ABSTRACT
The integration of building performance simulation and design optimization in the early stages of the architectural design process has attracted a high volume of research in recent years. However, both building simulation and design optimization require a significant amount of computing time, especially when there are multiple design objectives to achieve. In this paper, we present a technique—offline simulation—to effectively reduce the computing time in such design optimization problems. The validation of this method is presented in the context of a case study with parametric form-finding for a nursing unit design with two design objectives: minimizing the nurses’ travel distance and maximizing daylighting performance in patient rooms. The results show that computing time can be reduced significantly during the simulation and optimization process. The technique presented is based on Genetic Algorithm (GA). The use of GA in architectural design has become a trend for design optimization. Currently, however, only the general method of GA is applied to architectural problems. This research provides a new type of study that utilizes architectural domain knowledge to customize GA techniques in order to significantly improve the design optimization process.
INTRODUCTION

Building performance simulation and design optimization are powerful techniques for helping architects make better design decisions. However, they are very time consuming and require a significant amount of computing power. As a result, the integration of both techniques is unrealistic in real-world design practice. Our research focuses on reducing the computing time in design optimization when building simulation techniques are involved.

Time and computational complexity analyses are used to evaluate an algorithm’s consumption of computing and time resources. Previous research studies have shown that building simulation is a very time-consuming and labor-intensive process. For instance, in a high rise office building energy simulation study, more than thirty hours are needed to perform a one-year hourly simulation, and the time required for monthly simulations varies from thirty minutes to around six hours using four desktop computers running at the same time (Ahn et al. 2013). Researchers point out that the time and resources needed for simulation are major reasons that simulation tools have not been fully embraced by architects (Shi 2011).

When a standard Genetic Algorithm (GA) is used with simulation for optimization, a significant computer effort is expected (Renner and Ekárt 2003). As a result, various methods have been researched for increasing the speed of GA. The literature on this topic can be divided into three groups. One involves improving the infrastructure, running GA on a faster machine or using multiple machines working together. The Parallel Genetic Algorithm uses a group of cooperating computers to solve complex problems in less time (Muhlenbein 1991). Cloud computing (Armbrust et al. 2010) has also been introduced as a way to reduce the computing time of optimization problems.

The second group of research investigates the construction of approximate simulation models, for example, surrogate models that mimic the actual simulation model but use less computing power (Forrester, Bressloff and Keane 2006). The third group in the literature is focused on making the GA work more efficiently. Associative parametric models can be used to describe a large and complex geometric system with fewer variables, which would make the optimization process faster (von Buelow et al. 2010).

In this paper, we propose and test an improved GA with offline simulation, utilizing architecture’s domain of knowledge. The aim of the research is to encourage architects and engineers to use simulation and optimization in their daily practice. This research facilitates the fast creation and evaluation of design alternatives through a process of search, simulation and optimization, in order to meet specified architectural design objectives. It focuses on the early stages of the design decision-making process and is composed of the following computational methods: parametric modeling, performance simulation, design optimization and GA.

OFFLINE SIMULATION

In existing optimization processes, if building simulation programs are involved, simulations must be performed each time the building parameters (chromosomes in GA) change to form a new GA solution. The result of each simulation is used in the GA fitness function to produce another generation of solutions. This process continues until GA finds the optimal solution or reaches a pre-defined calculation time limit. As a result, the simulation program must run until GA finds the optimal solution. The number of simulations that need to be conducted is equal or proportional to GA’s population size.

In this research, we introduce the idea of offline simulation to reduce the number of simulations. Compared to real-time simulation, offline simulation refers to a computer simulation model that can execute at a time prior to the general GA optimization process. In order to save time, we separate building simulation from the GA optimization process, conduct all required simulations in advance and reuse the simulation results whenever appropriate in the GA’s fitness evaluation process. In other words, the correlations between building performance and decision variables can be obtained from offline simulations. These correlations can be used and reused in the GA fitness function. This way, simulations do not need to be repeated in GA and, as a result, a significant amount of time can be saved.

