An Integrative Algorithmic Platform Coupled with Gradient Descent and Parametric Analysis Methods to Optimize Skylight Sizes

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Abstract

While daylighting strategies show 20-70% savings in lighting loads, recent research has attempted to optimize fenestration by parametric analysis or Genetic Algorithm. Since both techniques need descent amount of iterations, they are time consuming and computationally expensive. In this paper we applied an optimization method of gradient descent to an integrative platform, coupling daylight and energy tools. We calibrated skylight sizes while minimizing total energy consumption. The results show that the gradient descent method converges faster with more accurate results. In addition, parametric analysis was applied to the integrative algorithm to optimize skylight sizes based on both daylight and energy performances.

Introduction

A concern over CO_2 emissions has motivated researchers to study energy efficient strategies in buildings. Commercial buildings account for 19% of source energy in the U.S. while electrical lighting consumes 20.5% of source energy in the commercial building sector (EIA-1, 2003). Considering that one-storey buildings make up 67% of commercial buildings in the U.S. (EIA-2, 2003), toplights as essential daylighting strategies for one-storey buildings can replace electrical lighting and decrease total energy consumption. In this paper we propose an Integrative Algorithm (IA) to simultaneously simulate energy and daylight performances and apply an Optimization Algorithm (OA) based on a gradient descent method to find the most energy efficient Skylight to Floor area Ratio (SFR). In addition, IA was incorporated with parametric analysis to find an inclusive optimal SFR, considering daylight, glare and energy factors.

Integration between different tools is needed in order to take into account the impacts of daylight on the overall energy consumption. There has been an increasing effort to improve tools' capabilities by coupling them to examine the impact of daylight on electrical lighting loads as well as heating and cooling loads (C. Reinhart, 2011),(Trubiano et al., 2013),(Konstantoglou and Tsangrassoulis, 2016). In addition to the necessity of integration between different tools, the exhaustive process of parametric analysis and none-deterministic approach of Genetic Algorithm (GA) make it challenging to find robust design solutions. To boost the application of toplights, we facilitate the process of integration and optimization by developing an integrative algorithmic platform that can be incorporated with gradient descent and parametric analysis methods to find the optimal SFR.

Literature Review

Preliminary studies show that electrical lighting loads can be reduced by 20-70% if good daylighting practices are implemented (Motamedi, 2012; Ghobad et al., 2013; Doulos et al., 2008; Li et al., 2006; Lee and Selkowitz, 2006; Onaygl and Gler, 2003; Embrechts and Bellegem, 1997; Opdal and Brekke, 1995; Roisin et al., 2008). Energy optimization calibrates configurations of fenestration in order to minimize thermal and electrical loads. The most common methods to optimize fenestration have been GA and parametric analysis. Parametric analysis is an exhaustive search that considers all possible fenestration sizes with a defined resolution; hence, it is time consuming and computationally expensive. Goi et al. conducted research to optimize Window Wall Ratio (WWR) by using EnergyPlus, estimating both thermal and daylight performances. For a typical two-storey office building in a temperate oceanic climate, Goi et al. did a parametric analysis and conclude that an optimal WWR is in the range of $35 - 45\%$ (Goia et al., 2013). In addition, Yoon et al. did a parametric analysis to optimize energy consumption of different toplighting strategies for different climates. They coupled a lighting rendering software tool (Radiance) with building energy simulation software DOE 2.1 E (Yoon et al., 2008). They sized the glazing area to meet 2% Daylight Factor (DF), the requirement of LEED[1] at that time (version 2). DF is an inappropriate metric for annual daylight analysis because it does not take into account different climates, sky conditions, complex geometries of interiors, surrounding objects and orientation of windows (Nabil and Mardaljevic, 2006).

Another comprehensive parametric analysis regarding skylights was published in 2014, "Skylighting Design Guidelines". This report explains how to integrate skylight design with other building elements

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including glazing types, roof structures, insulation, shading devices and daylight control systems. "Skylighting Design Guidelines" also applied the *Skycal* tool to estimate potential energy savings by installing skylights. It implemented parametric analysis for an SFR range of 0-12% and calculated energy savings for an office building in different cities of California (EnergyDesignResources, 2015). After finding the optimal energy efficient scenario through parametric analysis, the report studied the daylight performance of the optimal energy efficient SFRs. The *Skycal* software is a simple spreadsheet in Microsoft Excel tool in order to facilitate skylight design decisions. Its energy engine is DOE-2.1E which applies the Split-flux method for daylight performance. The DOE-2.1E has its own shortcomings when it comes to simulate daylight performance. It only uses CIE[2] overcast and clear skylights, both of which do not represent real sky conditions (Kota and Haberl, 2009). In addition, the Split-flux method of DOE-2.1E considers all surfaces as perfectly diffuse reflectors and lacks the ability to consider different optical surfaces (Kota and Haberl, 2009). Due to these limitations, DOE-2E cannot properly simulate reflective surfaces such as light shelves, it does not consider reflection from adjacent buildings, and it is not able to simulate complex fenestration systems or atrium (Kota and Haberl, 2009).

