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Automation in Construction 11 (2002) 173–184

AUTOMATION IN CONSTRUCTION

www.elsevier.com/locate/autcon

A design optimization tool based on a genetic algorithm

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Abstract

Much interest has been recently devoted to generative processes in design. Advances in computational tools for design applications, coupled with techniques from the field of artificial intelligence, have lead to new possibilities in the way computers can inform and actively interact with the design process.

In this paper, we use the concepts of generative and goal-oriented design to propose a computer tool that can help the designer to generate and evaluate certain aspects of a solution towards an optimized behavior of the final configuration. This work focuses mostly on those aspects related to the environmental performance of buildings.

Genetic Algorithms (GAs) are applied as a generative and search procedure to look for optimized design solutions in terms of thermal and lighting performance in a building. The GA is first used to generate possible design solutions, which are then evaluated in terms of lighting and thermal behavior using a detailed thermal analysis program (DOE2.1E). The results from the simulations are subsequently used to further guide the GA search towards finding low-energy solutions to the problem under study. Solutions can be visualized using an AutoLisp routine.

The specific problem addressed in this study is the placing and sizing of windows in an office building. The same method is applicable to a wide range of design problems like the choice of construction materials, design of shading elements, or sizing of lighting and mechanical systems for buildings.

Keywords: Artificial intelligence; Genetic algorithms; Building design; Low-energy design; Generative systems; Optimization in architecture; Architectural design; Genetic algorithms in architecture; Artificial intelligence in architecture; Environmental design

1. Introduction

Computer simulations have proven in the last few decades to be a powerful tool for studying the environmental performance of buildings. The interaction between design features, climate, occupants and mechanical and electrical systems in a building is a complex one, and only by resorting to simulations is it possible to fully understand all the factors involved in the process. By using simulation tools, it is possible to engage in a design practice based on feedback loops between making design decisions and evaluating their environmental impact, as a way to inform the on-going process of design.

The objective of this paper is to go a step further in integrating the computer media in the design process by making use of it not only as a simulation tool, but as a generative method too. Simulations are normally used in a scenario-by-scenario base, with the designer generating a solution and subsequently having the computer evaluating it. This is however a slow and tedious process and typically only a few

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PII: S0926-5805(00)00096-0

scenarios are evaluated from within a large range of possible choices. In opposition to this method, we propose an approach of goal-oriented design [13], where the computer is used to extensively search the design solution space looking for high performance solutions in terms of specified goals. This way the computer automatically generates and evaluates possible configurations, and presents the designer with optimal or near-optimal solutions for the problem under study.

The use of optimization rather than simulation [17] is thus proposed as a way to integrate the computer media in the design process. The method used to implement the idea of goal-oriented design was the application of a search and optimization technique borrowed from the field of artificial intelligence, Genetic Algorithms (GAs). A GA is a procedure loosely based on Darwinian notions of survival of the fittest, where selection and recombination operators are used among candidate solutions to look for high performance ones [6]. We use GAs to search for design solutions, evaluate them and continue the search guided by the results of that evaluation. The designer is then provided with the results of that looping process.

Two important steps in the design process are the generation of a solution to the problem under study, and the evaluation of how good a response it represents to that problem. The field of artificial intelligence provides the designer with novel ways to generate and evaluate design solutions. By allowing the computational media to actively interact with and inform the design process, it is expected that solutions that were not immediately obvious to the designer may be generated. Throughout this process, the design object is enriched and expanded by its interaction with the media in which it develops.

2. GA-based design tool

Part of the difficulty of using generative tools to optimize architectural design is defining proper evaluation criteria for a given solution. Environmental analysis is a particularly adequate field for goal-oriented design because it is possible to specify quantifiable performance criteria to be achieved with the design, like lighting levels within the space, internal temperatures, and amount of energy spent in lighting, heating and cooling.

In this study, we propose an approach where the evaluation criteria are related to the environmental performance of the building, both in terms of lighting and thermal behavior. The tool described is mostly aimed at intermediate to late stages of design, since at early stages of design there is often no optimum solution, instead there is a large range of possible solutions all potentially having a good performance in responding to the problem under consideration. As the design process progresses, there is however an increased opportunity for optimization, for the solution becomes increasingly more defined and more concrete requirements are asked of its components. Examples of addressable problems are sizing of glazing elements according to climate and orientation, choice of type of glazing, choice of construction materials for walls and roofs, type and sizing of shading elements, and many others.

