FACADE DESIGN OPTIMIZATION FOR DAYLIGHT WITH A SIMPLE GENETIC ALGORITHM

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ABSTRACT

The aim of the present study was to determine the applicability of a genetic algorithm for the optimization of daylighting systems, as well as the requirements for the lighting simulations to be used. Furthermore, by testing the daylighting performance of a building's facade when several parameters are allowed to change simultaneously, the results were used as a complement of previous parametric studies.

The goal of the optimization was to maximize energy savings by reducing visual discomfort while maintaining good daylight penetration. The results were obtained by dynamic simulations using Radiance. Discomfort glare produced by daylight was calculated for several viewpoints inside the building, adapting the blinds' position accordingly for each time step tested. Fitness was defined as the proportion of the annual lighting requirements that can be replaced by daylight.

The results show a fast convergence in the beginning, followed by a minimal improvement in subsequent generations. Several trials over 200 generations showed similar evolution and consistent results, suggesting that genetic algorithms can be used effectively for facade design optimization considering daylight performance. Finally, some possible improvements and modifications are further discussed.

KEYWORDS

Optimization, Daylight, Dynamic Simulation, Genetic Algorithm

INTRODUCTION

When assessing the performance of a daylighting system, it is important to consider not only the amount of daylight that can enter the building, but also the amount that cannot be admitted due to visual discomfort problems [Nabil and Mardaljevic 2005]. Therefore, it is also necessary to consider the behavior of the building's occupants, and when and how they will allow daylight inside the rooms [Reinhart and Voss 2003].

As a result, the potential savings will be determined by the amount of daylight that can enter the building, and the amount of glare produced by the daylight source. There is a complex relationship between the many factors that affect these two amounts, which makes it difficult to determine the incidence of each factor in the global performance.

Parametric simulations can give an idea of the variation in daylighting performance related to the variation of one parameter. However, it is not possible to test all the combinations over a search space of multiple dimensions.

Genetic algorithms can perform a series of simulations in a multi-dimensional search space, increasing the relevance of the cases simulated. In this sense, genetic algorithms can be seen as a complement of parametric studies, in addition to being an optimization tool. The main obstacle to their implementation is the fact that the number of simulations required, although comparatively reduced, can still pose an important demand to computer resources.

For the present study, in order to reduce computation times, a sub-set of the annual meteorological data was used, as well as an adaptation of the daylight coefficients method, and the population was limited to ten individuals. Additionally, in order to ensure a faster convergence in fewer generations, absolute elitism was used to select the individuals in each generation.

MODEL DEFINITION

A set of 21 parameters encoded the size, number, and position of windows and fixed protections (figure 1, table 1) and the reflectance of the different surfaces. Each one was encoded by using real-number variables (alleles) conforming real-parameter vectors (chromosomes) [Wright 1991; Rasheed et al. 1997] and bounded by upper and lower limits, which ensured the consistency of the simulated cases.

Two of the parameters defined general proportions of the windows, producing a certain degree of redundancy. By allowing the same model to be encoded by different combinations of chromosomes, the search space becomes overpopulated, improving the chances of finding a fitter model [Mitchell, 1996; Dasgupta and Michalewicz 1997].

