Optimizing Building Envelope Component Design for Thermal and Lighting Performance

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Benjamin J. Futrell
School of Architecture
Infrastructure and Environmental Systems Ph.D. Program
University of North Carolina at Charlotte
Charlotte, NC, 28223, USA

Ertunga C. Ozelkan, Ph.D.
Systems Engineering and Engineering Management
University of North Carolina at Charlotte
Charlotte, NC, 28223, USA

Abstract

Judicious building design can significantly reduce energy required to heat, cool, and illuminate buildings, which accounts for approximately 30% of our nation’s energy use. Building upon the authors’ previous research on optimizing buildings for natural lighting, a novel approach to optimizing light and heat exchanges across the building envelope (i.e., exterior surfaces such as walls and windows) is proposed; a method is introduced that analyzes the magnitude of these exchanges across envelope components and how effectively they meet luminous and thermal requirements. Each design is evaluated on how its hourly heat transfer (conducted and radiated) impacts annual heating and cooling loads. In addition, window design is evaluated based on the ratio of actual to potential room area illuminated to a target threshold on an annual basis. This thermal and lighting evaluation approach forms the basis of a bi-objective building envelope optimization method. A simple classroom design problem is used as a case study. It is expected that this method will be superior to similar ones, which typically measure performance at the building level, thus aggregating and masking the effects of building envelope components on individual rooms (thermal zones).

Keywords

building energy simulation, building energy performance optimization, daylighting, multi-objective optimization, simulation optimization.

1. Introduction

The fundamental purpose of buildings is to allow humans to thrive by providing shelter from often hostile environmental forces. In modern buildings, thermal and luminous comfort conditions are primarily sustained by energy-intensive equipment; not surprisingly, the operation of buildings comprises approximately 47.6% of our nation’s annual energy use [1]. To solve our nation’s increasing building energy demand and environmental degradation problems, building energy consumption must be reduced. The heating, cooling, and lighting loads placed upon engineered systems are impacted by building design factors controlled by architects: orientation, floor plan shape, window placement and size, material selection, etc. The building itself is a system of energy (in the form of sensible heat and radiation – including light) conducting, transmitting, and storing elements (walls, windows, and building mass, respectively) that interface between the exterior and interior environments. Because architects design buildings with principal regard to functional and aesthetic needs, the loads created by the architectural system are rarely rigorously analyzed (usually only meeting minimum code requirements), let alone optimized. In Charlotte’s South Atlantic region, heating, cooling, and lighting represent the three largest end uses of energy in commercial buildings.
and institutional buildings, 23.4%, 12.4%, and 24.2% respectively [2]. Good daylighting design practices can eliminate 40-80% of lighting electricity use. Daylighting design has mainly to do with how windows and light-reflecting surfaces incorporated into building design. The windows that provide daylight to a space are also the weakest thermal barrier between the inside and outside environments and have a significant impact on heating and cooling loads. Optimum daylighting design varies based on climate and geographic location, orientation, and surrounding exterior context and is commonly in conflict with thermal performance. These considerations make optimizing for daylighting and thermal performance a unique problem for every building designed. The purpose of this study is to optimize building design for daylighting and thermal loads, and thus minimize the need for electric lighting and space conditioning.

As shown in this and other studies [3], the building thermal energy and daylighting optimization problem is a relatively complex nonlinear relationship between design parameters and performance responses. Here, we have developed a simulation-optimization technique to solve this problem integrated with GenOpt and its implementation of a hybrid Generalized Pattern Search implementing Hooke Jeeves and Particle Swarm Optimization algorithm [4]. An application of the proposed methodology is presented that optimizes a prototype grade school classroom based on a design developed for Charlotte Mecklenburg Schools (CMS) by Cort Architecture. The prototype design optimizes the annual uniform diffusion of daylight from the window and clerestory throughout the classroom and minimizes the sum of annual heating and cooling loads (the thermal energy necessary to extract from the room air to maintain the thermostat set point temperature).