3. Problem under study

The particular problem we present in this paper is the optimal sizing of windows in a building to optimize its lighting, heating and cooling performance. The exact sizing of windows occurs typically at later stages of design, but will have a significant effect on the environmental behavior of a building. The optimal sizing will depend on the climate the building is located in, the glazing used, the orientation the window is facing, and the type of use of the building (offices, housing, etc.).

Windows display a complex environmental behavior due to different requirements often being in conflict with each other, making the evaluation of their overall performance a complex one. During the heating season, as window sizes increase, there is an increase in daylighting availability and thus a decrease in the need for artificial lighting, leading to less electrical energy consumption. There are also more useful solar gains through the window that tends to reduce heating expenditure. On the other hand, there is an increase in heat loss through the glass, which in turn requires more spending in heating. Less use of artificial lighting will also lead to lower internal heat gains in the building, leading to an increased need of heating.

During the cooling season, as window sizes increase, there is a decrease in the need for artificial lighting, which leads to less electrical energy consumption and also to lower cooling loads generated by the lights themselves. On the other hand, there are increased solar gains leading to more spending in cooling.

These interactions are simulated in the following way: given a design configuration, for each hour in the year daylighting levels inside the space are calculated at reference points. These numbers are then compared to the required lighting levels set by the designer. The artificial lighting system, which is continuously dimmable, is set to provide just enough light to make up from the difference between available daylighting and required light levels. The electrical energy spent by the lights is quantified, and so are the heat gains released into the space by them.

The system then goes on to calculating internal temperatures inside the space by taking into account external climatic conditions, the characteristics of the building fabric (wall, roof and window materials), solar gains through the windows, internal gains from occupants, equipment and artificial lighting, etc. Those temperatures are compared to set points defined by the designers, and heating or cooling is provided if required to compensate for the difference between calculated temperatures and predefined setpoints. The energy spent in heating and cooling is determined, and added to lighting energy to determine total annual energy consumption in the building.

The building simulated is assumed to be an office building, where internal conditions are usually tightly controlled, and systems like dimmable artificial lighting are likely to exist. The hypothetical office building module used consists of a square core zone, 30.5 m on a side, surrounded by four identical perimeter zones, each of 30.5×4.6 m. The module faces the four cardinal directions. Each perimeter zone is divided into 10 office spaces of equal size (3.1×4.6 m). The reference point for daylighting calculation is located 3.1 m from the window, at desk height. The required horizontal illuminance at this point is 540 lx. The window glazing was set as double pane with a layer of spectrally selective glass, with a shading coefficient of 0.34 and visual transmittance of 0.41.

The problem was studied for two locations: Phoenix, Arizona, a cooling-dominated situation; and Chicago, Illinois, a heating-dominated climate. The aim is to provide some insight on how the optimal sizing of windows varies with different climatic conditions.

4. GAs, description and application

We now further describe the optimization algorithm used. A GA is a global search technique adequate for searching noisy solution spaces with local and global minima. Because it searches from a population of points, not a single point, the probability of the search getting trapped in a local minimum is limited. GAs start searching by randomly sampling within the solution space and then use stochastic operators to direct a hill-climbing process based on objective function values [6].

Under GA terminology, a solution to a problem is an *individual* and the group of solutions existent at each stage is a *population*. Each time a new population of individuals is created, it is called a *generation*. In binary GAs like the one used in this study, each individual is represented by a binary string called a *chromosome*, which codes all the parameters of interest corresponding to that individual. A chromosome is formed of *alleles*, the binary coding bits. The *fitness* of any particular individual corresponds to the value of the objective function at that point.

Genetic operators control the evolution of the generations of problem solutions. The three basic genetic operators are reproduction, crossover and mutation. The probability of a given solution being chosen for reproduction is proportional to the fitness of that solution. Crossover implies that parts of two randomly chosen chromosomes will be swapped to create a new individual. Mutation involves randomly changing an allele in a solution to look for new points in the solution space. Although there are more elaborate versions of these operators, the basic principles remain similar for most GAs.

A GA starts by generating a number of possible solutions to a problem, evaluates them and applies the basic genetic operators to that initial population according to the individual fitness of each individual. This process generates a new population with higher average fitness than the previous one, which will in turn be evaluated. The cycle will be repeated for the number of generations set by the user, which is dependent on problem complexity. Despite their apparent simplicity, GAs have proved to have high efficacy in solving complex problems for which conventional hill-climbing derivative-based algorithms are likely to be trapped in local solutions.