A CASE STUDY: DESIGN OBJECTIVES

The validation of the offline simulation method is presented within the context of a case study for parametric form-finding in a nursing unit design with two design objectives:

- a) to minimize nurses’ travel distance from the nurses’ station to each patient room; and
- b) to obtain an appropriate level of daylight illuminance in all patient rooms based on the LEED standard (healthcare supplement) (USGBC 2009).

In any study related to the behavior and working efficiency of the nursing staff, one of the most important variables is the distance that a nurse is obligated to walk in a hospital. Walking has been identified as a major time-consuming activity for nurses, and evidence from
previous studies suggest that the time saved by walking can be turned into more time spent on patient care activities (Zimring et al. 2004). Individual nurses across all study units travel between one and five miles per ten-hour daytime shift. Average travel distance ranges between 2.4 and 3.4 miles with a median of 3.0 miles per ten hours (Hendrich et al. 2006). Unnecessary walking may lead to time waste and add to fatigue and stress. In the case study, the objective is to minimize the total nurses’ walking distance.

Daylight is an essential element for patients’ wellbeing. Research shows that patients in sunny rooms feel less pain and stress and take less medication as compared to patients in rooms with less sunlight (Walch et al. 2005). This case study uses the LEED standard as a guideline for the daylight illuminance level calculation. LEED requires 75 per cent or more of the perimeter area to achieve a daylight illuminance level between 110 lux and 5,400 lux. Therefore, in this case study the daylight illuminance in every inpatient unit layout design is expected to meet this requirement.

DESIGN PLATFORM AND TOOLS

Parametric models can generate a very complex building geometry with a number of variables, rules and constraints that are defined by the designers. Several design software tools offer parametric modeling features. Of these software options, the integrated Rhino/Grasshopper program has widely been used because of its powerful modeling capability, intuitive interface and abundance of plug-ins that greatly expand its functionality. It also provides a ready-to-use GA plugin–Galapagos–which can be used for optimization. Hence, this case study uses Rhino/Grasshopper as the design platform. The following is a complete list of tools used in this case study:

1. Rhinoceros, a NURBS based 3D modeling program.
2. Grasshopper, a visual programming plug-in for parametrically editing models in Rhino.
3. Galapagos, a GA tool in Grasshopper.
4. DIVA, a thermal and daylight simulation plugin for Grasshopper.

DIVA conducts daylight analyses for Rhino models through Radiance and DAYSIM daylight simulation engines.

Galapagos-DIVA have been used in previous work for daylight analysis and optimization in the early architectural design process (for example, Gallas and Halin 2013 and Portugal and Guedes 2012).

BASELINE MODEL

Here we present the simplified yet representative case study used to validate the method of offline simulation. The design problem is to find the optimal nursing unit layout that would allow for the least travel distance for nurses and a daylight illuminance that meets the LEED standard. The layout of the nursing unit is defined by a set of parameters, restrictions and objectives. The parameters include constants and variables. The constants include:

a) a fifteen by fifteen grid with a total number of 225 cells, each measuring fifteen by fifteen ft, as possible room spaces;

b) a central nurses’ station represented by the blue square, sized twenty-nine ft by twenty-nine ft;

c) an eight ft corridor outside of the central nurses’ station;

d) the city of Boston as the location of the building in DIVA; and

e) a window size of six ft by six ft in every patient room.

(Figure 1) shows the constant parameters in a possible layout solution; the red squares represent the patient rooms.

The variables are the locations of twelve patient rooms. A patient room can be located in any cell with the following restrictions:

a) a patient room cannot overlap with any other patient room, nurses’ station or the corridor; and

b) in order to introduce natural light into each room, a patient room cannot be surrounded by other rooms in all four directions. In other words, at least one of the four cells surrounding each room should be vacant for window opening.

