The Design of the Optimal Light Shelf in Educational Setting

Simulation vs. Optimization in assessing daylight performance

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Abstract: *There has been an increasing challenge on architects to design buildings that meet diverse range of performance criteria; and hence, achieve high levels of efficiency in terms of their environmental performance of buildings. This, however, requires new approaches in problem-solving to inform the design process. Particularly, if there is a need to satisfy many criteria to achieve an optimized behavior of the system. This paper investigates two approaches of simulation and optimization as the means to integrate the computer as a tool in the design process. While computer simulation tools are useful for measuring accurate performance, yet they have drawbacks. Simulation tools evaluate one solution on a case-by-case basis. Thus, it is arguably a time-consuming process, where architects feed in a limited number of solutions aiming to find an optimized solution. This approach, therefore, eliminates a larger number of potential solutions that could enrich the design process at an early stage of the design process. To overcome these constraints, a computer optimization approach is emerged yielding promising results using Genetic Algorithms (GAs), where the computer is considered the solution-generator and performance-driven force. GAs generate and evaluate solutions using a simulation tool in an algorithm offering an optimal or near-optimal solution. GAs are effective in solving complex problems, defining criteria between multiple objectives and are, thus, less time-consuming. The aim of the paper is to explore potentials of simulation and optimization approaches, and further define the criteria needed to help determine the suitable approach for assessing environmental performance in buildings according to the architectural problem in question. The findings of the paper will feed into the second phase of the research to enable the application of optimization approach to optimize daylighting performance in educational buildings.*

Keywords: Daylighting, Light Shelf, Environmental Design, Simulation, Building Optimization

6. INTRODUCTION

Design problems in architecture are neither linear nor static problems. They are, rather, iterative and dynamic processes that are continuously in change. Thus, there are many possible solutions as a result of the interaction between various variables, which may sometimes behave oppositely to each other. The challenge is to find the optimum design alternative that yields the highest performance level in a relatively short time (Jones, 2009; Chutarat, 2001).

Daylight is the science of admitting and introducing natural light to space. Natural light comes from two sources; the sun as direct light and the sky as diffused light that enters the building through windows (Mardaljevic et al., 2009). In a daylit working environment, the usual distribution patterns of daylight affects areas near to windows much more than areas deeper far from windows. The former areas become overlit, while the latter areas become underlit which then would require artificial lighting (EFA, 2014). Accordingly, in a square shaped classrooms there is a need to further improve the range of daylight distribution patterns to be more uniform and provide the required levels of light to the students in the middle of the room.

The aim of daylight is not only about admitting adequate illumination levels in space, but rather preventing direct sunlight and controlling how much light is entered. Direct sunlight exposure causes serious inconveniences to the users of the space. First, the overlit area becomes much more illuminated than the required for performing task. Second, the areas exposed to direct sunlight are more susceptible to cause glare which discomforts users. Third, the accompanied overheating due to the continuous exposure of direct sunlight on façade increases the indoor temperature, which consequently increases the cooling demands. Therefore, there is a need for a more holistic approach to integrate the use of shading concepts with daylighting in order to maximize the benefits of natural light while eliminating the downsides (Garcia-Hansen, 2006; Ander, 2014).

1. LITERATURE REVIEW

1.1. Daylight in Educational Facility

Natural light proved to significantly contribute to the psychological health and biological processes of human beings. In an educational setting in particular, daylight improves the performance and productivity of students and employees. However, it is difficult to daylit classrooms due to the deep depth of classroom and the different tasks performed in it (Bruin-Hordijk and Groot, 2010; Rea, 2000).

There are many systems for the design of daylight in educational buildings. Classrooms are designed to receive daylight through sidelight systems; from strip linear continuous windows to floor-to-ceiling window system. The strip fenestration system using long horizontal windows in walls was adopted in the architecture studio in Oporto in Portugal in 1996 (Caldas and Norford, 2001). The use of continuous windows, as opposed to conventional windows was also supported by Al-Mohaisen and Khattab (2006), as it arguably provides uniform daylight distribution. Another study conducted on nine different classes and opening configurations by Bruin-Hordij and Groot (2010) concluded that classroom with two sidelight fenestrations has the best daylight performance.