Typical population sizes for GAs range from 30 to 200, based on earlier studies such as those of Grefenstette [7], where suggestions for optimal population choices based on parametric studies are presented. In this study, we use a strategy named micro-GA [11], which starts with a small population (in this case, of only five individuals) and quickly makes it converge to a solution. Convergence is measured by comparing the chromosomes of the individual solutions. If they differ by less that 5%, it is considered that the population has converged. When that happens, the micro-GA generates a new random population while carrying over the individual with the best fitness in the previous generation — a strategy known as elitism. This way, new individuals are often brought into the search, without loosing track of the ones that did better until that point. An advantage of using the micro-GA procedure is that the algorithm tends to perform a local search around the best solutions during the generations prior to convergence, since at that stage solutions only differ by a few alleles. This local search is important in finding local minima around good solutions, and is usually hard to implement in conventional GAs.

GAs have been used in building applications related to energy consumption, mostly to optimize the sizing and control of HVAC systems [3,8,24]. At the structural analysis level, GAs have been used for design optimization of trusses [1,4,6], beams [12,22] and columns [9]. Several applications of evolutive design to spatial problems have been found for floor layout problems, where GAs are used to assign uses to specific areas in a building [2,5,10,15]. Attempts have also been made to apply GAs to the design of three-dimensional shapes, to help designers at early stages of design. The difficulty of finding appropriate objective functions for design evaluation has made some of these attempts to remain at experimental level, with selection and cross-over being performed manually by the designer [14].

Some other optimization methods have also been proposed for applications to building related problems. Monks et al. [13] used a combination of simulated annealing and steepest descent to optimize parameters related to surface geometry and choice of materials to achieve a set of acoustical based goals. Radford and Gero [16,17] proposed the use of dynamic programming to optimize window sizing and glazing materials to reduce building energy consumption.

5. Thermal simulation method

The thermal and lighting simulations are performed using DOE2.1E, a popular hourly thermal simulation program [19]. It calculates daylighting based on the daylight factor method [18,23]. Previous attempts to use DOE-2.1E to optimize design parameters of buildings include using regression analysis on data created by parametric DOE-2 runs [21] and the use of indices and weighting factors [20].

The method used in this study was to create a link between the GA and DOE2.1-E, on the UNIX platform, and make a call to DOE2.1-E each time it is necessary to calculate the fitness of an individual. The objective function of a solution is thus the result of running a DOE2.1-E thermal simulation of the building under study, with the parameters determined by the individual chromosome of that solution.

AutoLisp procedures allow the results to be visually inspected as AutoCad drawings, both two- and three-dimensionally. The designer can in this way visualize the several steps of evolution of the process, as well as the final results.

6. Description of hand method

To test if the proposed method would actually be able to locate optimal solutions for the problem under study, the algorithm was first tested against a hand-worked example of limited size, for which the optimal solution was found by sampling all possible solutions.

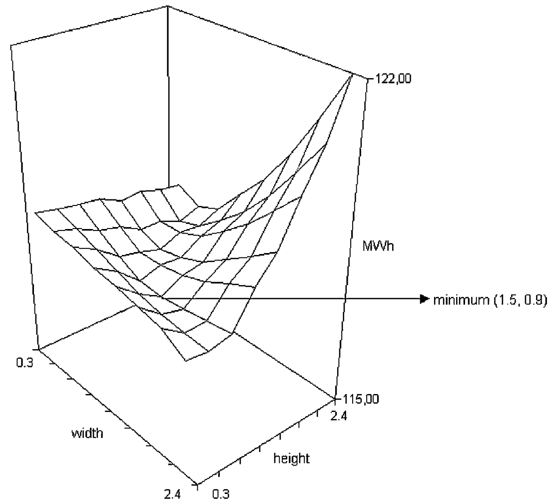

Fig. 1. Annual energy consumption (MWh) for south window dimensions.

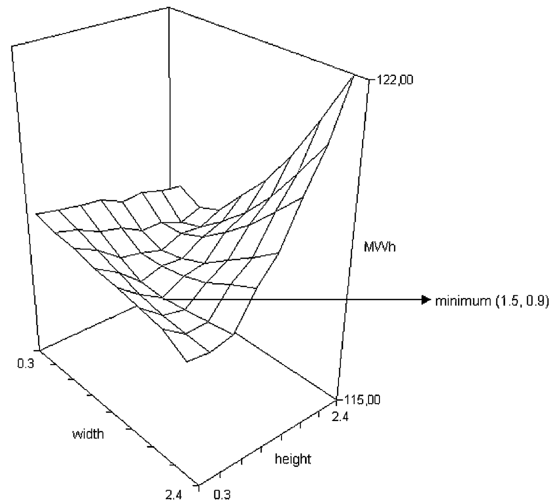

Fig. 3. Annual energy consumption (MWh) for west window dimensions.