In addition to parametric analysis, GA more than any other method has been used in the field of building design optimization (Rakha and Nassar, 2011; Caldas and Norford, 2003). GA finds the fittest solution through principles of evolution (Caldas and Norford, 2003). The solving time is also one of GA's shortcomings since for a good quality solution GA needs a decent sized population. GA is a non-deterministic method as its solutions can be varied even for the same set of initial genomes(Modrak et al., 2011). The quality of results also heavily depends on the fitness functions and its genetic operators(Modrak et al., 2011). Rakha et al. applied GA to improve daylight performance by changing the reflective and shape of the ceiling (Rakha and Nassar, 2011). Moreover, Caldas et al. implemented this algorithm to optimize energy efficiency by varying fenestration configurations, building forms and HVAC systems (Caldas and Norford, 2003). They used DOE2.1E as daylight and thermal engines while considering DF as a daylight metric (Caldas and Norford, 2003). As mentioned in the beginning of this section, DF is not an appropriate metric for annualized and climate-based daylight simulations. In addition, as discussed before, DOE2.1E has its own disadvantages regarding daylight simulation.

Although GA has been a dominant optimization method in the building industry, the modeler needs to obtain considerable knowledge about mathematics and programming. Galapagos, an easier version of GA, was proposed by David Rutten[3] which is a Grasshopper plug-in component. It uses the same theory of GA but it offers a friendly-user interface which facilitates its application among professionals that do not have extensive programming and mathematical knowledge.

Sheikh and Gerber applied Galapagos to optimize louver positions in front of windows based on daylight performance. The results from the Diva tool was fed into Galapagos. Three main design criteria were encompassed: 75% of the space achieves useful illumiannce range (200-1500), highest and lowest lumiance values in the field of view should not exceed 1:10 ratio, and the area deep in the room should receive acceptable illuminance range (Sheikh and Gerber, 2011). This study is one of the initial attempts to optimize design based on daylight performance by incorporating an optimization algorithm into the design decisions. It is worth to mention that this study did not consider energy performance (Sheikh and Gerber, 2011). In 2015 Gadelhak used the same integrating approach to narrow down the search by maximizing DA with a 500 lux target for 50% of time. Two cases have been studied: case one with limited variables including several internal/external shading sizes and case two with a wide range of variables searching for a free from shading device (Gadelhak, 2013). The results show that the near optimal solusion(s) was found for the case one since theses solutions presented better daylight performance. However, in the second case the researcher speculated that Galapagos proposed optimal solutions that might not provide better daylight performance compared to other solutions (Gadelhak, 2013). It was pointed that Galapagos needs to be fed with limited variables to provide more precise and robust optimal solutions (Gadelhak, 2013). Another study using Galapagos was done by Gonzlez and Fiorito where they optimized external solar shadings. 320 lux was defined as a target daylight level. The result of Diva was fed into with Galapagos for GA optimization. Diva embeds EnergyPlus and Radiance as its thermal and daylight engines (Gonzlez and Fiorito, Gonzlez and Fiorito). Because the fitness function of GA was to minimize CO_2 emissions, the optimization process in the study was not set to maximize daylight performance.

An opportunity for further investigation arises because the integration process in the current tools are hidden, and the parametric analysis and GA methods entail specific shortcomings. Currently commercial off-the-shell software tools exist that integrate daylight and energy performances such as Diva[4], Design-

[2] Commission Internationale de l'clairage: the International Lighting Commission

[3] *www.grasshopper3d.com/profiles/blogs/evolutionary − principles*

[4] *www.diva4rhino.com/user−guide/grasshopper/daylight*

Builder[5] and IES VE[6]. Most of the parametric analysis and GA studies have applied these integrative tools. However, they are not free resources; thereby, they do not illustrate a clear path toward integration process. In addition, the aforementioned shortcomings of the parametric analysis and GA methods motivate researchers to implement new optimization algorithms in order to calibrate fenestrations. However, such implementation needs to be incorporated within the integration process. Therefore, it is necessary to have access to the integration process in oder to apply new optimization methods.

In this study we propose an integrative algorithmic platform that couples daylight and energy performances and apply a gradient descent optimization method to find the most energy efficient skylight solution. We apply exhaustive search, parametric analysis, on a case study to verify the result of the gradient descent method. In addition to the parametric analysis for energy performance, we implement parametric analysis to study daylight performance of different scenarios by including the glare probability and daylight availability. The goal is to evaluate if the most energy efficient SFR proposed by the gradient descent method offers the best daylight performance.

Methodology

This section is divided into four major subsections. In the first subsection we discuss all simulation tools and engines used in this paper. The second subsection illustrates an integration method to couple the tools and optimize SFR. In the third subsection we present a prototype office model to examine the integration algorithm and the proposed optimization method. We explain assumptions and numbers of iterations needed to do exhaustive search, parametric analysis. In the final subsection, we discuss all different metrics we used for daylight and energy performances. We will expand on all four subsections in the following paragraphs.