1.2. Problem Under Study

The problem under study is how to reach the optimal configuration and position of a shading device to maximize useful daylighting and shading performance. Shading devices appear to have a complex behaviour due to interactions between contradictory requirements. In a typical horizontal overhang, as the length of device increases in order to provide for shading, there is a decrease in the daylighting availability inside and thus an increase in the demand for artificial lighting leading to increased energy demands. On the other hand, when the length of shading device decreases, there is an increase in the natural lighting but there is smaller shading performance, and thus, an increase in the overlit areas exposed to direct sunlight, leading to glare and overheating. This, in turns, raises indoor temperature and consequently more cooling loads would be needed. Several research work was conducted in order to introduce and evaluate daylight systems in conjunction with shading, lighting and glare (Torres and Sakamoto, 2007; Gonzalez and Fiorito, 2015; Chutarat, 2001; Gadelhak 2013).

1.3. Problem Formulation

Among the various types of the shading devices, few devices can arguably improve daylight in the back of a room. Light shelf is a typical horizontal overhang that divides the window opening vertically into two parts; upper part for the clerestory window and lower part for the viewer window. It is usually installed in the façade which has the highest sun exposure. Light shelf functions, therefore, as both: shading and light redirecting device (Gadelhak, 2013; A.G.S, 2000).

(1) Shading device: it is extended outwards to shade the viewer window and block direct sunlight and prevent overheating.

(2) Light Redirecting device: it reflects the incident daylight to the ceiling and further again to the back of space for deeper illumination.

In addition to the use of shading elements, this research suggests the use of self-shading as a second strategy in an integrated approach with shading devices, in a way to enhance the global shading performance of the building. Building self-shading techniques are achieved by using several strategies that include tilting facades; recessing or protruding façade parts. This is to reduce the surface area of building skin exposed to direct solar radiation and, thus, decrease the solar heat gain transferred (O'conner, 1997).

1.4. Simulation vs. Optimization Approaches

There has been many ways to integrate computational and advanced tools in the decision making of design process at an early stage (Caldas and Norford, 2002). This paper discusses the process, potentials and limitations of the two approaches; simulation and optimization. Further, it defines the criteria needed to help determine the suitable approach for assessing environmental performance in buildings according to the problem in question.

1.4.1. Simulation Approach

Simulation is a trial and error mechanism (Wagdy and Shalaby, 2013), which first starts when architect models and generates an initial solution based on specific case by case (Caldas and Norford, 2002). The next step is preparing this model to go into simulation process where many input data are fed into the model such as, surface materials; analysis grid; location and orientation of the building; weather climate; simulation type and output; and simulation period. The process then runs the simulation experiment (Carson and Maria, 1997) and displays the results for the given solution. The last step is the architect's decision whether to terminate the process and select the tested solution as the most convenient solution, or to make modifications manually to the design solution and to further reiterate the simulation processes and so forth (Wagdy and Shalaby, 2013).