The location chosen for the testing was Phoenix, AZ. We first determined the solution space for each of the four cardinal directions. We considered eight window widths and heights for each orientation, from 0.3 to 2.4 m at discrete steps of 0.3 m, creating a solution space of 64 points. While the dimensions for an orientation were varied, the windows facing the other orientations were kept 1.2 m wide and 0.9 m high. For each orientation, a 100-generation GA was run.

The solution spaces for each of the four orientations are shown in Figs. 1–4. In general, the solution spaces proved to have several local minima and a global minimum for all orientations but north. There are no local minima for the north orientation. The presence of local minima makes the problem inappropriate for derivative-based search methods and makes GA a reasonable approach.

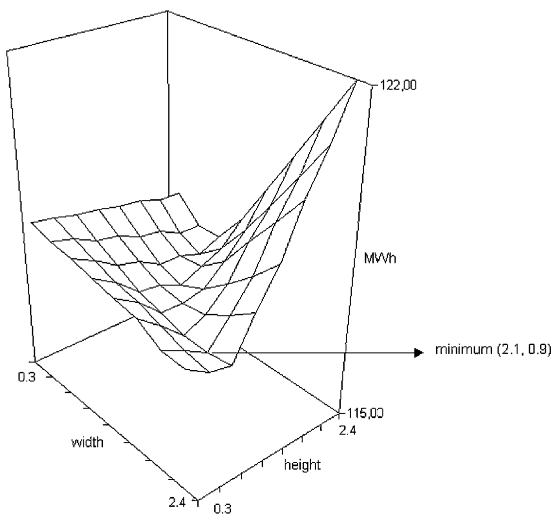

Fig. 2. Annual energy consumption (MWh) for east window dimensions.

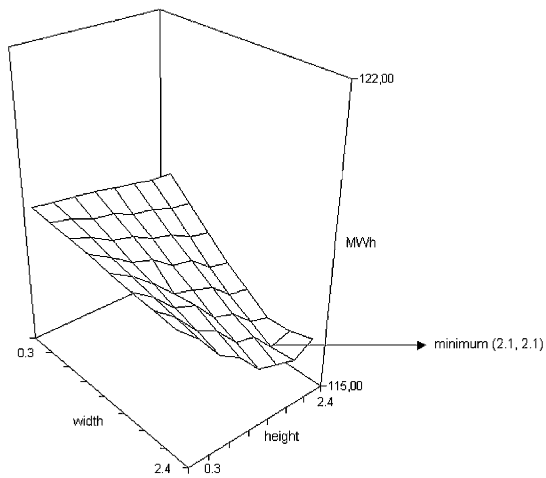

Fig. 4. Annual energy consumption (MWh) for north window dimensions.

7. Results and discussion

Fig. 1 shows the solution space for south-facing windows for the Phoenix climate. It can be seen that there is a relatively flat surface of configurations corresponding to low energy consumption. Within that flat surface, there are however several local minima and a global minimum. Being stuck in a local minimum would not be too serious in this case since the objective function difference in relation to the global minimum is small. However, we are interested in the global algorithm behavior and not only in the particular results for this example.

The global minimum of 116.94 MWh is located at point (2.1, 0.9), corresponding to a window 2.1 m wide and 0.9 m high. There were two local minima of 117 MWh for points (1.2, 1.5) and (0.9, 2.1). The GA located the global minimum in generation 18, and the (0.9, 2.1) local minimum in generation 21. It can be seen that the global minimum and one of the local minima correspond to windows with the same area (1.9 m^2), but with different aspect ratios that show the effect of accounting for daylighting penetration in the space. The more horizontal window corresponds to a slightly lower energy consumption. The optimal area is 5% larger than the area of the second local minimum.

