INTEGRATING PERFORMANCE AND PARAMETRIC DESIGN TOOLS FOR URBAN DAYLIGHT ENHANCEMENT

Mohamed Aly¹ and Khaled Nassar¹ ¹The American University in Cairo

ABSTRACT

The majority of the natural lighting, in urban slums and rural areas arround the world, is blocked off and virtually no light reaches the building spaces in lower floors as well as the streets and urban spaces. Painting the buildings' surfaces may increase the availability of daylight below. Some surfaces may be easier to paint and will require less cost or effort to paint than others. This paper formulates a combinatorial optimization problem to address this situation and uses different approaches to solve the problem. The problem is solved using different optimization algorithms namely; genetic algorithms, partical swarm optimization, generalized pattern search and a hybrid approach. A comparison between is the different approaches given and recommendations on future research are made.

INTRODUCTION AND PROBLEM DESCRIPTION

Dense urban environments in today' cities often lack daylight in urban and architectural spaces. In several countries around the world, many buildings are constructed close to each other resulting in severe sky obstructions, more particularly for rooms at the lower floors as well as in streets and urban spaces (Lia et al., 2011). Figure 1 shows a sample slum area in Cairo, Egypt, where such conditions exist. Innovative daylighting technologies that transport natural light from outside towards the inner part of deep plan rooms are appropriate devices to improve daylight uniformity and visual comfort. Good visual effects and less lighting energy use may result if proper designs are employed. One of the ideas studied in literature is light redirection systems such as laser cut panels which can generally increase the daylight in the rear of the scale model room, improve the daylight uniformity and have the potential to reduce the electric lighting energy use (Dahlan et al., 2009). Other ideas include light pipes (Song KD, 2007) and light redirecting panels (Plympton et al., 2000).

However the majority of the solutions focus more on the lighting conditions in the interior spaces of the buildings in these dense areas and not on the outdoor urban environment itself. This necessitates the use of non-traditional solutions to allow for daylight to penetrate into these urban spaces.



Figure 1, Sample Case Study showing Dense Slum Areas and poor natural lighting condition

One of the ideas to enhance the natural lighting in dense urban spaces such as the ones described above is to repaint the exterior surfaces of the buildings in those areas. This may increase the ambient lighting conditions in the outdoor areas. Newly developed reflective paints can produce a significant increase in the natural lighting reaching the streets. These reflective paints may be able to reflect more of the direct and indirect sunlight back into the narrow streets and urban spaces.

However, the painting of exterior surfaces in these highly dense areas may be difficult, costly and time consuming due to the relatively high cost of those paints as well as the high cost and difficulty in setting up scaffolding systems in these tight areas as well as the disruption and inconvenience to the residents. In addition, the highly reflective paints could negatively harm the outdoor thermal conditions due to their high reflectivity and high emissivity properties.

It is imperative therefore, to find a tradeoff between the negative aspects and the positive aspects of repainting the exterior surfaces. It is crucial to note that not all the exterior surfaces will contribute equally to the positive and negative aspects of this problem. There will be some surfaces that are more important than others in terms of their contribution to the lighting conditions in the streets and urban spaces. In addition, some surfaces may be easier to paint and will require less cost or effort to paint than others. This may be due to their lower surface area or due to the type and use of building for example. Therefore, each building will have its own cost to paint and on the other hand will make a (sometimes a disproportionate) contribution to improving the daylight in the urban spaces below.

In particular it may be wise to select only those surfaces that would make the most effective impact on the exterior lighting conditions in these spaces. This means that we need to determine which surfaces receive which kind of paint (or whether they need to be painted at all). All different combinations of surfaces and paint types need to be assessed due to the interaction between the cost and daylight performance in the urban surfaces.