Tools

We implemented EnergyPlus[7] as a thermal engine and Radiance[8] as a daylight engine. EnergyPlus is one of the most robust, trustworthy building simulation tools that is able to model energy consumption for heating, cooling, ventilation, lighting, as well as plug and process loads. Radiance is a state-of-the-art illuminance prediction that is able to distinguish different optical aspects such as reflection, refraction, scattering and transparency (Reinhart, 2011; Tregenza and Wilson, 2011). We used Radiance through its host, Ladybug and Honeybee[9]. This tool is an environmental plug-in for Grasshopper, which is a graphic programming language accessed within Rhino. We developed the integrative and optimization algorithms by scripting in a Python component of Grasshopper.

Integration and optimization process

Fig. 1 outlines an Integrative Algorithm (IA) which couples EnergyPlus as well as Ladybug and Honeybee while Fig. 2 shows an Optimization Algorithm (OA), which incorporates IA with the gradient descent method to find the optimal SFR. As shown in Fig. 1 and Fig. 2, Grasshopper Python was used to integrate Radiance with EnergyPlus and optimize total energy performance.

IA starts with getting its basic geometry and inputs from an EnergyPlus model (idf) (Fig. 1). Then, Grasshopper Python is implemented to add skylights to the roof of the geometry based on a defined SFR (x_n). Next, Radiance and Daysim will be simulated through their host, Ladybug and Honeybee, in order to estimate daylight performance. After daylight simulation, "int.gain" file is generated which represents the reduced electrical lighting loads since it takes into account a daylighting role in illuminating the room. Again, Grasshopper Python is used to feed this new lighting schedule to EnergyPlus. Next, EnergyPlus calculates total energy consumption $f(x_n)$ for the defined SFR (x_n).

The gradient descent method was applied in this paper as an optimization algorithm which finds a local minimum of a function by taking steps proportional to the negative of the gradient of the function at the current point. Because a closed-form equation for the energy efficiency function is unknown, calculating the gradient is a challenge. As the proposed IA calculates total energy consumption $f(x_n)$ for the defined SFR (x_n), by running IA for two different random SFRs, the initial gradient can be calculated by OA. In this study the first and second random SFRs were 30% and 20%, respectively. After estimating the first gradient, the next SFR, x_{n+1} is calculated based on the previous gradient, $f'(x_n)$, and the previous SFR, x_n, 20% (Eq. 1). The following equation is the fundamental part of OA.

$$x_{n+1} = x_n - \gamma f'(x_n), \tag{1}$$

where $\gamma = 10^{-8}$.

After generating x_{n+1} by OA, the new SFR is fed into IA to calculate the subsequent total energy consumption $f(x_{n+1})$ (Fig. 2). The total energy consumption is fed into the OA equation in order to calculate the next gradient $f'(x_{n+1})$. The process of running IA to calculate total energy consumption (f), using OA to estimate gradient (f') and generating SFR (x) will be repeated until the magnitude of the gradient is below a small threshold, e.g. 0.0001. Using a small threshold guarantees that the gradient is almost zero which corresponds to the SFR value with the minimum en-

[5] *www.designbuilder.co.uk/*
[6] *www.iesve.com/*
[7] *www.energyplus.net*
[8] *www.radiance − online.org/*
[9] *www.grasshopper3d.com/group/ladybug*