For the east orientation, the global minimum was similar to those for the south orientation (2.1, 0.9), and the local minima were located in points (1.8, 0.9) and (1.2, 1.5). The GA located point (1.8, 0.9) by generation 16, but did not manage to locate point (2.1, 0.9) in 100 generations. Point (1.8, 0.9) stands next to the global minimum, and has an objective function value only 0.03 MWh higher than it. The observed behavior is a consequence of the fact that GAs have a difficulty in succeeding in very local searches. GAs are global search procedures and are often able to locate the global minimum for the problem. However, the search can get very close to

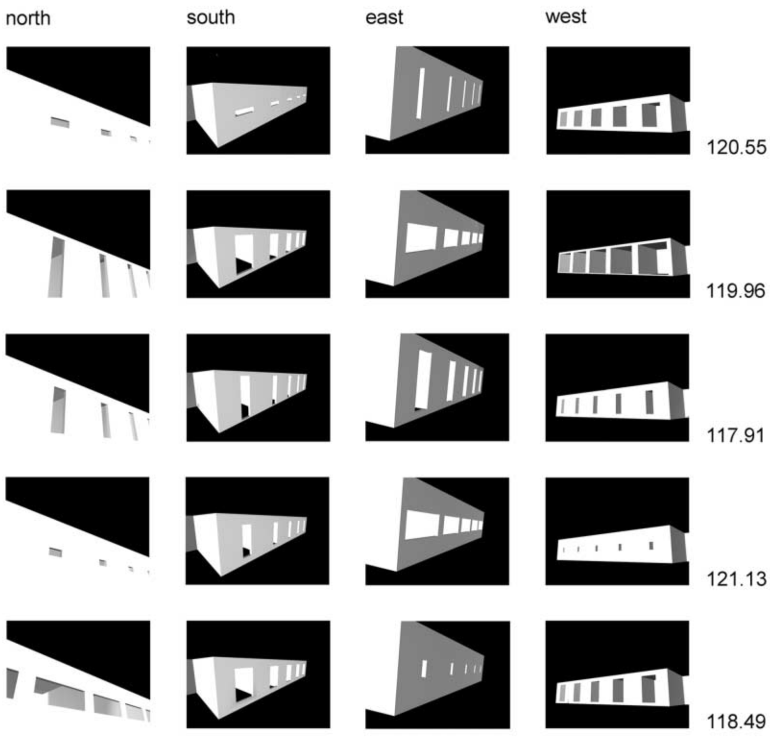

Fig. 5. Initial solutions for Phoenix climate, experiment 3. Each row represents an individual solution. The numbers on the right show annual energy consumption in MWh for each solution.

the global minimum without actually finding it. It should be noted that the actual difference in objective function values is negligible in this case.

For the west orientation, the solution landscape proved to be flatter than for south and east orientations. Although solar angles are symmetrical for the east and west orientations, temperatures and occupancies are not. The global minimum was at point (1.5, 0.9) and local minima were found at points (0.6, 2.1), (0.9, 1.5) and (2.4, 0.6). The GA located the global minimum by generation 10.

For the north orientation, there was only a global minimum at point (2.1, 2.1), with no other local minima. The GA located the global minimum very quickly, at generation 7. This good performance of the GA is thought to be due to the smooth configuration of the solution space in this case. Apart from the minimum, the GA located a series of high-performance solutions in its vicinity, all by the end of generation 8.

8. Extension of the method to a larger solution space

The resort to a hand-worked example proved the GA succeeded in most cases in finding a global minimum for the problem. In the cases it did not reach the actual minimum it localized points very closed to it, which provides enough confidence in the results to extend the method to larger problems for which it is not possible to calculate manually the solution space, given its size.

The GA was then used to search in a hyperspace of eight dimensions for the optimal size of windows to all orientations simultaneously, resulting in a solution space of 16,777,216 points. For the experimental building under study, it is possible to know the global minimum for the eight-dimensional space by combining the individual minima for each orientation. This is due to the way the building was set up, with no interactions between the different orienta-