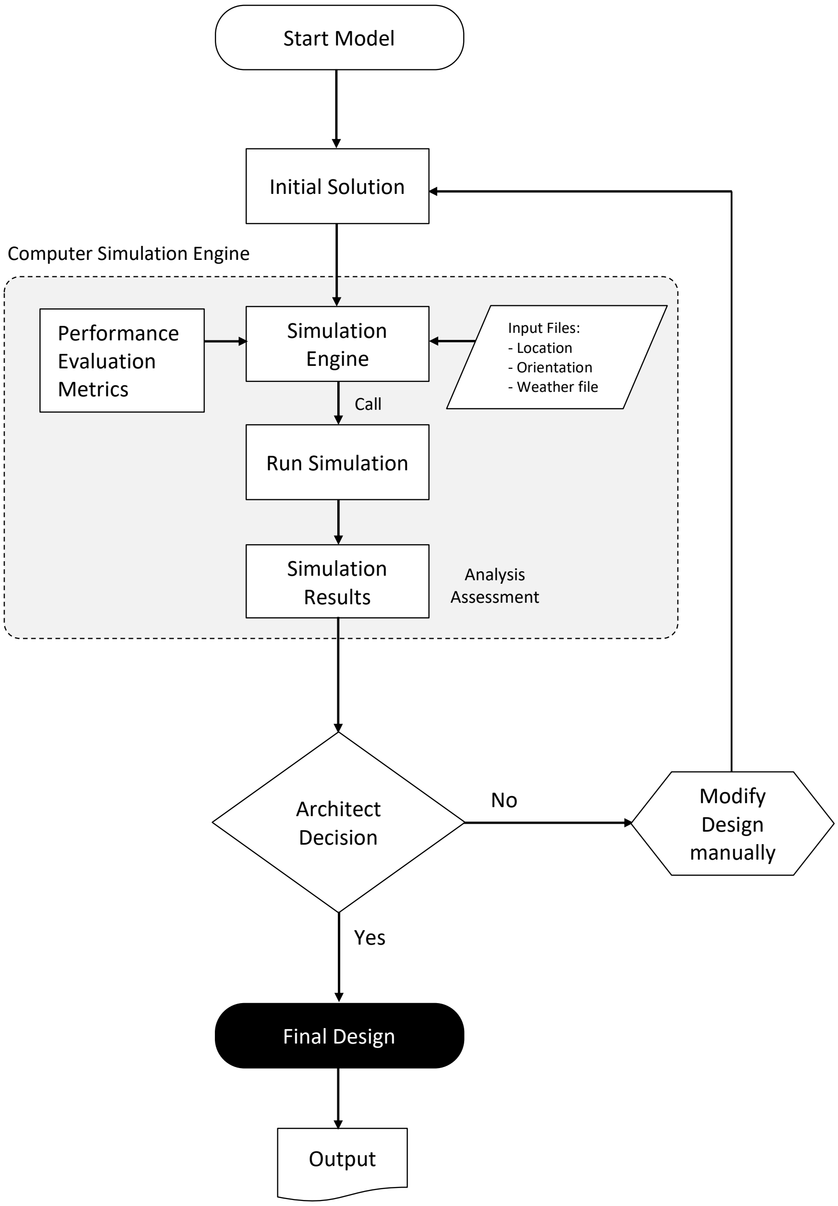

Figure 1: Logic Flow chart for the integration of simulation process into design process. (adapted from Carson and Maria, 1997; Hong et al. 2000; Morbitzer, 2003)

1.4.2. Optimization Approach

Optimization starts the same way as the simulation approach, generating an initial solution model. Similarly, the model proceeds in the simulation experiment to further yield the results of the initial design solution. The next step is the coupling between the simulation program and optimization algorithm (Nguyen, Reiter and Rigo, 2014). The algorithm contains an objective function which the architect would be aiming to either maximize or minimize. The simulation results then feed into the optimization algorithm to evaluate the extent to which the performance of the solution is meeting the objective. Having the solution scored the highest performance, the process will be automatically terminated providing the architect with the optimal or near optimal solution. Otherwise when the solution does not satisfy the objective performance, it goes back from the start feeding into the initial model.

