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Qualitative and Quantitative Optimization of Skylights: a Comprehensive and Inclusive Analysis of Skylight Sizes for an Office While Providing Enough Daylight, Avoiding Glare and Saving Energy

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Qualitative and Quantitative Optimization of Skylights: a Comprehensive and Inclusive Analysis of Skylight Sizes for an Office While Providing Enough Daylight, Avoiding Glare and Saving Energy

by

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Dedicated to my dear husband, Ehsan.

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Qualitative and Quantitative Optimization of Skylights: a Comprehensive and Inclusive Analysis of Skylight Sizes for an Office While Providing Enough Daylight, Avoiding Glare and Saving Energy

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While windows connect inside to outside, daylight entering through windows is a key element in architectural design. Although electrical lighting is able to replace daylight as an essential lighting requirement, daylight has qualitative and quantitative aspects that distinguish it from its competitor, electrical lighting. One of the most unique characteristics of daylight is its variability in time, including different qualities of daylighting from sunset to sunrise, and from equinox to solstice. In addition, by regulating a circadian rhythm and hormone secretion, daylight impacts the physiological and psychological well-being of human beings. Moreover, daylight through windows carries information that flows from outside to inside and makes occupants aware of the outside world. While availability of daylight has been praised in building design, uneven distribution of daylight, reflective surfaces and excessive daylight may cause glare issues and visual discomfort which need to be avoided in daylight design.

Beyond all the mentioned qualitative aspects of daylight, daylight, as a free resource, is able to illuminate the space and replace electrical lighting and lower electricity utility bills. This quantitative aspect of daylight has been the center of attention among researchers, designers and builders, as lowering CO_2 emissions and environmental design have gained momentum in the building industry. Different stakeholders have various interests in qualitative and quantitative aspects of daylight, which eventually shape the design context. The interests of different stakeholders, including owners, environmentalists and occupants, may merge or conflict in different projects, which shows that daylight quality and quantity may have different weights, depending on the context of the project at hand.

This dissertation aims to provide an algorithmic platform to consider a context for skylight design by including all the interests of different stakeholders while either scaling importance of the different interests or requiring minimum qualities and performance targets. This dissertation proposes different methodological approaches for its platform to include both qualitative and quantitative aspects in designing skylights for a one-storey office building in different climates. Three different approaches investigated in this study includes unconstrained optimization, constrained optimization and monetary metrics.

In the unconstrained optimization approach, the algorithmic platform has been developed to implement Parametric Analysis (PA) and Gradient Descent (GD) methods in order to optimize Skylight to Floor area Ratio (SFR) while saving energy consumption, as a quantitative aspect of daylight, and improving daylighting quality by providing sufficient daylight without causing glare discomfort. This platform was built as an Inclusive Integrative Algorithm

(IIA) to weight different qualitative and quantitative aspects of daylight. The algorithm is able to perform single or multi-objective optimization by either applying GD or PA. In this approach, a single-objective optimization, considering only energy efficiency, showed that the optimal SFR was 6% in the examined climates of Austin, Chicago and San Francisco, for 300 lux lighting level and Lighting Power Density of 0.8 watt/sqft. The unconstrained optimization approach implemented a weighting system for an aggregated metric, including Mean Daylight (MD) and imperceptible Daylight Glare Probability (iDGP) and Ratio of Energy Saving (RES), which resulted in a SFR of 11% as the inclusive optimal solution for all the examined climates.

In addition to the discussion of inclusive optimization considering both daylight and energy performance and scaling their importance, this study initiated the use of GD for the unconstrained optimization in single and multi-objective optimization. The result showed that GD is considerably faster than the traditional method, PA, while predicting the optimal solution with higher resolution. For example, GD resulted in 6.22% SFR for the San Francisco climate as an energy efficient optimal solution by only 9 iterations. However, PA required 10,000 iterations to find the optimal solution with the same resolution. Thus, GD has shown a promising result for the future of multi-objective optimization in building design.