2. Literature Review
Energy efficient building design optimization research has received much attention in recent years. Due to the complex physical functional relationships between design factors and performance, search heuristics, primarily genetic algorithms (GA), have been used more than other methods (see e.g. [5-10]). Below, we will review some of the most related papers.

An interactive expert system for daylighting design exploration is discussed in [5]. The goal of this paper was to move beyond simulation programs that just report information about daylighting performance by providing necessary information to aid the building designer in making performance improving design changes; however, the search for optimum solutions was left up to the user. A GA-based design optimization tool is presented in [6]. This work focused on a generative and goal-oriented design process that integrated GA to search for high-performing/near optimum design solutions. GAs for ceiling form optimization in response to daylight levels was discussed in [7]. This paper’s focus was on the shape of the ceiling with regard to how well it reflects and diffuses sources of daylight for the satisfaction of interior illumination needs. Design explorations of performance driven geometry in architectural design using parametric modeling and GA can be found in [8]. The paper presented a software program, ParaGen, to evaluate the great number of feasible design alternatives made possible by today’s parametric building design programs. A related study on design optimization was reported in [9], which presented another software program named GenOpt. GenOpt was created by the Simulation Group at Lawrence Berkeley National Laboratories to help realize the full potential of computer simulation in building energy performance evaluation. Another optimization software, ThermalOpt, was reported in [10] for implementing a methodology for automated building information modeling (BIM)-based multidisciplinary thermal simulation. ThermalOpt is a software tool that interfaces various building modeling and simulation programs that streamlines the process of modeling and simulation of design alternatives.

The project presented in this paper builds upon the research discussed above. Most optimization methods above were GA-based and proved to be successful at finding high performing solutions based on their respective performance criteria. Here, a complex daylighting and thermal design problem is solved. Furthermore, this project uses sophisticated climate-based daylighting simulation methods, not used by others, to evaluate daylighting performance.

3. Model
The objective of this optimization problem is to maximize illuminance and thermal performance of a building across various scenarios. Before defining the specific objective function in consideration, we would like to define illuminance and thermal performance along with related terms.
First, illuminance (a.k.a. incident light) at a point \( E \) is determined by integrating over the hemispherical field of luminance (a.k.a. surface brightnesses) seen by that point (Equation 1 [11]). It is measured in lux (lx), lumens per square meter, or foot-candles (fc), lumens per square foot. Besides the location of the point within the building/room, there are multiple external factors \( \Omega \) that influence the light field seen at any point in the building, including the building surface geometry, surface material properties (e.g., reflectance and/or transmittance), and a sky and sun model derived from historical climate/location data (month, day, hour, latitude, longitude, global horizontal irradiance and direct normal irradiance) [18].

To compute illuminance, a backwards ray-tracing method can be used based on a discrete number of sampling rays \( 2n^2 \), where \( n \) is an integer parameter) as shown in equation 1 below [11]. The amount of luminance associated with each ray is calculated and, accordingly, the illuminance of the point is determined as a summation of the individual luminance values.

\[
E(\Omega) \approx \frac{\pi}{2n^2} \sum_{j=1}^{n} \sum_{k=1}^{2n} L(\theta_j, \phi_k | \Omega)
\]

where \( \theta_j = \sin^{-1}\left(\sqrt{\frac{j - X_j}{n}}\right) \)

\( \phi_k = \pi \left(\frac{k - Y_k}{n}\right) \)

\( X_j, Y_k = \) uniform random numbers between 0 and 1

\( 2n^2 = \) total number of sampling rays

where the \( L(\theta_j, \phi_k | \Omega) \) function is based on the luminance in the direction \( \theta_j, \phi_k \) as seen by the calculation point.