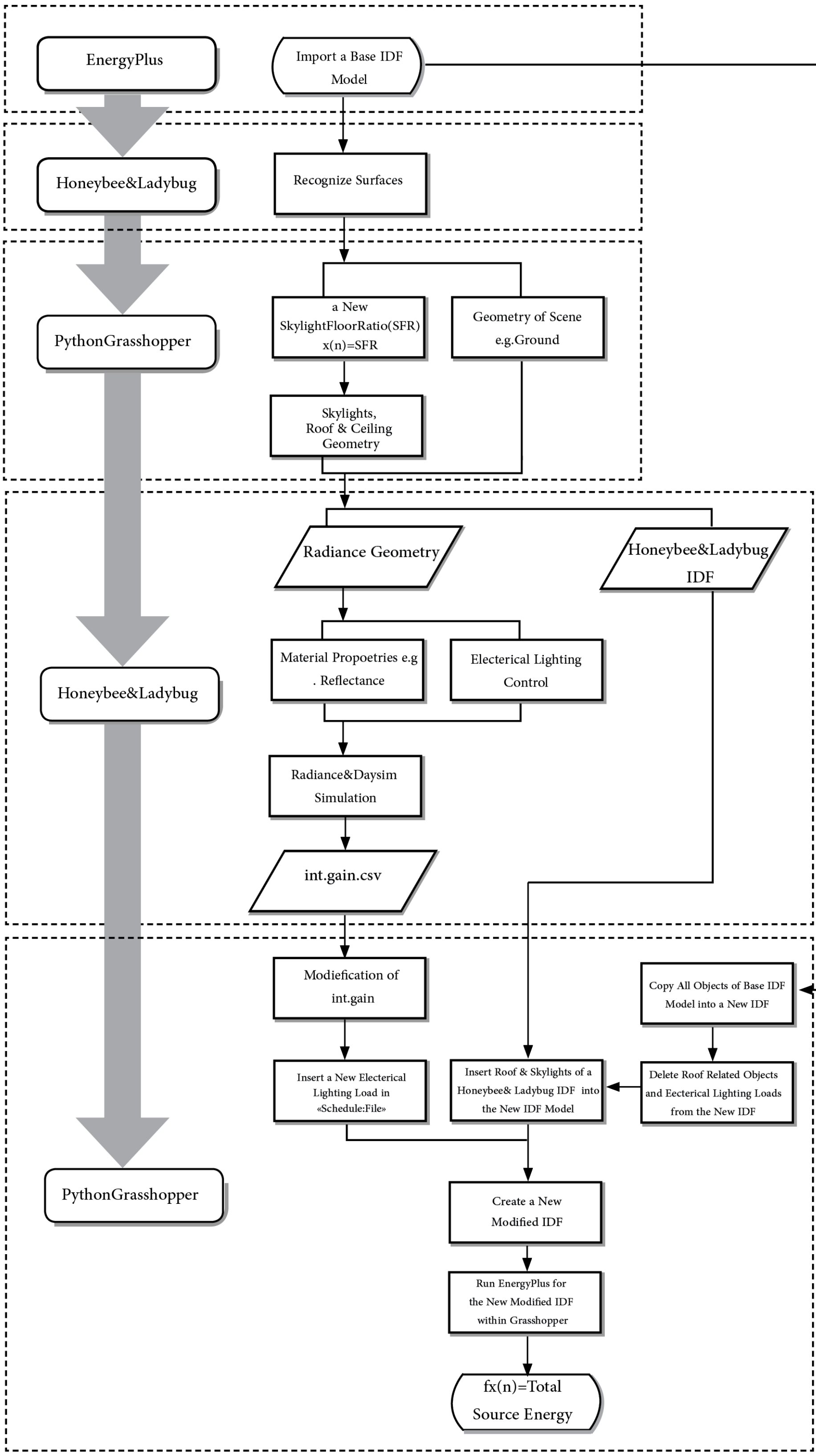

Figure 1: Flowchart Showing the Process of Integration between Different Tools (Integrative Algorithm (IA)).

1. Input model from EnergyPlus (EnergyPlus)
2. Define x_n (x_n represents SFR which is a random number in the first iteration; otherwise it is generated in step 4)(PythonGrasshopper)
3. Run IA :
   3.a) Run Radiance/daylight simulation (Honeybee&Ladybug)
   3.b) Feed lighting schedule (int.gain) from Radiance to EnergyPlus (PythonGrasshopper)
   3.c) Run energy simulation and generate total source energy consumption (fx_n) (EnergyPlus)
4. Apply gradiance optimization method (Eq.1) and generate x_{n+1} and $f'x_n$ (PythonGrasshoper)

Figure 2: Optimization Algorithm (OA).

Table 1: Model parameters

BUILDING DESCRIPTION		**SURFACE PROPERTIES**		
Building Prototype	Small Office	**Opaque Surfaces**	**R of Wall Insulation(h.ft2.F/Btu)**	9.05
Climate	San Francisco		**R of Roof Insulation(h.ft2.F/Btu)**	35
Total Floor Area	5400 ft2 (90ft*60ft)		**R of Floor Carpet (h.ft2.F/Btu)**	1.2
Number of Floor	1	**Skylights**	**Fraction**	(0%*, 1%, 2%,,100%)
Floor to Roof	14.5 ft		**VT**	0.44
Floor to Ceiling	9.5 ft		**SHGC**	0.4
Power Density of Lights	0.82 (w/ft2)		**U /(Btu/h.ft2.F)**	0.32

*0% skylight fraction is the base model.

Table 2: Radiance and Daysim parameters.

SURFACE REFLECTION		**ELECTERIC LIGHTING CONTROL SYSTEMS**	
Wall	0.5	**Control Types**	Auto dimming with swith off occupancy sensor
Ceiling	0.8	**Sensor Points**	30 Points (5*6)
Floor	0.2	**Target illuminance for the spac**	200 Lux
Site Ground	0.2	**Minimum dimming level in percentages**	20
RADIANCE PARAMATERD			
_ab_	2	_ar_	0.1
_ad_	1500	_aa_	300
_as_	256	**Quality of rendering**	0*-low

* **Quality of rending does not matter for estimating energy consumption**

ergy consumption.
The optimization method proposed in this approach allows for a fine resolution of SFR. For instance, if x_n is 8% SFR, x_{n+1} can be defined to be 8.01% which is a resolution of 0.01% for SFR.