In addition to the unconstrained optimization, this dissertation applied the second approach, constrained optimization, by imposing different thresholds for two sets of metrics, including daylight availability and glare. Where Useful Daylight Illuminance (UDI) and spatial Daylight Autonomy (sDA) of 100% were used, the inclusive optimal SFRs were 9-10%, 8-10% and 9% for the climates of San Francisco, Austin and Chicago, respectively. For the other set of daylight metrics, MD of 50% and Mean Daylight Glare Probability (mDGP) of 35% were used, which resulted in optimal solutions of 7-14%, 7-11% and 8-13% SFR for San Francisco, Austin and Chicago, respectively. Therefore, multi-objective optimization considering both daylight and energy performance resulted in different inclusive optimal solutions to energy optimization alone. The study also concludes that optimal solutions depend on applied metrics and daylight thresholds.

For the third approach this research investigated the monetary gains from energy efficiency and increased productivity. Assuming that productivity does not occur in spaces with poor daylight performance, inclusive optimal solutions will be the scenarios that most probably boost productivity. The study indicated that the energy cost saving is always negligible compared to the monetary gains from minimum increased productivity (1%). This conclusion may influence an owners perspective toward the quality of daylight performance and its resultant productivity increase.

Although the proposed algorithm (IIA) has been used to perform multi-objective optimization for skylight design, this platform can be used in the design process to optimize any fenestration, including widows, based on daylight availability, glare and energy factors. As GD is a faster and more accurate method, it can facilitate the application of multi-objective optimization for daylight analysis in the early stage of design.

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Chapter 1

Introduction

The[1] paradox of daylight has challenged designers and occupants for many years. What kind of a daylighting design is appropriate: a windowless office where energy and cost efficiency make occupants lose any sense of the passage of time versus a beautiful floor-to-ceiling window that distracts occupants with flooded light and glare? (Edwards and Torcellini, 2002; Osterhaus, 2009) The sun had been the primary light source in buildings until the popularity of artificial lights in the 1940s (Edwards and Torcellini, 2002). Electrical lighting changed workplace design by meeting most of the occupants' lighting requirements (Edwards and Torcellini, 2002). Although daylighting lost its role as an essential requirement of lighting design, daylighting through sidelights (windows) and toplights (roof apertures) has always been an important matter for architectural expression and aesthetic reasons. Only recently has daylighting reclaimed its role in buildings' lighting design due to, on one hand, the occupants' dissatisfaction and health issues, and, on the other hand, energy

[1]Parts of this dissertation were published in Journal of Energy and Buildings and at International Building Performance Simulation Association: Motamedi, S. and Liedl, P (2017). Integrative algorithm to optimize skylights considering fully impacts of daylight on energy, The Journal of Energy and Buildings. `http://www.sciencedirect.com/science/article/pii/S0378778816318898`, Motamedi, S. and Liedl, P (2017). An Integrative Algorithmic Platform Coupled with Gradient Descent and Parametric Analysis Methods to Optimize skylight Sizes, IBPSA Conference, San Francisco. Motamedi was the main author of both papers, conducting the research and writing the papers, while Liedl played a role of an adviser and an editor.

and environmental concerns (Edwards and Torcellini, 2002; Boubekri, 2008). Natural light has quality aspects, since it affects human beings both physiologically and psychologically (Boyce et al., 2006). In addition, daylighting in buildings has a quantitative side that includes its ability to replace electrical lighting and eventually decrease energy consumption. Therefore, in the building industry, designers have been intrigued for years by the question: how can the quality and quantity aspects of daylighting be integrated and eventually boost the quality of human-beings lives and environment?