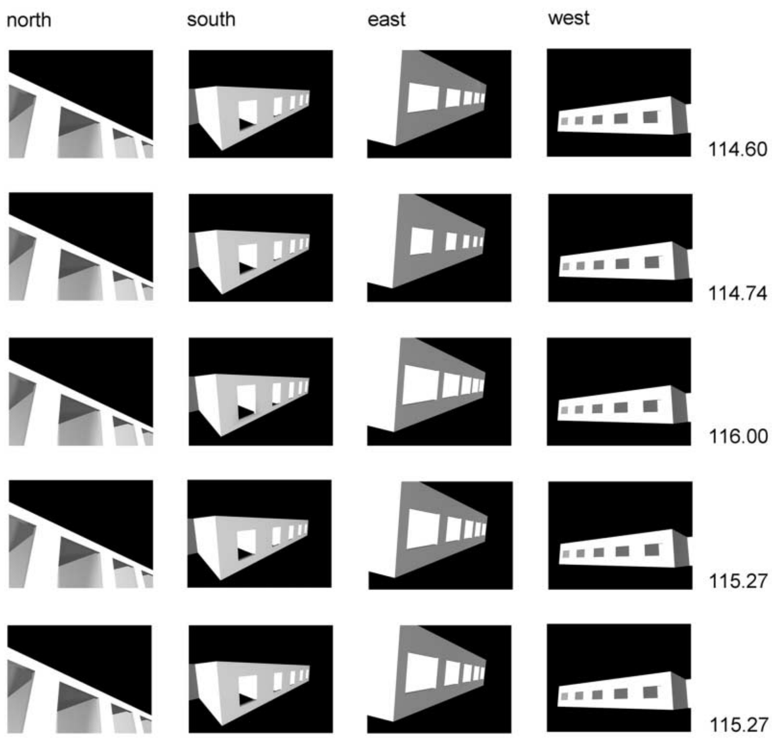

Fig. 6. Final solutions for Phoenix climate, experiment 3. Each row represents an individual solution. The numbers on the right show annual energy consumption in MWh for each solution.

tions either in terms of space or building systems. The trial building was designed in this way so that the objective function would be separable, allowing the global minimum to be known to better test the performance of the algorithm. However, regular buildings are not always designed this way and thus it is usually not possible to optimize for each direction separately and then combine the individual results.

From the hand-worked example, it is possible to know that for Phoenix climate, the best possible result corresponds to the point (2.1, 2.1, 2.1, 0.9, 2.1, 0.9, 1.5, 0.9) (first listing north window dimensions — width, height — then south, east and west), corresponding to an annual electrical energy consumption of 114.53 MWh. The worst point in the hyperspace is (0.3, 0.3, 2.4, 2.4, 2.4, 2.4, 2.4, 2.4), with an annual electrical energy consumption of 131.4 MWh, about 15% higher than the best possible result.

Figs. 5 and 6 show the evolution for one experiment from the initial solutions to the final generation of optimized designs. It can be seen that initially there is a high variance in the design patterns that progressively converges into the optimized solutions.

Fig. 7 shows the evolution of design generations to the Phoenix climate for another experiment. For reasons of space, only every tenth generation is shown here, until generation 80 when the solution has converged. It can be seen that although many different configurations are tested along the search, the design steadily tends to the final optimized solution: large windows for north orientation (2.1 × 2.1 m), where available daylighting can be maximized

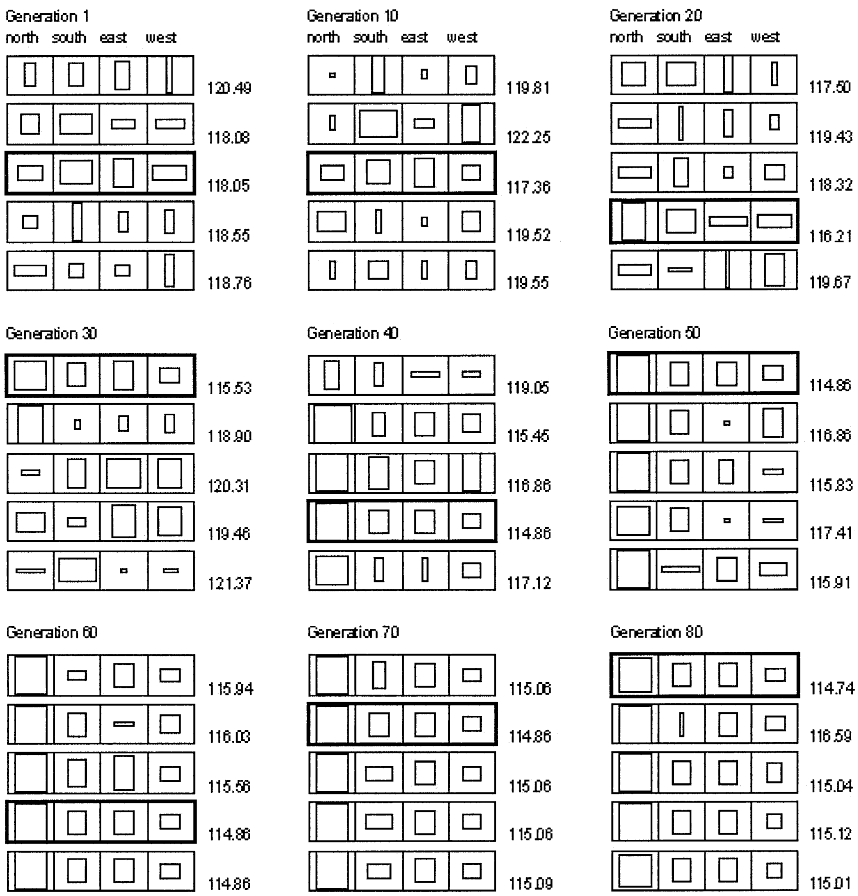

Fig. 7. Generations 1–80 for Phoenix climate, experiment 1.