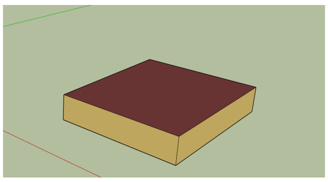

Figure 3: Base model

Although the gradient descent method is assumed to be fast and to find the solution with a higher resolution, tuning the algorithm requires knowledge about the fundamental concept of the algorithm. The gradient method finds the optimum by taking the next steps "proportional" to the negative of the gradient of each step and its previous step. "Proportional" steps is a function of γ in Eq. 1. It should be estimated by looking into two or three iterations and verifying that the gradients lead to the appropriate next steps. In the case of skylight optimization the steps are appropriately taken if the SFR of the next step is close to the previous one but results in smaller energy consumption (Fig. 4). Even though Gradient Descent is fast, resulting in accurate solutions with higher resolution, as mentioned, its implementation needs diligence.

Iteration	x	fx	$fx_{(N+1)}$-$fx_{(N)}$	Proportional Step	x_{new}
1 (random)	0.2	140263	-19431	0.0019431	0.098
2 (random)	0.1	120832			
3	0.098	120172			
Test : fx_3 (120172) < fx_2 (120832)					

Proportional Step = dfx/dx (Gradient) / 10^8 = $[(fx_2 - fx_1)-(x_2 - x_1)]/ 10^8$

x_{new} = x_2 - Proportional Step

Figure 4: This Figure is an Example of How to Take Proportional Steps in Gradient Descent. The Sequence of Steps is Shown by Arrows.

Experiment

In order to examine the accuracy of the proposed IA and OA, we compared the results of the proposed algorithmic platform with a parametric analysis for a case study. The base model is a simple box representing a one-storey office building in Austin, Texas. The base model lacked any sidelight because in this study we were concerned about the impacts of sky-

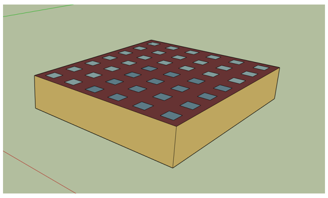

Figure 5: Proposed Model SFR 20%

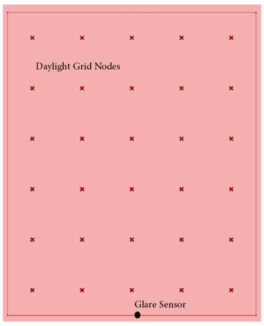

Figure 6: Daylight Grid Map and Glare Sensor

lights on energy performance (Fig. 3). The proposed models was built upon the base model with different SFRS (Fig. 5). Given a fixed percentage of the roof area assigned to skylights, many small skylights are uniformly distributed across the roof of the proposed model. The distance between the skylights in the middle of the roof is twice as the distance between the last skylights and the walls in order to avoid dark edges and to create a more even daylit space. We built the base model based on ANSI/ASHRAE/IES Standard 90.1 Prototype Building Model Package (EnergyCodes, 2016), which was published by Department Of Energy (DOE). The chosen prototype was a small office located in an Austin climate zone. According to the EnergyPlus Weather file (epw), the ASHRAE climate zone of Austin is 2A which is humid subtropical having mild with no dry seasons and a hot summer. The base model in this research, however, had one thermal zone and adopted a flat roof with no interior walls in order to be suitable for the skylight study. All parameters of the models such as R-value, SHGC, schedules and construction are listed in Table 1. In addition, Table 2 presents important assumptions for Radiance and Daysim such as reflectance properties, illuminance target and a sensor control system.

For the parametric analysis a resolution of 1% SFR was considered while the proposed optimization method had a finer resolution of 0.01% SFR. If the parametric analysis had the same accuracy as the optimization method, more than 10,000 alternatives would have been necessary. As the reason to do parametric analysis was to evaluate the result of the optimization method, we coarsened the accuracy of parametric analysis to 1% which could result in 100 iteration. However, we, first, did the parametric analysis for 11 alternatives with a resolution of 10% (0%, 10% . . . 90%, 100%) in order to approximately lo-

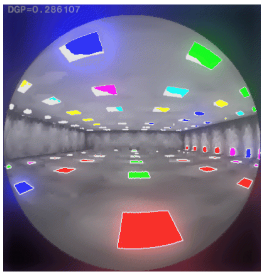

Figure 7: DGP and False Color Image from a Sensor in the Back of the Room.

cate the optimal solution. We found out the optimal SFR with the 10% resolution is 10% SFR, indicating that the optimal SFR would be between 0% and 20%. Next, we did parametric analysis for another 19 alternatives with a resolution of 1% for SFRs in a range of 1% and 19%. Therefore, the total iterations of parametric analysis for energy optimization was lowered to 30.

While parametric analysis and gradient descent methods were used to calculate the energy performance, we did another parametric analysis in order to study the holistic performance of different alternatives, including both daylight an energy performances. This parametric analysis considered daylight availability and glare as the metrics of daylight performance. The goal was to evaluate the daylight performance of the most energy efficient scenario proposed by the gradient descent method. In the next subsection, we describe different metrics applied for the optimization method, parametric analysis of energy performance and parametric analysis of holistic performance.