In this case study, we convert two objectives into a single objective by using a weighted sum of the objective functions with pre-defined (architects’ subjective) weights. For both travel distance and daylight illuminance, 100 points are given as the highest fitness score. The total nurses’ travel distance is calculated as the sum of the distances from the center of the central nurses’ station to the centers of all the patient rooms. The calculation of the nurses’ station to patient room distance and the total distance are simplified in the case study. In a practical situation, nurses’ walking distances are usually affected by the distance from the nurses’ station to the patient bed, following each nurse’s travel path and affected by the order of that nurse’s activities. Neither daylight nor travel distance sub-fitness functions should be linear in the overall fitness function.

For daylight illuminance, losing the same amount of daylight affects more a darker room than a brighter room (Rutten 2011) (Figure 2). The same additional increment of travel distance makes a nurse feel much more fatigue, if that nurse has traveled a longer distance than someone who has just started a shift (Figure 3).

Daylight Illuminance is evaluated by the percentage of sensor grid points in a room achieving a daylight illuminance level between 110 lux and 5,400 lux. In this case study, the above percentage is 89 per cent if all rooms face south and 70 per cent if all rooms face north (and in between for east and west). Fitness values of...
100 and 0 are assigned to rooms with south-facing and north-facing windows, respectively. For any nursing unit layout solution, the fitness score for daylight illuminance is defined as follows:

\[
\text{Fitness}_{\text{daylighting}} = 100 \times \left( \sqrt{1 - \frac{\text{89\%-Daylight Percentage}}{\text{89\%-70\%}}} \right)
\]

70 per cent \(\leq\) Daylight Percentage \(\leq\) 89 per cent

A fitness score of 100 is given to the nursing unit layout with the shortest total travel distance possible, 388 feet (see Figure 4, left) and 0 is given to the layout with the furthest total travel distance possible, 1,708 feet (see Figure 4). For any nursing unit layout solution, the fitness score for the travel distance is defined as follows. (We chose the power of two in the case study for simplicity of calculation.)

\[
\text{Fitness}_{\text{travel distance}} = 100 \times \left( 1 - \frac{\text{Distance} - 388}{1708 - 388} \right)^2
\]

388 \(\leq\) Distance \(\leq\) 1708

According to LEED IEQ Credit 8.1 “Daylight and Views-Daylight,” daylight illuminance simulations should be conducted under clear sky conditions at two different times. In this research, those times are 9 a.m. and 3 p.m. on September 21. Thus, in DWA, “clear sky with sun” and “illuminance” are selected for the sky conditions. However, DWA can only conduct simulations at a specified time point in each run. In order to satisfy the LEED requirement, the optimization process must run two separate times, one on September 21 at 9 a.m., and the other at 3 p.m. Although the setup for both optimization processes has the same objectives and parameters (except the solar time) in DWA, the results may be different because daylighting conditions differ. We perform both a 9 a.m. and 3 p.m. calculation in our case study.

The DWA daylight simulation accuracy increases if more sensors are used in the patient rooms. However, the more sensors it uses, the more computing time it needs. Consequently, designers should balance the need for accuracy with the associated computing time, based on the project’s requirements. In the baseline model used in this research, one hundred sensors are evenly distributed in each room (1,200 sensors in twelve rooms total) at the level of desk height. All simulations are run on a standard laptop (ThinkPad series, Windows 7 64-bit, Intel(R) Core(TM) i5-2520M CPU @ 2.50 GHz, 8GB memory). In Galápagos, the population size per generation is fifty, initial boost is two, inbreeding factor is 75 per cent, and maintain factor is 5 per cent. For this particular study, a single run of the daylight simulation in DWA requires approximately six minutes to complete. However, when DWA is associated with Galápagos in the optimization process, it can be very time consuming because each solution requires a simulation. In our experiment, seventy-eight hours of DWA run time + Galápagos could only calculate thirteen generations of GA, and the results were not nearly optimal in our examination. The complete optimization could take more days, which is not practical even for this simplified case study.