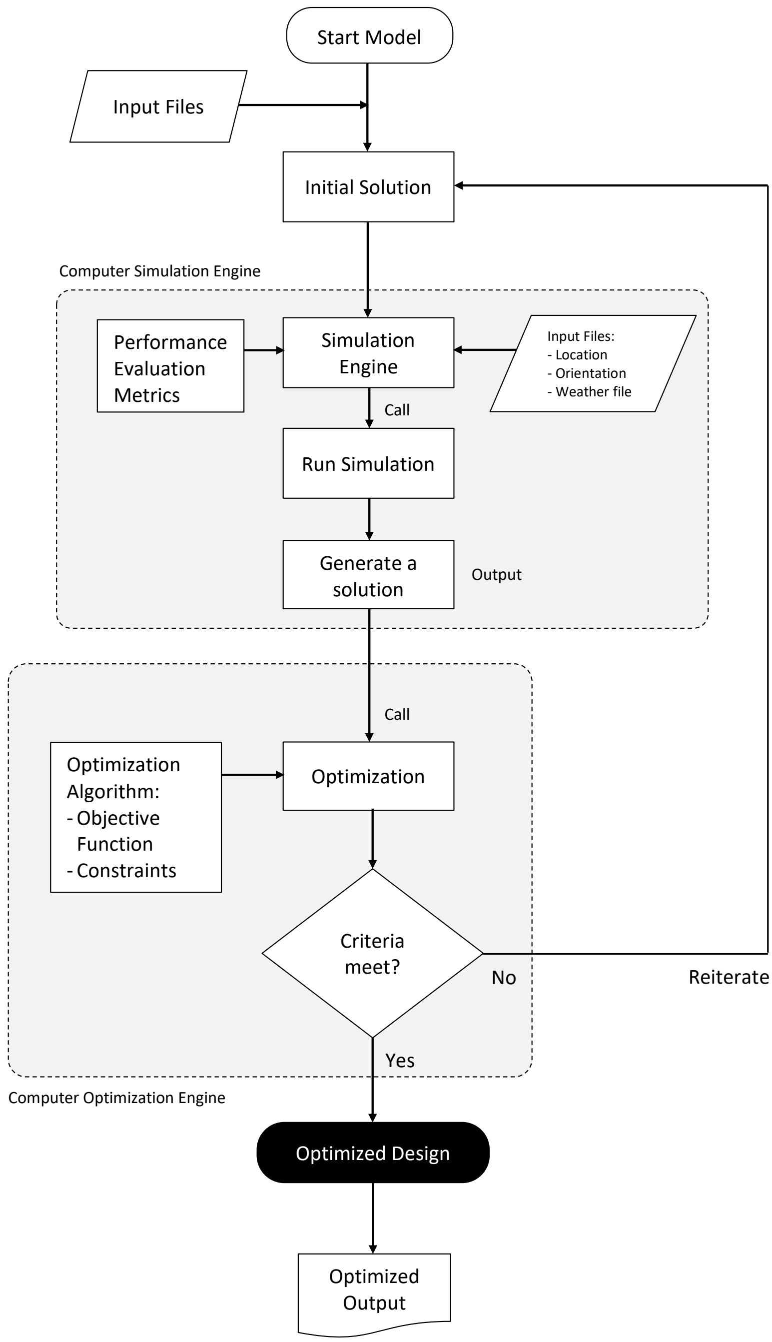

Figure 2: Logic Flow chart for the integration of optimization process into design process. (adapted from Andersen et al. 2008; Wagdy and Shalaby, 2013; Charron and Athienitis, 2006)Selection Criteria of the Approach

In order to be able to evaluate or determine whether simulation or optimization better serves the design process, there is a need to explore the potentials for both approaches. Table 2, lists the different evaluation criteria to allow define potentials for using simulation vs. optimization. The criteria relate to the problem under study in the following aspects; problem size, variables, constraints, objective function, and design solution.

1.4.2.1. Problem Size

The design problem is usually defined by three main components, namely; variables, constraints and objective function (Radford and Gero, 1980). The problem becomes more complex when the number and type of variables increase (Alaimi and Wright, 2014). Thus, increasing in the number of possible solutions, which consequently leads to an increase in the total number of simulations required to find the optimum solution. Multiple variables and solutions for the design of light shelf can be shown in the next section in Table 1.