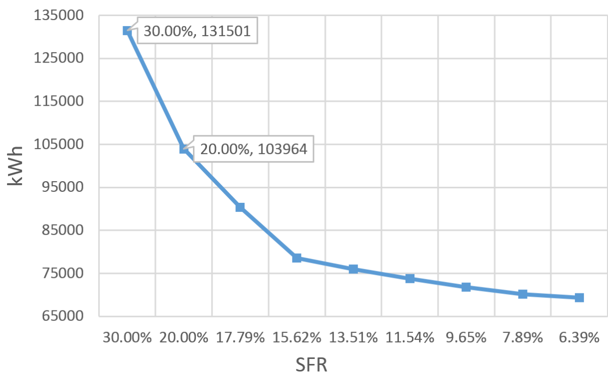

Figure 8: Different Alternatives by Gradient Descent Method.

Metrics

kWh was used for the assessment of energy performance in the optimization method and parametric analysis, while for daylight performance different metrics have been used. Daylight influences HVAC loads by reducing electrical lighting loads. Daylight as a free-source and cost effective alternative replaces artificial lights and decreases the electrical lighting loads. The reduction of the electrical lighting load decreases internal heat gain generated by electrical lighting load. In addition to this reduction, the low R-value of skylights and direct solar gain through skylights will potentially change heating and cooling loads. Hence, not only lighting loads but also heating, cooling and fan (HVAC) loads should be included in design decisions. In addition, to generate one unit of electricity, three units of fossil fuel needs to be burned in a power plant. As a result, we applied total source energy, including lighting and HVAC loads (kWh), in order to consider the impact of daylight on energy consumption and to encompass the importance of the energy source.

For daylight assessment we used an illuminance metric for horizontal daylight availability as well as a luminance metric for glare probability. The daylight metric for the glare analysis was Daylight Glare Probability (DGP). DGP is a luminance-based metric for glare: its values are "imperceptible glare" (below 35%), "perceptible glare" 35−40%, "disturbing glare" 40−45% and '"intolerable glare" (above 45%). DGP was tracked for a sensor located on the back of the space while facing the opposite direction (Fig. 6). This view was chosen since it represents the worst case scenario while looking over all the skylights (probable glare sources) down the room (Fig. 7). The DGP was calculated for all the occupied hours in a year for the mentioned sensor. We calculated the percentage of the annual occupied hours in which DGP is "imperceptible". For the sake of brevity, the DGP of "imperceptible" glare over a year is called DGPi. Hence, 20% DGPi means that in 20% of the ASHRAE occupied hours the DGP tracked for the sensor meets the target of "imperceptible" glare. In addition, for the daylight availability, we applied a mean annual illuminance. We calculated the percentage of occupied hours that an average node in a daylight grid map receives at minimum 200 lux. This percentage is called Mean Daylight (MD) in this study. All the grid nodes were considered as daylight sensors, which are shown in Fig. 6.

Three factors of energy, daylight availability and glare in this study have different units and involve different connotations. As kWh represents total source energy consumption, the percentage is the unit of MD and DGPi. A percentage was chosen as a unit to unify all the metrics while representing the performance of energy consumption and daylight quality, including glare and daylight availability. Therefore, to harmonize the unite of total source energy consumption (kWh), we converted this to the ratio of total source energy consumption of each scenario to that of the worst case scenario, which is 100% SFR. In this paper, the Ratio of Energy Saving is abbreviated to RES. Therefore, 20% RES shows the percentage of saving over the 100% SFR. We aggregated energy and daylight performance and represented these with an

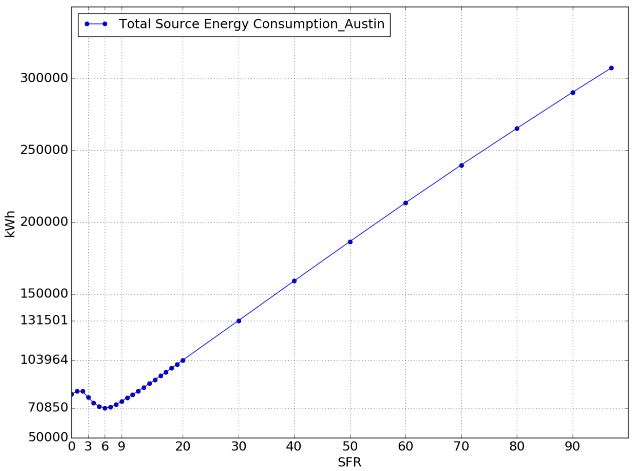

Figure 9: Different Alternatives by parametric analysis

average performance $f(x)_{avg}$ by using the following equation (Eq. 2):

$$f(x)_{avg} = \frac{\alpha MD + \beta DGPi + \gamma EnergySaving}{\alpha + \beta + \gamma} \quad (2)$$

in this approach α, β, and $\gamma = 1$.
In this study we considered the multipliers (α, β, and γ) as 1 in order to keep an equal weight for all the factors including energy, daylight and glare. The multipliers impose a weighting technique which can influence the optimal result.