Next, we would like to elaborate on the external factors \( \Omega \). Without loss of generality, external factors were divided into two groups: design parameters or decision variables \( \Omega_1 \) and fixed parameters or inputs \( \Omega_2 \). Thus, \( \Omega = \Omega_1 \cup \Omega_2 \). Let \( \omega_1 \) denote an individual decision variable such that \( \omega_1 \in \Omega_1 \). Typically, these decisions will need to be within allowed minimum and maximum specifications, which we denote as \( \omega_{\min} \) and \( \omega_{\max} \), respectively. Similarly, we will let \( \omega_2 \) denote an individual fixed parameter or input such that \( \omega_2 \in \Omega_2 \).

For daylighting evaluation, illuminance is typically measured at calculation points at workplane height (~30 inches above the floor). An illuminance \( E \) measurement is said to be within target if it is within \( E_{\min} \) and \( E_{\max} \) (typically, 300 lux and 2500 lux [12]). Here, we use a narrower primary target range between 500 lux and 1000 lux. Measurements within this range are given full credit (a value of one) while outside values are given partial credit (a value between 0 and 1) that is proportional to the distance away from either the upper or lower boundary of the target range. This scoring system ensures a unique score for every design solution and aids the optimization algorithm converging quickly on optimum solutions. Therefore, here, the objective is to identify a design that maximizes this daylighting performance score (denoted here using \( P \)).

For thermal performance, a heating or cooling load is defined as the amount of heat needed to be added to or removed from the room air mass to maintain the room air mass temperature at the thermostat set point temperature. Heat is transferred from the room air mass by heat exchange across the building envelope. These exchanges include conduction through all envelope elements, shortwave (solar) and longwave (infrared) radiation between the external environment and building interior through windows, and infiltration and exfiltration of air through cracks and gaps in the building envelope. Ultimately, heat is transferred to and from room air by convection with interior surfaces, which are warmed or cooled by conducted and/or radiated heat. Because of its transient nature caused by dynamic weather conditions and thermal capacitance of materials, a full description of how these heat transfer processes are modeled, is not possible here. However, the thermal load of a room can then be expressed as:
\[ q_{sys} = q_{ce} + q_{iv} + q_{conv} \]

where

\[ q_{sys} = \text{heat transfer to air needed to maintain thermostat setpoint temperature} \]

\[ q_{ce} = \text{convective part of people, lights, and equipment} \]

\[ q_{iv} = \text{load due to infiltration and ventilation air} \]

\[ q_{conv} = \text{convected heat transfer from room surfaces} \]  \hspace{1cm} (2)

In equation (2) above, the terms \( q_{ce}, q_{iv}, \) and \( q_{conv} \) are determined each through non-linear differential equations which are omitted here to keep the presentation concise and focus on the optimization aspects. For more details the reader may refer to [13]. For thermal evaluation, the sum of annual hourly heating loads (heat in Btus needed to be added to room air to maintain thermostat set point temperature) and annual hourly cooling loads (heat in Btus needed to be removed from room air to maintain thermostat set point temperature) was used. Cooling loads are typically expressed as negative values; therefore, the absolute values of heating and cooling loads are summed. For ease of comparison with other buildings, this sum was converted to kBtu/sq ft of building floor area (denoted here using \( Q \)).

The bi-objective optimization problem then becomes:

\[
\max_{1 \in 1} \sum_{z \in z} \begin{cases} 
1 & \text{if } E_{\min} \leq E_1 \leq E_{\max} \\
E_1 / E_{\min} & \text{if } E_1 < E_{\min} \\
E_{\max} / E_1 & \text{if } E_1 > E_{\max} 
\end{cases}
\]

\[
\min_{1 \in 1} Q = \sum_{z \in z} \{|q_{sys}| / ft^2\}
\]

subject to

\[
\text{Equation (1)}
\]

\[
\min \leq 1 \leq \max
\]

In this case, the following design parameters or decision variables (\( \Omega \)) were selected:

- \( CH = \) Ceiling Height
- \( CW\_LT = \) Clerestory Window Light Transmittance
- \( CW\_SHGC = \) Clerestory Window Solar Heat Gain Coefficient
- \( CWW = \) Clerestory Window Width
- \( DW\_LT = \) Daylight Window Light Transmittance
- \( DW\_SHGC = \) Daylight Window Solar Heat Gain Coefficient
- \( ESL = \) Exterior Shade Length
- \( LL = \) Lightshelf Length
- \( VW\_LT = \) View Window Light Transmittance
- \( VW\_SHGC = \) View Window Solar Heat Gain Coefficient
- \( WW = \) Window Width
And the fixed parameters or inputs $\Omega_\Omega$ included the following:

- $x = x$ - coordinate of the illuminance calculation point
- $y = y$ - coordinate of the illuminance calculation point
- $m = \text{month of year}$
- $d = \text{day of month (varies between 28 and 31 depending on month)}$
- $h = \text{hour of day (only occupied daylit hours used)}$
- $\alpha = \text{simulation parameters (including number of sampling rays)}$
- $\beta = \text{static model geometry and material properties}$

For sampling illuminance, calculation points were uniformly distributed at workplane height on a 3’ x 3’ grid. This resulted in a 9 by 13 grid of calculation points (thus there are 9 values for $x$ coordinates and 13 for $y$ coordinates). $E_{\text{min}} = 500 \text{lux}$ and $E_{\text{max}} = 1000 \text{lux}$ were selected.

4. Solution Method

The optimization problem in (3) is relatively complex due to the physical relationship described in Equations (1) and (2). If-then statements make the problem discontinuous as well. The “if-then” statements in the objective function can be replaced by binary decisions (thus yielding a mixed integer non-linear optimization problem) but this does not simplify the problem either, due to the complexity of the illuminance function. As discussed in the literature, there are simulation packages (a.k.a. ray-tracing programs) for computing the illuminance function [14-16]. One of these packages, RADIANCE [14], is utilized here in conjunction with EnergyPlus[17] and GenOpt. GenOpt is a general optimization program that can interface with any simulation program that reads and writes text files for input and output. GenOpt includes several direct search meta-heuristic optimization algorithms that do not require computation of directional derivatives. Here, we use GenOpt’s hybrid Generalized Pattern Search implementing Hooke Jeeves and Particle Swarm Optimization algorithm. The Epsilon Constraint Method was applied to obtain the Pareto Front for the bi-objective optimization problem.

5. Application: Prototype Model

The design of a classroom, shown in Figure 1, for daylighting and thermal performance was chosen as an optimization problem. As discussed before, eleven design factors were selected for optimization: ceiling height (CH), clerestory window light transmittance (CW_LT), clerestory window solar heat gain coefficient (CW_SHGC), clerestory window width (CWW), daylight window light transmittance (DW_LT), daylight window solar heat gain coefficient (DW_SHGC), exterior shade length (ESL), lightshelf length (LL), view window light transmittance (VW_LT), view window solar heat gain coefficient (VW_SHGC), window width (WW).
Figure 1: Building design factors optimized

CH was varied by increasing the height of the ceiling. The top of the daylight window (the upper glass of the side window) moved with the CH. The bottom of the daylight window and the top of the view window always met at two-thirds the distance from the bottom of the view window to the top of the daylighting window (this is good daylighting design practice). Likewise the lightshelf and top edge of the exterior shade remained at the meeting of the daylight window and view window. CWW was increased or decreased by uniformly varying the width of the three clerestory windows from their centers. The clerestory windows’ centers remained fixed. The exterior shade length increased and decreased along its 45 degree angle from the exterior wall. Lightshelf length increased and decreased perpendicularly from the exterior wall. WW was increased or decreased by uniformly varying the width of the three daylight and view window pairs from their centers. The pairs’ centers remained fixed.

Table 1 shows the minimum and maximum settings of the investigated design factors.