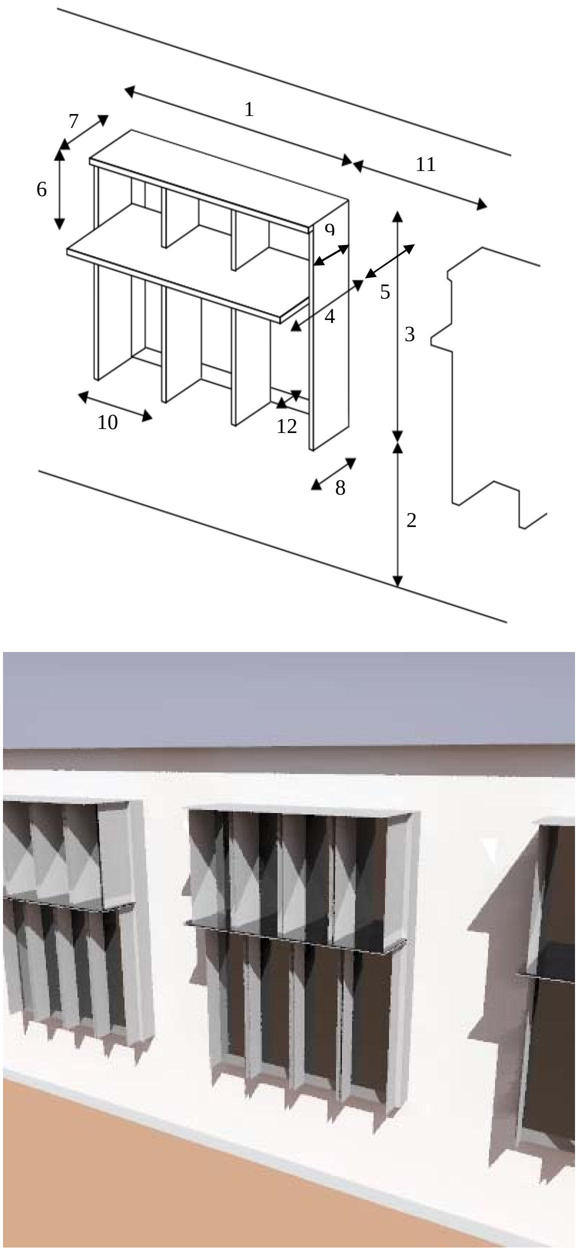

Figure 1 - Geometric Parameters and example of model produced

The set of 21 parameters was translated at run time into a Radiance model definition of a 20m section of the façade, applying additional controls to ensure the model is always consistent with the initial geometric assumptions.

This model was then combined with a static model for the rest of the room. The exterior environment consisted only of the sky and a simple definition of the ground. The section of the façade simulated was sufficient to eliminate the effect of lateral walls in the results.

Table 1 List of parameters

	Min. value	Max. value
1-window width	1	12
2-sill height	0	2.5
3-window height	0.5	4
4-ext lightshelf depth	0	0.8
5-int lightshelf depth	0	0.8
6-lightshelf height	0.5	3
7-overhang depth	0	1
8-low sunshade depth	0	0.5
9-high sunshade depth	0	0.5
10-Nr. shades / window	2	5
11-Nr. windows	3	7
12-window sill depth	0.1	0.4
13-wall reflectance	0.3	0.6
14-ext lightshelf reflec.	0.3	0.6
15-int lightshelf reflec.	0.3	0.8
16-window sill reflec.	0.2	0.7
17-sunshade reflectance	0.2	0.6
18-window size factor	1	1.5
19-shading size factor	0.3	1
20-window transmittance	0.5	0.9
21-reflective Lightshelf (Y/N)	0.7	2

SIMULATION METHOD

Each case studied was simulated by means of a dynamic daylight simulation, considering the weather conditions of Tokyo, Japan.

The positions of four observers were defined at the center of the room. For each time step, the visual conditions of each observer were calculated, and the position of the blinds for that time step was decided according to the incidence of glare. The glare index utilized (1) was an adaptation of the daylight glare probability from vertical illuminance, modified according to empirical results obtained in Japan [Torres 2006].

$$DGP_3 = \frac{1}{1 + e^{(12.1311\ -\ 3.1185 \cdot \log_{10} E_V)}} \qquad (1)$$

This simplified daylight glare probability uses only the vertical illuminance at eye level to calculate the glare incidence. It is based on a simplified calculation of DGP by Wienold and Christoffersen, but should not be confused with the daylight glare probability index, which calculates the incidence of individual glare sources [Wienold and Christoffersen 2005].

The control model used a stochastic function that decided the position of the blinds randomly, with a probability equal to the probability for an occupant to close the blinds under such glare conditions. Only open/closed positions were considered.

A second simulation calculated the illuminance value at the working plane for each observer, given the weather conditions and the position of blinds.