Results and Discussion

The results of this study and their subsequent discussions are presented in three different subsections: "Optimization", "Energy Performance" and "Holistic Performance". In the "Holistic Performance" subsection we take into account glare, daylight and energy factors for all the scenarios, and we evaluate the daylight and glare performances of the optimal energy efficient SFR, which is proposed by the gradient descent method.

Optimization

Although the methods of gradient descent and parametric analysis reached the same optimal SFR, both required different numbers of iterations. Fig. 8 shows the energy performance of 9 alternatives generated by the gradient descent method. Starting with the random first SFR of 30%, it took 9 alternatives for the optimization algorithm to converge on 6.39% SFR as the optimal ratio. Fig. 9 presents the energy performance of all the alternatives using the parametric analysis method which gave the optimal SFR as 6%. Considering the higher resolution of the gradient descent method, both methods agree on the same optimal SFR, 6.396%. The parametric analysis required 30 iterations to discover the optimal SFR with a resolution of 1%, compared to 9 iterations of the optimiza-

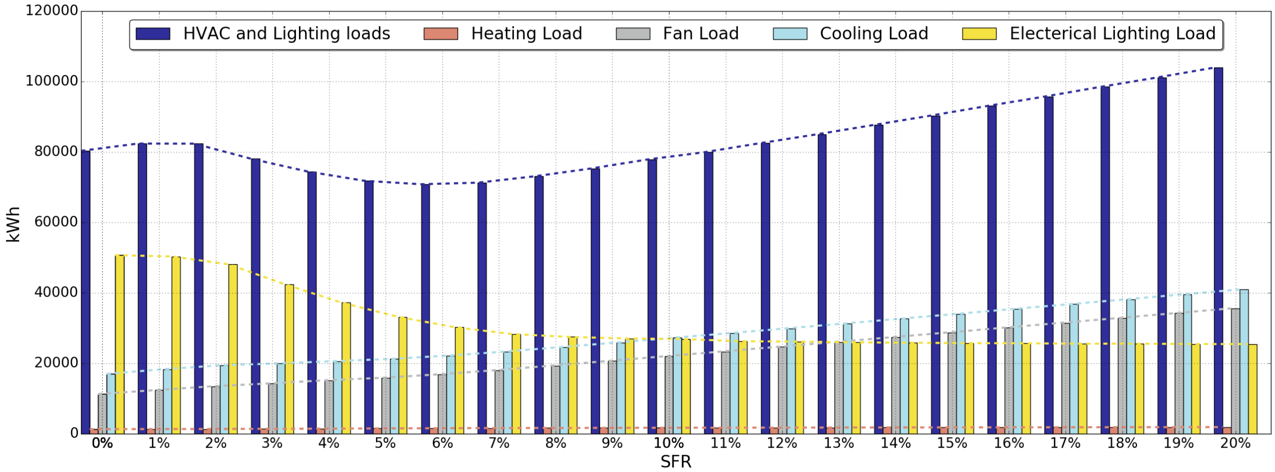

Figure 10: Break Down of Total Source Energy into Electrical Lighting, Cooling, Heating and Fan Loads.

tion method with a resolution of 0.01%. While the parametric method requires more iterations and calculation time, finding a robust SFR is guaranteed. In contrast to the parametric analysis, the optimization method is not computationally expensive. However, it is more cumbersome with regard to initial scripting and finding an appropriate threshold for convergence. This emphasizes that the optimization method requires a modeler with extensive knowledge regarding optimization and energy simulation in order to find the solution.

Energy Performance

As daylight influences both electrical lighting and HVAC loads, we analyze their impacts for the SFRs between 0% and 20%. In Figure 10, the x-axis represents different percentages of SFR while the y-axis indicates energy performance. In this figure, the dark blue column is the sum of electrical lighting and HVAC loads. As shown in Figure 10, skylight ratios of 1% and 2% are not as energy efficient as the base model with 0% SFR. However, by increasing skylight ratios to more than 2%, the energy consumption drops until it reaches its minimum, at 6% SFR. Compared with 0% SFR, 6% SFR saves up to 40% of the source energy of lighting loads, while heating, cooling, fan and total HVAC loads are increased respectively by 20%, 30%, 50% and 37%. In addition, the sum of lighting and HVAC loads is reduced by 12% in regard to source energy, compared to 0% SFR model. After 6% SFR, the total energy consumption increases by adding more skylights. However, any SFR between 3% and 12% is more energy efficient than either 0% SFR (base model) or any SFR larger than 12%. This implies that if the skylight area is expanded up to 12% of its roof area, the model still saves energy.

Holistic Performance

Figure 11 illustrates the result of the parametric analysis, considering the three metrics of DGPi, MD and RES for the three factors of glare, daylight and energy, respectively, in addition to the aggregated percentage metric. A larger DGPi, MD and RES percentages imply better performance.