<table>
<thead>
<tr>
<th>Design Factor</th>
<th>Minimum - Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>CH (height of ceiling above floor)</td>
<td>8’ – 12’</td>
</tr>
<tr>
<td>CW_LT</td>
<td>0.3 – 0.8</td>
</tr>
<tr>
<td>CW_SHGC</td>
<td>0.1 – 0.7</td>
</tr>
<tr>
<td>CWW</td>
<td>3’ – 8’</td>
</tr>
<tr>
<td>DW_LT</td>
<td>0.3 – 0.8</td>
</tr>
<tr>
<td>DW_SHGC</td>
<td>0.1 – 0.7</td>
</tr>
<tr>
<td>ESL</td>
<td>0’ – 4’</td>
</tr>
<tr>
<td>LL</td>
<td>0’ – 3’6”</td>
</tr>
<tr>
<td>VW_LT</td>
<td>0.3 – 0.8</td>
</tr>
<tr>
<td>VW_SHGC</td>
<td>0.1 – 0.7</td>
</tr>
<tr>
<td>WW</td>
<td>3’ – 8’</td>
</tr>
</tbody>
</table>

Daylighting performance was evaluated by measuring daylight illuminance delivered to calculation points at workplane height (30 inches above the floor), uniformly distributed throughout the room as described previously, for every hour of the year that the classroom is scheduled to be occupied. Again, this was accomplished by using a ray-tracing program RADIANCE, along with hourly climate data for Charlotte [18]. As described in formulation (3), calculation point values within a desired illuminance range (i.e., between 500 to 1000 lux, neither too bright nor too dark) were rewarded while calculation point values outside of this range were partially rewarded. Thermal performance was evaluated by simulating and summing the heating and cooling loads for the classroom for every hour of the year. This was accomplished by using EnergyPlus and the same climate data file for Charlotte.
6. Numerical Experiments

Tables 2 and 3 show the parameters of the hybrid GPS Hooke Jeeves/PSO algorithm used for Experiment 1. The performance P (sum of target range sample measurement) was maximized and Q minimized, as in formulation (4). In this application, P was multiplied by -1 and divided by the maximum possible P score to transform it to a minimization problem between 0 and -1. Dividing by the maximum possible P was done to simplify relative comparisons between design solutions and results in a value we refer to as the fraction of ideal daylighting performance. Q was used as the constrained variable in the Epsilon Constraint method. Six initial optimization runs were executed with constraints ranging from 15 to 40 kBtu/ft\(^2\) (determined a priori to be the minimum and maximum Q for this design problem) in increments of 5 kBtu/ft\(^2\). It was observed that daylighting performance did not improve when thermal performance was allowed to be greater than 20 kBtu/ft\(^2\), compared to the daylighting performance values of solutions with thermal performance values forced below 20 kBtu/ft\(^2\). Therefore, Epsilon Constraint increments of 0.5 were used to search within the 15 to 20 kBtu/ft\(^2\) range. Each optimization run took approximately 550 function evaluations and four hours to reach convergence. Figure 2 plots the Pareto Efficient solutions found and Table 4 lists their design parameters.

### Table 2: Parameters of the GPS Hooke Jeeves Algorithm

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mesh Size Divider</td>
<td>2</td>
</tr>
<tr>
<td>Initial Mesh Size Exponent</td>
<td>0</td>
</tr>
<tr>
<td>Mesh Size Exponent Increment</td>
<td>1</td>
</tr>
<tr>
<td>Number of Step Reductions</td>
<td>3</td>
</tr>
</tbody>
</table>