In order to find the best tradeoff between the cost and daylight we may perform exhaustive enumeration of all the possible combinations of paint types and surfaces. However due to the combinatorial explosion of the problem at hand, exhaustive enumeration may not be possible. In fact, the number of options to be considered given n paint types and \overline{m} different buildings is $(n+1)^m$. For example, consider an urban area with just 15 buildings and 2 types of paints (in addition to no paint at all), then we will need to consider 3^15 different options, i.e. 14,348,907 different possible combinations. Obviously, even for just a simple configuration performing fourteen millions simulations is not feasible. Therefore, we need to resort to optimization techniques. We formulate the problem and solve it using two different approaches; the first by Diva+Grasshopper+Gallapagos and the other by Genopt). In addition, a particle swarn algorithm, and two implementations of the generalized pattern search were used to solve the problem. To test the proposed idea, a sample case study is selected as will be explained below.

PROBLEM FORMULATION

In order to address the combinatorial explosion issue we formulate an optimization problem as a mixed integer optimization problem for selecting which surfaces (buildings) to paint with the different kind of paints. Generally we have two objectives to account for. The first is to minimize the cost of the entire painting operation by simply minimizing the sum product,

$$TC = \sum_{i=1}^{m} \sum_{j=1}^{n} C_i^j \times A_i \times x_j, \quad x_j \in \{0,1\}, C_i^1 = 0 \quad (1)$$

Where C_i is the unit cost of painting building *i* with paint type *j* and A_i is the area of building i. x_j is a binary variable to represent whether building *i* will be painted with paint type *j*. *j* must be at least equal to 2 to represent a paint or no paint with C_i^1 equal to 0, representing no paint. Also a constraint needs to be added indicating that each building can only be painted with a certain type of paint,

$$\sum_{j=1}^{n} x_j = 0 \tag{2}$$

We may also add a constraint indication that there is an upper limit on the total cost in certain cases. On the other hand we need to maximize some daylight measure D which is a function of the x_j . Dynamic daylighting measures such as useful daylight index and daylight autonomy are used as criteria for optimization. In order to convert the problem to the classical minimization problem we consider the reciprocal of the D. This makes the objective of the optimization problem equal to

$$Obj = \frac{TC}{D(x_1, x_2 \dots x_{jn})}$$
(3)

We may also need to add different weights to the two objectives. In this case we need to formulate the problem as a goal programming problem due to the different units of the two components of the objective function. Goal programming is a branch of multiobjective optimization which is able to handle multiple, normally conflicting objective measures. Each of these measures is given a goal or target value to be achieved. Unwanted deviations from this set of target values are then minimized in an overall objective function. In our case a weighted sum dependent on the goal programming variant is used. As satisfaction of the target is deemed to satisfy the decision maker(s), an underlying satisfying philosophy is assumed. This makes the new objective function

$$0bj = w1 \times \left[\frac{TC - TC_{target}}{TC}\right] + w2 \times \left[\frac{D_{target} - D}{D_{target}}\right]$$
(4)

By varying the different weights assigned to the two components of the objective function we are able to determine a Pareto set for cost and daylight. This will be explained further below.

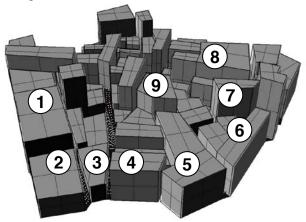


Figure 2, A sample case study showing the different buildings that could be painted

SOLUTION USING DIFFERENT OPTIMIZATION TOOLS

The small urban environment in figure 2 is used as a case study to apply the formulation above. We need to determine which one of the buildings receives which kind of two different kinds of paints (if at all) to minimize the objective function similar to the one in (Equation 4) above. Note that in this case we will solve the problem by assuming that entire buildings will have to be painted as a whole, i.e. we do not allow for partial paintings of buildings. It may be the case however that those only selected facades of the buildings can be painted and not the entire building. This will of course increase the size of the optimization problem and the solution time, but we may be able to find solutions with lower costs since we may be able to minimize the areas to be painted. We can take this idea further and suggest that in certain cases (where architecturally feasible) we can subdivide particular surfaces based on contribution to the objective function to further reduce cost. In our problem solved here however, we will only consider entire buildings and we will use three different dynamic daylight metrics.