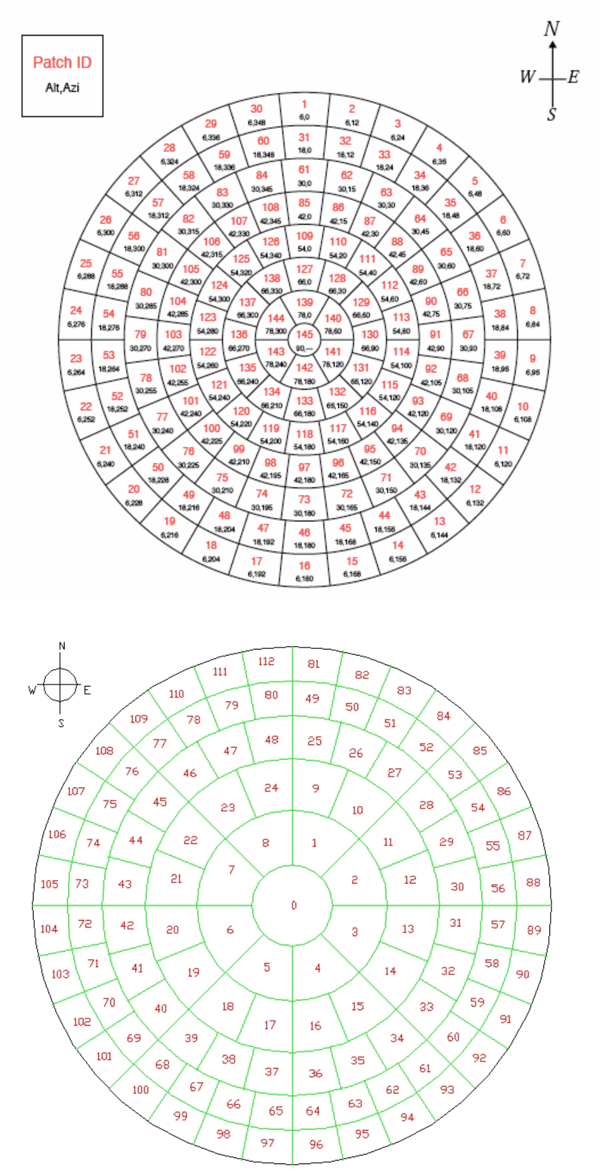

Figure 2 – Original (above, from Mardaljevic 1999) and modified (below) sky subdivisions for daylight coefficients

For all the calculations, an adaptation of the daylight coefficient method was used [Tregenza P. and Waters I. 1983; Mardaljevic J. 1999] optimized for the simulation of vertical openings (figure 2). For this, the sky subdivisions were augmented in size near the zenith and reduced near the horizon, but reducing the total number from 145 to 113.

The method was implemented in Radiance using the rtcontrib command [Ward G. 2005], which allows the calculation of the contribution of each sky subdivision to the values in the scene with only one simulation. The results are then multiplied for each time step by the average luminance of each sky subdivision. These luminance values depend solely on the weather conditions and were pre-calculated and equal for all models. In this way, the simulation times are greatly reduced.

However, in order to allow for the number of simulations that an implementation of a genetic algorithm requires, further simplification was necessary, which was achieved by considering only one of every twenty days in the year. In this way, the variability of the weather throughout the year is maintained as much as possible.

GENETIC ALGORITHM

For the actual implementation of the genetic algorithm, further simplification was necessary. The population was limited to only ten individuals, which has been shown to produce acceptable results [Wright and Alajmi 2005].

In order to accelerate convergence, absolute elitism was employed, meaning that only the best individuals were selected for breeding. To avoid convergence to local maxima, three individuals were randomly chosen and also included in the breeding group.

Fitness was defined as the proportion of the total lighting requirements that could be replaced by daylight. Since the design illuminance on the work plane considered was 500lx, fitness was defined as:

$$F = \frac{U_a}{500lx} = \frac{\sum_{h}^{H}\sum_{o}^{O} U_{ho}}{H \cdot O \cdot 500lx} \qquad (2)$$

where U_a is the annual average for all observers of the usable daylight illuminance; U_{ho} is the daylight illuminance on the working plane, for a certain hour and observer, when the condition of blinds is considered; and H, O are the number of hours and observers respectively. Therefore, a fitness of 1 would imply meeting the total illumination needs for all the occupants, only with daylight.