Table 1
Solutions for Phoenix climate

Experiment	Best solution found	Objective function value (MWh)	Percentage above minimum (%)
1	2.1/2.1/1.2/1.5/1.2/1.5/1.2/0.9	114.74	0.018
2	2.4/2.1/2.1/0.9/2.1/0.9/0.9/1.5	114.65	0.01
3	2.1/2.1/1.2/1.5/2.1/0.9/1.5/0.9	114.60	0.006
4	1.8/2.1/1.2/1.8/0.9/1.5/1.2/0.9	114.89	0.03
5	2.4/2.1/2.1/0.9/1.2/1.5/1.5/0.9	114.65	0.01

without incurring on high solar heat gains in the summer. Due to the mild winter climate and the use of double pane windows, heat losses through this large glazing area are not enough to penalize this solution when the overall energy consumption is calculated. Average size windows (1.2×1.5 m) are chosen for east and south orientations, showing a balance between admitting useful daylighting and winter solar gains and preventing too much solar gain in the summer. Smaller windows (1.2×0.9 m) are chosen for west since that is the worse orientation in terms of summer overheating: the building is already warm at the end of the afternoon and excessive west gains, will lead to internal overheating. These solutions are dependent on the type of glazing used: a different glazing option would probably lead to different optimum window sizes.

In total, five experimental runs were made for Phoenix climate, to compare results from different trials. A maximum number of 100 generations were used for each experiment. The results are summarized in Table 1. In general, the GA performed well, being able to find high-performance solutions close to the global minimum. The results are even more satisfactory considering that 100 generations is a relatively low number for GAs, and the population

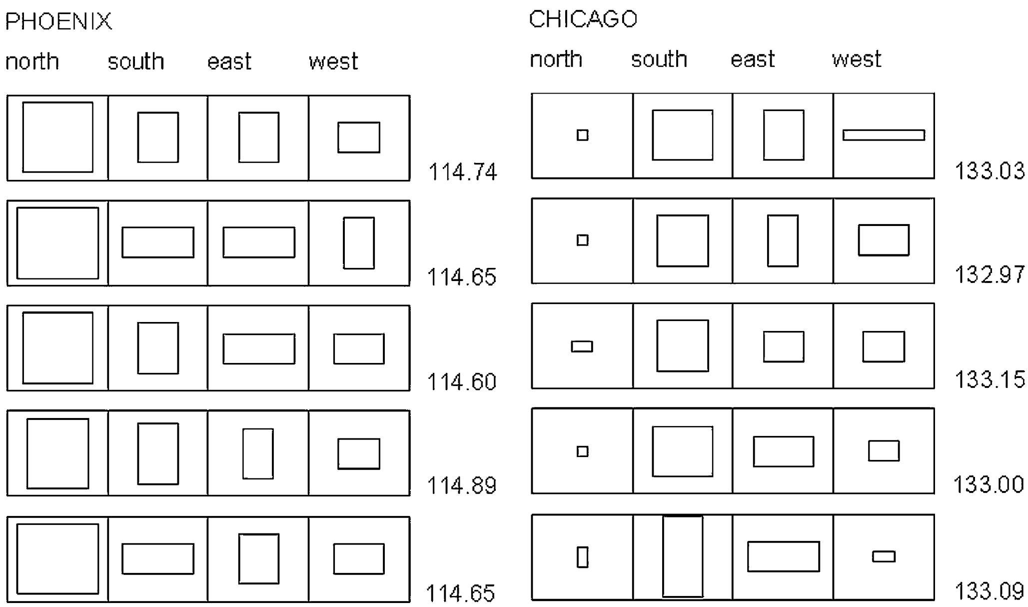

Fig. 8. Comparative results for Phoenix and Chicago locations.