Here, we summarize the problems we encountered during design optimization when using GA and energy simulation as the platform: a) due to the limitations of the software (Grasshopper +...
Galapagos + DIVA, only one specific time of a day (for example, 9 a.m.) can be calculated per simulation. If design optimization involves a building simulation at a different time (for example, 3 p.m.), the entire process must be re-performed. Thus, the information from both building simulations cannot be combined into one design optimization to find the optimal solution; b) Design optimization is very time consuming. Most architectural design projects have tight schedules. Therefore, it is unrealistic for architects to spend days on one optimization problem.

OFFLINE SIMULATION

Because the current design optimization process has the above-mentioned problems, offline simulation is introduced to a) integrate multiple building simulations at different times (for example, 9 a.m. and 3 p.m.) into one optimization problem; and b) reduce computing time when a building simulation is coupled with design optimization by separating the simulation from the optimization process. We separate the building simulation from the GA optimization process and conduct all required simulations in advance. This way, the simulation results can be reused in similar situations (for example, all the rooms with windows facing the same direction will have the same daylight illuminance results in any GA generation and across the generations), and time consuming simulations will not need to be run for each solution.

Because the locations of patient rooms are variables, one question is how to define the window opening directions. In terms of daylight, both a very large window facing north and a relatively small window facing south might satisfy the LEED daylight requirement. However, window-opening directions not only affect the interior daylight level, but also have a significant impact on building energy consumption. In LEED, a project can earn up to twenty-four points in the "energy performance" category. The points that a building can earn depend upon the percentage of improvement in building energy consumption as compared to its baseline performance. This is calculated using a computer simulation model for the entire project based on Appendix G of the ANSI/ASHRAE/IESNA Standard 90.1-2007 (ASHRAE 2007). The baseline model performance is defined as an average of the results of four simulations from four orientations: the original orientation of the building and the orientation rotated by 90°, 180° and 270°. The results of the thermal energy simulation using DIVA shows that the building consumes the least amount of heating and cooling energy when the window is facing south. The second best orientation is east; the third is west, and the worst is north. Based on this analysis, we conclude that the window opening priority order should be south - east - west - north. Using this predefined priority list saves time spent computing the GA; if the priority list is not used, all possible directions must be included in the search space and evaluated by the simulation and fitness functions. We divide the floor plan into four sections (Figure 5). A VB Script node written in Grasshopper is used to implement the following rules, the goal of which is to determine automatically each window's opening direction for the patient rooms during the GA process:

a) if the center of the room is in Section 1, the priority of window opening direction is south - east - west - north. VB will check the availability of adjacent rooms in the above sequence.

b) if the center of the room is in Section 2, the priority is west - south - east - north.

c) if the center of the room is in Section 3, the priority is north - south - east - west.

d) if the center of the room is in Section 4, the priority is east - south - west - north.

One of the research questions can be stated as follows: since the parameters are consistently changing during the optimization process, how do we categorize the results of each simulation so that each category of simulation only needs a single simulation prior to the optimization process? For daylighting simulations, all patient rooms in this study share the same parameters (room dimensions, window size and location, building materials, number and location of sensors in DIVA), except for room locations and window opening directions. However, as long as the patient rooms have the same window directions, the daylighting values of the rooms can be regarded as also being the same (in a simplified experiment, when shading is ignored). Based on this, the daylight simulations of all patient rooms in this project can be simplified as simulating four patient rooms with windows facing south, east, west and north, respectively. Therefore, before the start of GA optimization, a DIVA daylight simulation is conducted to calculate the daylight level in every patient room. The location of rooms...
does not matter for daylight evaluation, only for walking distance calculation. The offline, pre-simulated daylight illuminance levels of all directions (south, east, west and north) are used in the GA process. During the optimization process, although the room location and the window opening direction may change in any design solution, we can obtain the daylight fitness score of the entire design solution by counting the total percentage of sensors that meet the LEED illuminance value.