Different breeding methods were employed, making use of the real-value character of chromosomes. The first one, simple mutation, consisted of the alteration of the value of one parameter, randomly chosen.

Three recombination methods were also employed, making use of the real-value character of chromosomes. Simple crossover consisted in swapping the values of one parameter between two individuals. Additionally, interpolation and extrapolation crossovers were used. These consisted in changing the values of one parameter taking a value proportional to the fitness of the individuals.

RESULTS

The results for a typical run show a fast increment of the fitness during the first generations and a very slow change after approximately 100 generations (figure 3).

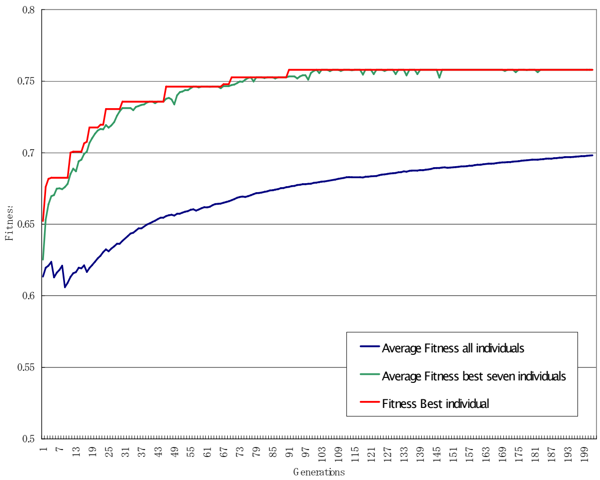

Figure 3 – Evolution of the fitness of the best individual, the average of the best 7 individuals and the total average, through 200 generations

Figure 4 shows a typical evolution of the best individual in each generation for six different generations. It can be observed that after the main characteristics of the façade are found, only minor changes in size determine an improvement of the fitness.

The result of the optimization is consistent with the constraints of the model. Since the only determinant factor considered for fitness was daylight, the windows occupy the maximum width and height allowed, improving the total daylight penetration.

Additionally, the protection elements disappear above the lightshelf, where sunlight cannot cause glare, but improve the daylight levels in the building. Below, the vertical fins protect the observers from the sun when it is at a lower altitude, reducing the need to close blinds.

CONCLUSION

The implementation of a genetic algorithm presented here is quite simple compared to other more elaborate implementations. However, it shows the viability of the method applied to daylighting systems, even with the use of relatively complex simulation methods.

The use of dynamic daylighting simulations was only possible thanks to the implementation of the daylight coefficients method, and the use of a simplified version of the daylight glare probability index.

The results were consistent between several runs of 200 generations, showing that the final result did not correspond to a local maximum, but to an optimized solution.

Constraints in the population size were strongly determined by the computation resources available. As this situation is bound to improve in time, better implementations with larger populations and more elaborate simulation methods will become possible. Additionally, there are several improvements that could be applied to the present method.

The first possible improvement is the use of selective fitness. The calculation of fitness can be divided between different parts of the year, giving a more specific assessment of each individual. In this way, selection and recombination can be performed between individuals of complementary characteristics, in order to better approximate an optimized solution.

A second possible improvement is to consider a more complete model for the performance of the facade, given that daylighting is only one aspect in a facade optimization. In order to implement this, thermal simulations should be coupled with daylighting ones, and the definition of fitness should include the total energy performance. One intermediate simpler solution could be to perform thermal and daylighting simulations separately, and chose a fitness definition that compensates for the incidence of each one, although this is not optimal.

In the case presented here, the fact that only daylighting constraints were considered caused that windows evolved to occupy the maximum available surface on the façade. Thermal constraints would mean that an intermediate size for windows should be sought.

ACKNOWLEDGMENT

The present research was developed as part of the doctoral studies at the University of Tokyo in 2005-2006.