Daylight Autonomy (DA), uses work plane illuminance as an indicator of whether there is enough daylight on the surface so that an occupant can work by daylight alone. Required minimum illuminance levels for street activiteis was selected as 200lux. Mardaljevic and Nabil (2005, 2006) proposed a dynamic daylight performance measure based on work plane illuminances, called Useful Daylight Illuminances (UDI). Rogers (2006) proposed another set of metrics that resulted from research on classrooms Continuous Daylight Autonomy (DAcon). This problem was solved using two different approaches.

First Approach Methodology

The first was to use DIVA for rhino; a plug-in for Rhinoceros modeling software used to interface Radiance and Daysim for annual simulation and illuminance computation; and grasshopper (Jakubiec, Reinhart, 2011) along with Galapagos to optimize the problem. DIVA-for-Rhino is a highly optimized daylighting and energy modeling plug-in for the Rhinoceros software. While Galapagos is a generic platform for the application of Evolutionary Algorithms. By building the model shown in figure 2 in grasshopper and then defining our variables and feeding them to Galapagos, we were able to determine which building to paint certain paint types to maximize our natural light and minimize cost. The value of the daylight component of the objective function is shown in figure 4.

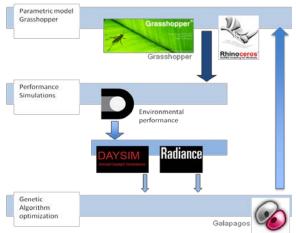


Figure 3, The first approach method diagram.

After 34 generations for each 40 different cases the optimization has stopped for achieving a near optimum better solution. The daylighting metric achieved the target in 75% of the tested area (streets) while maintaining minimal costs. Simple comparisons were made to highlight the benefits of the optimization are shown in figures 6.

Second Approach Methodology

The DIVA+Grasshopper+Galapagos approach has the drawback of only being limited to generic algorithms in order to minimize our objective function. Therefore, we also solved the problem using a second approach by coupling DaySim and Genopt (M. Wetter, 2001) to allow multiple optimization algorithms. DAYSIM is a validated, RADIANCE-based daylighting analysis software that models the annual amount of daylight in and around buildings. GenOpt is an optimization program for the minimization of a cost function that is evaluated by

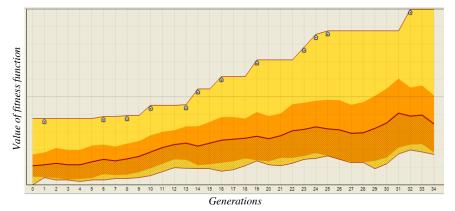


Figure 4, output of Rhino and Galapagos

an external simulation program. Unlike the first approach, the second approach has the advantage that GenOpt has a library with local and global multidimensional and one-dimensional optimization algorithms, as well as algorithms for doing parametric runs. It has been developed for optimization problems where the cost function is computationally expensive, which is the case in our problem since we need to calculate daylight coefficients for the dynamic daylight metrics. In addition GenOpt functions well in cases where the derivatives of the objective function are not available or may not even exist, which is again the case in our problem.

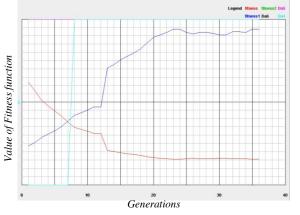


Figure 5, output of GenOpt Particle Swarm Algorithm(the daylight in blue & the cost in red).

In particular we tried several algorithms offered by GenOpt to determine which one would result in a lower objective value. We used three different approaches, the first being various implantations of Generalized Pattern Search Methods. Generalized Pattern Search (GPS) algorithms are derivative free optimization algorithms which can be implemented in different ways. We used two of these implementations, the Coordinate Search Algorithm and the Hooke-Jeeves algorithm. Both are implementations of the Coordinate Search algorithm with adaptive precision function evaluations. Secondly, we used a Discrete Armijo Gradient algorithm. The Discrete Armijo Gradient algorithm approximates gradients by finite differences and thus is well suited to our problem where there are discontinuous gradients.