### Table 3: Parameters of the Particle Swarm Optimization Algorithm

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neighborhood Topology</td>
<td>Von Neumann</td>
</tr>
<tr>
<td>Number of Particles</td>
<td>10</td>
</tr>
<tr>
<td>Number of Generations</td>
<td>10</td>
</tr>
<tr>
<td>Cognitive Acceleration</td>
<td>2.8</td>
</tr>
<tr>
<td>Social Acceleration</td>
<td>1.3</td>
</tr>
<tr>
<td>Maximum Velocity Gain</td>
<td>0.5</td>
</tr>
<tr>
<td>Constriction Gain</td>
<td>0.5</td>
</tr>
<tr>
<td>Mesh Size Divider</td>
<td>2</td>
</tr>
<tr>
<td>Initial Mesh Size Exponent</td>
<td>0</td>
</tr>
</tbody>
</table>
Figure 2: Pareto Front of daylighting and thermal performance

Table 4: Pareto Efficient Solutions

<table>
<thead>
<tr>
<th>Design Factor</th>
<th>Pareto Efficient Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>CH (inches)</td>
<td>126</td>
</tr>
<tr>
<td>CW_LT (0-1)</td>
<td>0.5</td>
</tr>
<tr>
<td>CW_SHGC (0-1)</td>
<td>0.7</td>
</tr>
<tr>
<td>CWW (inches)</td>
<td>72</td>
</tr>
<tr>
<td>DW_LT (0-1)</td>
<td>0.6</td>
</tr>
<tr>
<td>DW_SHGC (0-1)</td>
<td>0.375</td>
</tr>
<tr>
<td>ESL (inches)</td>
<td>41.25</td>
</tr>
<tr>
<td>LL (inches)</td>
<td>28.5</td>
</tr>
<tr>
<td>VW_LT (0-1)</td>
<td>0.5</td>
</tr>
<tr>
<td>VW_SHGC (0-1)</td>
<td>0.3</td>
</tr>
<tr>
<td>WW (inches)</td>
<td>49.5</td>
</tr>
<tr>
<td>Fraction of Ideal Daylighting Performance * -1</td>
<td>-0.7620</td>
</tr>
<tr>
<td>kBtu/ft²*yr</td>
<td>18.669</td>
</tr>
</tbody>
</table>
Several interesting patterns can be observed in the Pareto Efficient solutions. As thermal performance approaches its best possible value, ceiling height, window widths, and solar heat gain coefficients tend to be minimized. This is most likely due to the thermal benefit of minimizing solar heat gain and conducted heat transfer. In general, solar heat gain (a function of window areas, solar heat gain coefficients, and exterior shade length) is directly proportional to summer cooling loads and inversely proportional to winter heating loads; therefore, dissimilar solar heat gain profiles can have similar annual thermal performance values. However, in this problem, reducing summer cooling loads seems to have the greatest beneficial effect on annual thermal loads, at the cost of lower daylighting performance values. As window areas and SHGCs are reduced to benefit summer cooling loads, clerestory and daylight window light transmittance values tend to increase to compensate for the reduced amount of daylight admission. Also, the exterior shade length tends to be reduced (presumably to allow low angle window sun to be admitted through the view window to reduce window heating loads), and, in response, the view window light transmittance is reduced to prevent excessive daylight levels. The solutions with higher daylighting performance values also tend to have higher SHGC values. This suggests that when windows are sized to admit optimum amounts of daylight, higher SHGC values help counter the increased conducted heat losses through window during winter months and are more beneficial thermally, on a net annual basis, than minimized SHGC values that reduce summer cooling loads.

7. Summary and Conclusions
A hybrid GPS Hooke Jeeves/PSO algorithm was used in combination with the Epsilon Constraint Method to find Pareto Efficient solutions to the daylighting and thermal optimization problem. Since windows admit light and provide weak resistance to heat conduction and radiation heat exchange, it was thought that daylighting and thermal performance would be strongly conflicting objectives. However, our results show that, for this design problem with a southerly orientation in the Charlotte climate, these two objectives are not strongly conflicting. This is evident in the Pareto Front which ranges over relatively small differences in daylighting and thermal performances. Along the Pareto Front, both objectives are close to their best possible value. Formulation of this design problem for different orientations and climates may yield different results.
References