1.4.2.2. Variables: numbers and types

The variables are the parameters that control the design solution. Any change in the characteristics and encoded values of one variable will be followed by an instantaneous change in the whole design solution. As the number of variables increases, there is an increase in the dimensions of the solution search space size. In the aforementioned problem, there are eight variables most related to the design of light shelf, room surface reflectance, and glazing type, as listed in Table 1. Variables related to light shelf are shown in Figure 3.

Figure 3: Light shelf variables in cross sectional view and perspective showing the classroom interior.

where d: depth of light shelf from reference line;
h: height of light shelf from finish floor line;
v: position of viewer window from reference line;
c: position of clerestory window from reference line.

Table 1: Problem Variables (adapted from Chutarat, 2001)

Aspect	Variable No.	Variable / Dimension	Abr.	Variable Type	Upper Bound	Lower Bound	Increment Step	No. of Solutions
Light shelf	1	Depth of light shelf from reference line (m.)	d	Continuous	0.20	1.60	0.20	8
	2	Height of light shelf from finish floor line (m.)	h	Continuous	1.80	2.20	0.10	5
	3	Position of Viewer window (and recess of wall) (m.)	v	Continuous	0.10	1.20	0.10	12
	4	Position of Clerestory window (m.)	c	Continuous	0.10	1.20	0.10	12
Room Surface Reflectance	5	Ceiling Reflectance	R_c	Continuous	0.00	1.00	0.20	6
	6	Wall Reflectance	R_w	Continuous	0.00	1.00	0.20	6
	7	Floor Reflectance	R_f	Continuous	0.00	1.00	0.20	6
Glazing	8	Type of Glazing	T	Discrete	0: single	1: double	-	2

In reference to a problem studied by Tuhus-Dubrow and Krarti (2009), a problem which had an overall number of 256 solutions was categorized as a small-size problems, while a large-size problem would have an overall number of solutions that exceeds 20,200,000. In this respect, the total number of possible solutions can be enumerated using Equation (1), by the multiplication of all numbers of solutions in each variable in Table 1. ThFis results in 2,488,320 solutions, which is the same number of simulations required to cover all design possibilities. Total number of possible solutions can be calculated according to the following formula:

$$N_T = N_1 \times N_2 \times \dots N_i \times \dots N_n \,, \qquad 1 \le i \le n \tag{1}$$

where N_T is the total number of possible solutions; N_i is the number of solution for variable i; and n is the total number of variables.

In addition to the nature of variables which contains three types; continuous, discrete, and mixed-type (Chutarat, 2001). Continuous variables are defined between intervals of two values, for example the height of light shelf can be expressed as; 1.80 m. ≤ height ≤ 2.20 m. in an increment step of 0.10 m. On the other hand, discrete variables have limited number of options, such as type of glazing will either be single or double-glazed type. Therefore, it is a problem with large number of mixed-type variables results in categorizing it in large-size problems.

1.4.2.3. Constraints

Constraints constitute the boundary conditions that should not to be exceeded by the relevant variables. These can be classified into three groups; box constraints, selection constraints, and functional constraints (Wang, Rivard and Zmeureanu, 2006). Box constraints are defined as upper and lower intervals for continuous variables; e.g. the possible variation of the depth of shading devices is limited by 0.20 m and 1.60 m as defined upper and lower bounds respectively. Selection constraints are applied to discrete variables, e.g. the types of glazing and walls. Functional constraints are used to relate design variables and derived variables together. The variables discussed in the section above consist of seven continuous variables, and one discrete variable. The boundary constraints of such variables are shown in Table 1.