Table 2
Solutions for Chicago climate

Experiment	Best solution found	Objective function value (MWh)
1	0.3/0.3/1.8/1.5/1.2/1.5/2.4/0.3	133.03
2	0.3/0.3/1.5/1.5/0.9/1.5/1.5/0.9	132.97
3	0.6/0.3/1.5/1.5/1.2/0.9/0.3/0.9	133.15
4	0.3/0.3/1.8/1.5/1.8/0.9/0.9/0.6	133.00
5	0.3/0.3/1.5/2.4/1.8/1.2/0.6/0.3	133.03

size of 5 is very small. The maximum of 500 different solutions evaluated by the GA corresponds to only 0.00003% of the solution space dimension.

Results from these experiments are also displayed in Fig. 8. It can be seen that although total energy consumption is very similar, design solutions are somewhat different. This leads to the conclusion that different runs of the optimization tool may lead to different solutions with similar performance, a fact that may be of interest to the designer, who may try more than one run of the GA to get a sense of available alternatives.

Five similar experiments were also done for Chicago climate, a cooling dominated situation, to assess to what extent optimum window designs may be sensitive to climatic conditions. In this case, the global minimum was not known in advance and so it was not possible to determine the margin by which the solutions found differed from the optimum solution. Results are summarized in Table 2.

Fig. 8 also shows the solutions obtained for Chicago climate, which vary in significant ways from Phoenix solutions. Analyzing the results of the first experiment shows us that due to the extreme winter conditions, the north window size was reduced to the minimum allowed (0.3×0.3 m), since north windows are in this case a large source of heat losses and provide little solar gains in winter. The south window size increased in relation to the Phoenix solutions, to allow for more solar gains in winter (1.8×1.5 m). East window size remained basically similar (1.2×1.5 m), and west was reduced to a horizontal strip (2.4×0.3 m) that allows for some daylighting but prevents excessive heat loss.

The large differences between the solutions found for each climate, and also between orientations within the same climate, suggest the use of an optimization tool like the one proposed here may not only provide increased energy savings but also introduce a positive degree of variability in the design. It also suggests that unexpected solutions that might not be obvious to the designer may be pointed out by the computer, such as the case of the very large north-facing windows for Phoenix, or the horizontal strip facing west for Chicago.

Solutions optimized for environmental performance may not always represent optimal behavior in terms of other criteria. For example, the north-facing windows for the Chicago climate may be found too small to provide occupants with an adequate view. In those cases, the designer may modify the results provided by the GA while making use of the knowledge gained during the optimization process, such as knowing that north-facing windows should be kept as small as possible. A simple computer simulation can then be performed to determine to what extent the modified design's energy consumption differs from the optimized solution.

9. Conclusions

This paper presents a generative tool to optimize design elements of a building in terms of their environmental performance. It makes use of a GA as the search engine, a thermal and lighting simulation program, and an AutoLisp routine for visualization of results.

The method proposed was first validated in relation to a hand-worked example for which the optimal solution could be calculated manually. Results proved highly satisfactory and provided enough confidence for the process to be extended to a larger solution space for which there is no practical way of calculating the optimized solutions. The extension of the method was applied to a hyperspace of eight dimensions, corresponding to simultaneously sizing eight window dimensions in the building.

The results obtained showed that from initial populations with high diversity, the algorithm slowly converged to populations consisting of optimal or near-optimal solutions. For different runs of the problem, the solution obtained can have some variation, which shows that different configurations may correspond to similar standards of environmental performance. This may constitute valuable information to the designer, who is provided with a number of alternative solutions over which he can further overlap other design criteria not included in the optimization process. It was also observed that for different orientations the solutions achieved varied substantially, as expected from the different requirements the glazing elements had to respond to.

It was shown that for different climates the design solutions proposed by the algorithm differed considerably. The same building layout needs to have different design components according to the climate it is located in order to optimize its environmental performance. This optimization cannot be achieved in a scenario-by-scenario basis due to the size of the problems involved, but it is possible to perform using a search procedure like the one proposed in this study.

The problem presented here is just one example of the way goal-oriented design for environmental performance can be applied to inform the design process. The same procedure of generation and evaluation of different solutions guided by a search algorithm can also be applied to a variety of other problems in building design.

Acknowledgements

This study was developed as part of a Ph.D. dissertation in the Building Technology Program, Department of Architecture, Massachusetts Institute of Technology, with funding from Fundação para a Ciência e Tecnologia, Programa PRAXIS XXI, Portugal. We would like to thank Stephen Selkowitz, Robert Sullivan and Eleanor Lee at Lawrence Berkeley National Laboratory.

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