Finally, we used the Particle Swarm Optimization. Particle Swarm Optimization (PSO) algorithms are population-based probabilistic optimization algorithms (Marco Dorigo et al., 2008). PSO algorithms exploit a set of potential solutions to the optimization problem. Each potential solutions is called a particle, and the set of potential solutions in each iteration step is called a population. PSO algorithms are global optimization algorithms and do not require nor approximate gradients of the cost function.

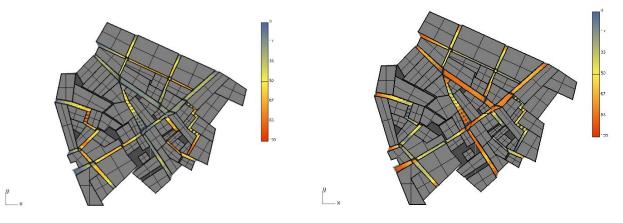


Figure 6 a, The Daylight Component of the Objective Function Before and After Optimization (UDI)

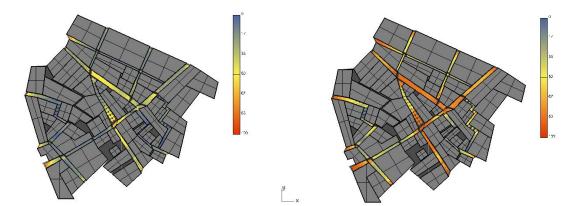


Figure 6 b, The Daylight Component of the Objective Function Before and After Optimization (Daylight Availability)

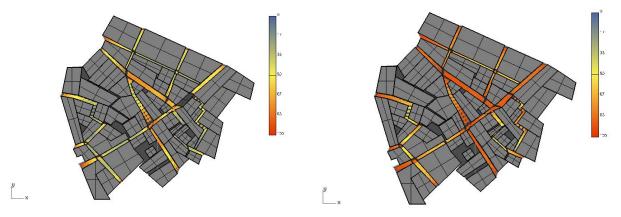


Figure 6 b, The Daylight Component of the Objective Function Before and After Optimization (Continuous Daylight Autonomy)

Out of the three different algorithms used in the GenOpt+Daysim approach the Particle Swarm algorithm was the best performer. It also outperformed the first approach (DIVA +

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> Grasshopper + Galapagos). The PSO algorithm was able to find a better solution faster than all other algorithms considered in GenOpt. Figure 5 shows the results of the iterations of the DIVA + Grasshopper + Galapagos genetic algorithm runs, while figure 5,7

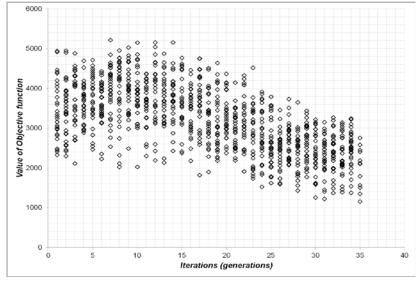


Figure 7, Iterations of the particle swarm algorithm of GenOpt

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shows the runs of the GenOpt PSO algorithm. Figure 8, shows the Pareto front for the objective function found using the PSO and also marks the optimized solution shown in figure 5.

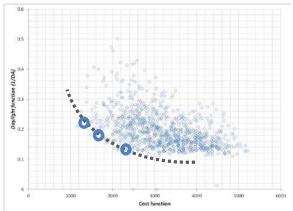


Figure 8, The Pareto front for the objective function

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

The work presented here demonstrates the need to integrate the cost with daylight measures in Urban environments. Two different approaches to optimize the use of reflective coatings were presented. However, several limitations exist and thus are recommended for future research. First, the optimization problem used dynamic daylight measures which are mainly developed for indoor environments and may not be the best choice for outdoor public spaces such as the ones considered here. Although the illuminance levels in the streets of these dense slum areas often fall below the 100 or even the 70 lux level, the dynamic daylight metrics used may not be the best measures to use. Second, we need to also consider the thermal effect of paints. This means that we need to couple the lighting simulation with thermal simulations to consider the effect on both outdoor and indoor environments.

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