Comparing the workflows of existing design optimizations (Figure 6) and offline simulation-based optimizations (Figure 7), the difference is that in offline simulation-based optimizations, building simulations are performed prior to the optimization process. This change can reduce a significant amount of computing time, as shown in the Results section below.

RESULTS
In this study, we convert a multi-objective optimization into a single objective optimization by using a weighted sum of the fitness functions with weights chosen based on subjective preferences. (Figure 10) shows two optimization results with different weights in their fitness functions. The image on the left is the result when using equal weights for travel distance and daylighting. The image on the right is the result when the weights between travel distance and daylighting are 1:2. While the optimal solutions are not surprising—they are consistent with our intuitive expectations regarding the results—the important point is the significant time saving when finding solutions with our new methods. For this nursing unit optimization case study, using the existing method of GA optimization, the computer needs seventy-eight hours to finish thirteen generations of GA calculation. By using offline simulation, the computing time is significantly reduced, to forty minutes, to finish thirteen generations of GA calculation. (Table 1) shows a comparison between the standard GA and the GA with the offline simulation method in terms of total time used, time used per generation and whether the optimal solution is found.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Time</th>
<th>Time/Generation</th>
<th>Optimal found?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard GA</td>
<td>78 hours</td>
<td>6 hours</td>
<td>Not nearly</td>
</tr>
<tr>
<td>GA with Offline Simulation</td>
<td>40 minutes</td>
<td>3 minutes</td>
<td>Close</td>
</tr>
</tbody>
</table>

Table 1: Comparison between Standard GA and Improved GA

CONCLUSIONS
The use of GA in architectural design has become a trend in design optimization. Currently, however, only the general method of GA has been applied to architectural problems. In this paper, we present the offline simulation method to achieve a more efficient GA optimization. The use of this technique demonstrates a significant time saving in the case study. We have provided a new type of study that utilizes architectural domain knowledge to customize GA techniques, and as a result have significantly improved the design optimization time. The offline simulation technique is beneficial when building simulations can be separated from the optimization process and conducted in advance. The simulation results can be reused in order to save computing time.

However, there are limitations in the use of the offline simulation method. In offline simulation, for example, the simulation result of each genome is pre-computed, so there is no mutual feedback among genomes. For example, self-shading (for example, a room may cast shadow to other rooms) is ignored in our simplified case study, thus the effect of shading was not included in the daylight illumination result. If obstruction is considered in more complex spatial layouts, offline simulation may not be appropriate. One solution to this problem is to find and pre-compute all possible shading situations in advance. This may increase manual labor and computing time for offline simulation, but it can be assisted by scripting to automate the process. In a complex problem, designers may need to optimize the total GA computing and offline simulation time. Future study is needed to further examine and resolve these limitations.

To discover the GA improvement techniques, architectural domain knowledge is needed. For example, the following knowledge is used in the case study: if two identical rooms (same shape, same windows and same shading) in a building are facing the same direction but located differently, they have the same illuminance at any given time because the sun is far enough away that the difference in light angles between the two rooms is negligible. Another example is that in many cases in the northern hemisphere, the best window direction for optimal thermal performance is south, followed by east, west and north. This knowledge was confirmed by our thermal simulation and used in the offline simulation. To sum up, designers can play an important role in improving optimization efficiency. We should utilize architects’ design knowledge to customize the optimization process, a process that would significantly save computing time and eventually make optimization practical for architectural design. In future work, we will expand these techniques to Pareto Optimization for multiple design objectives, and also explore other improvement techniques.
6 The Traditional GA Optimization Workflow.

7 The Improved GA Optimization Workflow with Offline Simulation.
REFERENCES


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IMAGE CREDITS

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