1.4.2.4. Objective Function

Since the purpose of the process is to reach the optimum design configuration for the light shelf that will enable maximum useful daylight availability in space, then there must be a specific function linked to the different variables and fed into the process. This function resembles a quantified goal of optimization to measure the extent to which the performance of a design solution reaches the highest performance while satisfying constraints (Chutarat, 2001). The objective function in the research is the proportion of the average light measured annually in classroom to the total lighting requirement level by daylight (Torres and Sakamoto, 2007). Since the daylight illuminance on the horizontal work plane in educational drawing classes considered was 500lx according to daylight standards (Rea, 2000; ESCLDC, 2008). The objective function can be expressed as:

$$Maximize: \quad F(x) = \frac{E(av)\ lx}{500\ lx} = \frac{\sum_h^H \sum_s^S E(ho)\ lx}{\mathrm{H}\times\mathrm{S}\times 500\ lx} \tag{2}$$

where *E(av)* is the annual average daylight illuminance for all sensors in classroom; *E(ho)* is the measured daylight illuminance on the working plane, for a certain hour and sensor; and *H, S* are the number of hours and sensors, respectively, when $h = 1$ and $s = 1$.

1.4.2.5. Design Solutions

There are large number of design solutions in total to the problem under study that occur as a result of the interaction between the different variables. This results in a multi-dimensional search space (Jones, 2009). In this context, there are eight dimensions in the search space that corresponds to eight variables (Table 1).

In an automated procedure, the simulation is coupled in an optimization algorithm where the computer directs the search with probability to find and generate the optimum or near optimum solutions. Similarly, the characteristics of the generated succeeding solution is dependent on its counterpart of the preceding solution. Hence, when the process is automated, solutions developed to a higher fitness solutions, are always derived from the initial solutions (Caldas and Norford, 2002).

Table 2: Evaluation criteria for the use of simulation and optimization processes.

No.	Aspect	Criterion	Simulation Process	Optimization Process
1	Purpose	Process	Architect evaluates design alternatives through the process	Architect uses computer to find the optimal or near-optimal design solution
2	Problem	Problem Size	N/A	Small-size problem (256 simulations) and Large-size problem (20,275,200 simulations)
3	Variable	No. of Variables	Small number of variables	Small and large number of variables
		Type of Variable	Continuous / discrete / mixed-type	Continuous / discrete / mixed-type
4	Constraint	Link to Variable	N/A	Constraints are linked to variable according to type of variable
		Type of Constraint	N/A	Box / Selection / functional constraint
5	Objective Function	Objective Function	N/A (it is not a problem-solving method)	Specific objective function is fed into optimization (it is a problem-solving method)
		Number of Objectives	One objective	One or multiple objectives
		Link to Variable	N/A	Objective function is linked to the variables
6	Solution	No. of Solutions	Evaluate one specific solution on a case-by-case basis	Generate number of possible solutions
		Probability of Solution	Architect predicts the optimal solution	Computer directs the search with probability to reach the optimal solution
		Search Space	Search space is small with few dimensions	Search space is large with multiple dimensions
		Derived Solutions	Initial solution is modified manually by designer	Initial solution automatically drives the performance of the succeeding solutions
7	Simulation	No. of Simulations	Large number of simulations required in order to cover all solutions	Small number of simulations required in order to find the optimal solution
8	Design Stage	-	An early design stage	An intermediate design stage
9	Time of Process	-	More time to simulate all number of design solutions	Less time to simulate few design solutions

2. DISCUSSION AND CONCLUSION

It is argued that computer simulation is one of the fundamental processes that significantly contributes to evaluating solutions to the design problem. While adopting a trial and error procedure where simulation informs the architect with the performance of the anticipated solution to either manually accept or reiterate the simulation for further solutions. This, however, may bear several obstacles in comparison to optimization approach. Therefore, as the complexity of design increases, simulation becomes less useful (Tsangrassoulis et al. 2005). Simulation evaluates one specific solution, while optimization generates and evaluates derivative solutions until it reaches the most efficient solution in terms of measured performance aspects. In this context, simulation is a time-consuming process, while optimization shortens the process to find the optimum or near-optimum results.

In light of the above, it may be concluded that optimization is more suitable to reach the optimal configuration of light shelf in terms of daylight performance. These results will feed into the second part of the research that will introduce the different optimization tools, and define the most suitable search method and optimization algorithm in order to maximize daylight performance.

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