The light blue line shows that the maximum energy saving occurs at 6% SFR where RES, DGPi and MD are 70%, 97% and 53%, respectively. The optimal energy efficient skylight size (6% SFR) has an acceptable glare performance, with DGPi of 99.6%; however, it does not outperform SFRs bigger than 6% in regard to horizontal daylight availability (MD). Although 6% SFR show an acceptable glare performance, its glare performance is not better than SFRs smaller than 6%. Figure 11 presents 0%, 100% and 6% as the optimal solutions regarding glare, daylight and energy factors, respectively. Therefor, although 6% is the optimal energy efficient SFR and it shows an acceptable daylight performance, it does not present the best daylight performance. This is because daylight, glare and energy factors are in conflict with each other at certain SFR ranges. For instance, by increasing the skylight area more than 6% SFR, daylight performance improves while energy and glare performances worsen. Therefor, a trade-off is needed to find an optimal scenario that consider all the daylight, glare and energy performances.

A percentage, as an aggregated metric, unifies all three metrics calculated by Eq. 2. The red line in Fig. 11 represents the average performance ($f(x)_{avg}$) of daylight, glare and energy factors. As shown in Figure 11, the inclusive optimal solution for both daylight and energy performances is 11%, which is in the upper bound of the energy efficient SFR range (3-12%). The red line in Fig. 11 implies that the average performance is heavily driven by horizontal daylight availability (MD), while DGPi does not play a cut-off role in shifting the optimal solution (11%) to a smaller and more energy efficient SFR. This shows the insensitivity of the glare metric (DGPi) in a lower range of SFRs.

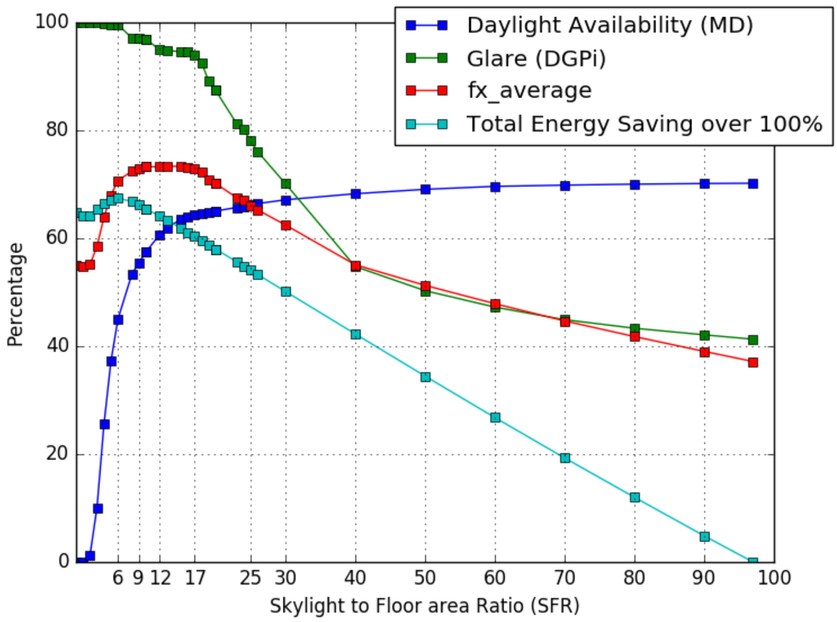

Figure 11: parametric analysis of DGPi, Mean Daylight illuminance (MD), Total Source Energy Saving over 100% *SFR and Average Performace of Daylight and Energy*

Conclusion

In this study we proposed and examined the integrative algorithm and optimization method to calibrate the size of skylights based on their total source energy consumption including electrical lighting and HVAC loads. Through two methods of parametric analysis as well as gradient decent optimization we concluded that energy saving reaches its optimal at 6% SFR for a one-storey office building in an Austin climate. Since the proposed optimization algorithm, gradient descent, is faster and more accurate than its competitor parametric analysis, it can facilitate design decisions with respect to energy efficiency in the early stage of design. The success of the proposed optimization method for skylight design is promising enough that we hope that it can be adopted by other researchers for optimizing other building aspects such as the size of windows, massing and HVAC design. In addition to the optimization of energy efficiency, we did a series of parametric analysis in order to include both daylight and energy performances of different SFRs. We proposed a parametric analysis with a weighting technique, considering different multipliers for glare, daylight and energy factors. This was possible by converting all the metrics to a percentage unit. The result shows that the optimal energy efficient SFR, 6%, not necessarily outperforms other alternatives when it comes to daylight performance. Considering holistic performance, the optimal solution lands on the upper bound of the energy efficient scenarios (11%). This is mainly because the glare metric (DGPi) we used in this paper has not played a crucial role in shifting the final solution to the lower bound of energy efficient SFR range. As DGPi shows insensitivity in the lower SFRs, future studies should accommodate other glare metrics. While we used an equal weight factor of 1 in the parametric analysis, more research is needed to calibrate the weight factors based on the building function and on-site studies. It is essential to develop a unified metric, considering glare, daylight and energy factors for future implementation of the gradient descent method in order to find an inclusive and holistic optimal solution.

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