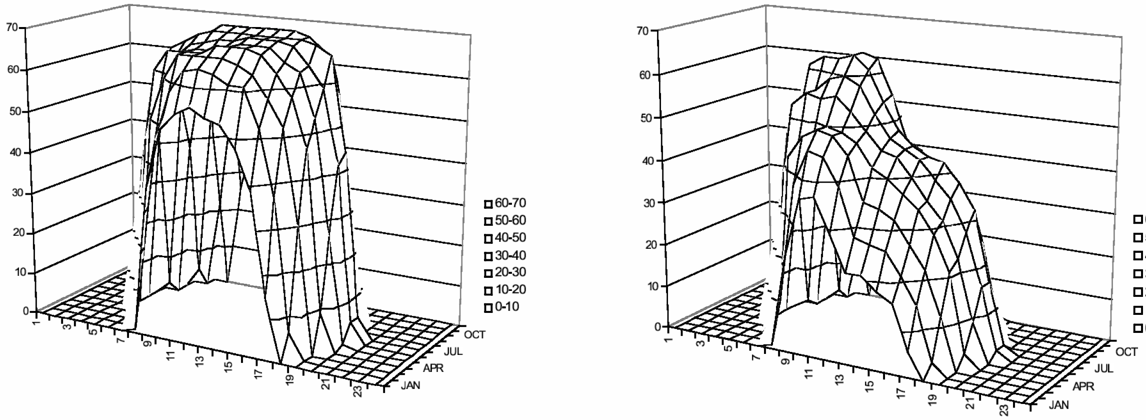
► Figure 13. Some poor performance solutions from the initial random generation



► Figure 14. Northeast view of solution #1, with rooms 3 and 7 identified



Room 7, on the contrary, has east-facing openings that are smaller than in room 3, and a very reduced north-facing window. This causes a substantial change in the profile for artificial lighting savings, as can be observed in figure14 (right). In this room, savings are more reduced, happen mostly during the morning hours, and only reach the 70% level in the peak summer months. The differences in façade design from room 3 to room 7 may be explained by the fact that room 7 has a large exposed roof, which generates much heat loss from that space. The GDS may thus have adopted smaller windows to counteract this effect, and avoid a situation where a single



▲ Figure 15. Artificial lighting savings due to daylighting use, solution #1. Left: Room 3. Right: Room 7

room has too much heat loss from its external envelope. Room 3, on the contrary, is protected in the top by room 7, allowing much larger openings in the facades without breaking the heat balance of the space.

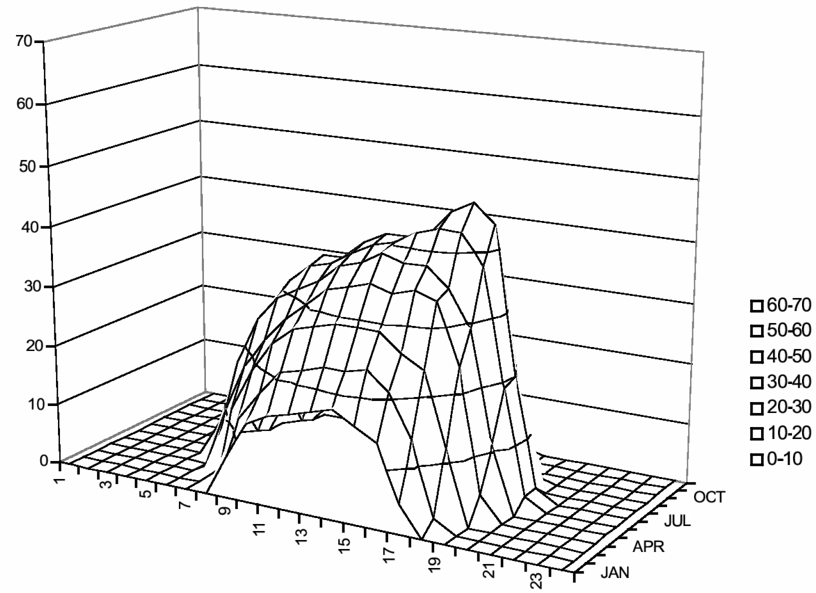
The east façade of room 7 displays both a window and a clerestory opening under the slightly tilted roof. The GDS may have used a clerestory to create a better distribution of daylight, since openings placed higher in the façade are able to bring light deeper into the space. The room is quite deep in that direction (about 13m), so the system may have split the glazing area in two, instead of just creating a large single window, to maximize the daylighting benefits of the glazing area, since heat loss would be almost similar in both cases.

The analysis of percentage artificial lighting savings graphs helped to clarify the reasons behind some of the solutions presented by the GDS, which were not initially obvious. Even though solution #1 is not the best for lighting, for it to be in the Pareto frontier it should be able to perform the best possible way in terms of lighting for the reduction in heating consumption achieved.

In the same building, other spaces exist that have very poor daylighting use, such as room 4 (northwest corner, 1st floor), whose artificial lighting savings are plotted in figure 16. Room 4 has only a north-facing window, of relatively reduced dimensions, and has no openings to the west. 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 significant, and the solution remains in the Pareto front.

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. In the limit, hourly reports can be generated, showing variables evolution for each hour of the year. This includes not only lighting information, which is also available in

► Figure 16. Plotting percentage of artificial lighting savings due to daylighting use, Room 4 of solution #1



other formats, but also information about cooling and heating loads in each space, construction elements (walls, roofs, underground floors, windows, etc.) that generate more energy loss/gain during a certain 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, avoiding a 'black box' behavior to the system. While in many situations users may only be interested in high-level, general information, detailed information can easily be made available when required. For research in shape generation with the GDS, this type of detailed report can help the designer to understand in 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 responded to design objectives for daylighting and reduced heating energy, leading to low-energy design solutions that differed with the objective to which they primarily responded. Results from the Pareto-based studies proved to be valuable in understanding how the trade-offs between conflicting objectives influence design solutions located by the Generative Design System.

The GDS presented in this paper 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 adopted, and the rules and constraints applied. Different initial conditions would lead to the emergence of other design solutions, suggesting this Generative Design 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. Nevertheless, the user interface must be significantly improved to allow designers to create constraints, rules and basic layouts in a more rapid and intuitive manner than the system presently allows.

The GDS did successfully locate spread-out, well-defined Pareto fronts, what provided enough confidence on the results obtained. Future research 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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