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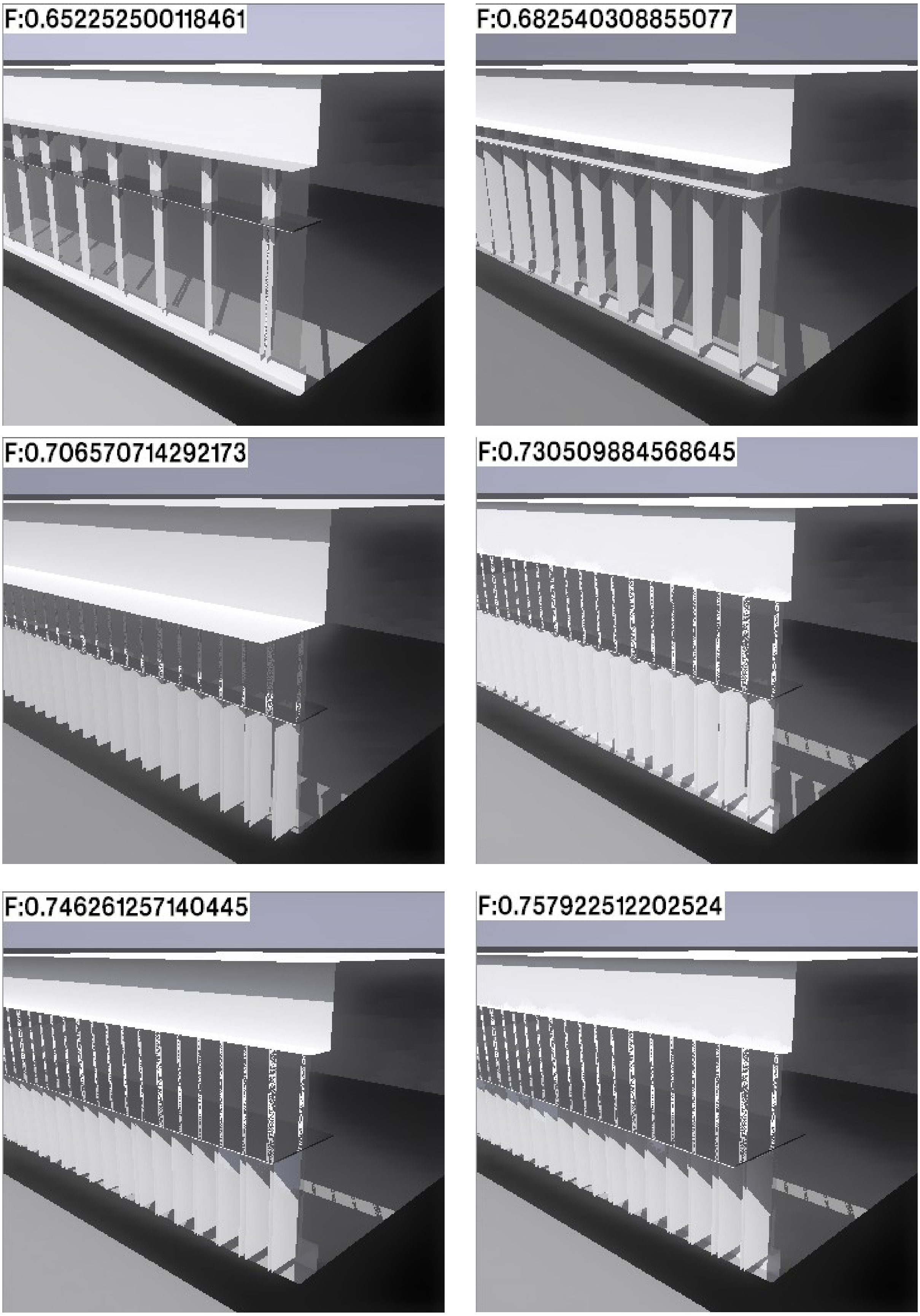

Figure 4 – Example of results for the best individual every 40 generations, from 0 to 200