As a part of sunlight, daylight may enhance quality of life and protect the environment. Sunlight is a portion of the electromagnetic radiation emitted by the sun that traverses space and the Earth's atmosphere (Jankovic, 2012). Daylight is the combination of direct and indirect sunlight outdoors during the daytime (Jankovic, 2012). A daylighting design may provide an even distribution of daylight and an extensive view, limit glare and thermal heat gain, and decrease electrical lighting loads; thus it is likely to make a positive contribution to occupant's health and progress, as well as alleviating environmental issues(Boyce et al., 2006). In this dissertation I refer to such daylighting, which represents all the positive aspects, qualitative and quantitative, as "effective daylighting." Daylight should not be perceived only in terms of its amount and its energy impacts, which may lead any research to optimization of efficiency. Instead, I expand the boundaries of analysis to consider the qualities and quantities mentioned above, while seeking for "effective daylighting" to increase "efficacy" of a human and natural system as a whole (Odum and Odum, 1976).

To rationally narrow down the topic of daylighting, I investigated an algorithmic platform to evaluate daylighting which enters solely through skylights, which is a type of toplighting configuration. Views and visual connections to the outside make toplighting and sidelighting different (Heerwagen, 2011). Extensive literature has been published debating what is considered to be “a good view” that connects people to nature and society, as well as reduces Seasonal Affective Disorder (SAD) and also fatigue (Heerwagen, 2011). Although toplights provide a view to the sky, the significance and quality of the view factor for toplights is negligible compared to the case of sidelights. Therefore, I narrow down the scope of the research by limiting my investigation of effective daylighting to skylight sizes, while holding properties of the envelope, including the glass, constant.

1.1 Relevant Background Knowledge

Developing an algorithmic platform to search for skylight design raises several questions that have been addressed or (partially) answered in the extant literature. These questions include whether skylight design can or should be sustainable; if the algorithmic platform as a digital technology should be deterministic in providing a solution; if daylight through skylights has any impact on humans’ well-being; if skylights can impact the environment through energy savings, and if the existing methods offer a holistic approach to address provision of effective daylight.

A concern over CO_2 emissions has motivated researchers to study energy efficient strategies in buildings. The energy impacts of daylight are measurable and are thereby considered as a quantitative aspect of daylight. Studies show that electrical lighting loads can be reduced by $20-77\%$ if good daylighting practices are implemented (Motamedi, 2012a; Ghobad et al., 2013a; 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). However, while lighting loads can be saved, adding apertures increases HVAC[2] loads due to daylight's impacts on solar heat gain, conductance heat transfer and internal heat gain (Motamedi, 2012a; Ghobad et al., 2013a; Reinhart and Wienold, 2011). Studying the energy impacts of daylight requires integration between daylight and energy software tools, such as Radiance and EnergyPlus (Reinhart and Wienold, 2011; Trubiano et al., 2013b; Konstantoglou and Tsangrassoulis, 2016). Recent attempts to couple daylight and energy engines has led to a flourishing of commercial integrative tools such as IES VE Pro, Diva, and Design Builder. The development of such new integrative simulation tools has promoted studies of fenestrations and their impacts on electrical lighting and HVAC loads (Bodart and Herde, 2002; Superlink, 1993; P. Ihm, 2009; Li and Wong, 2007; Yangi et al., 2010; Reinhart and Wienold, 2011; Li et al., 2008). Energy simulation tools have been used to study a specific case with a pre-defined location, function and form. To what extent fenestration can be increased to still save total energy consumption needs further optimization studies.

Energy optimization calibrates configurations of fenestration in order to minimize thermal and electrical loads. The most common methods to optimize fenestration have been Genetic Algorithms (GAs) and Parametric Analysis (PA). Parametric analysis exhaustively searches all possible solutions within a defined resolution, which makes the result robust but the process itself is time-intensive. As PA is an easy method not founded on complicated mathematical theory, many researchers/designers have applied this method to find the optimal energy efficient fenestration for either windows or skylights (Ghobad et al.,

[2]Heating, Ventilation, and Air Conditioning

2013a; Moe, 2010; Goia et al., 2013). However, the presence of more variables significantly increases the number of iterations, because the method searches for all possible scenarios. This begs the question as to whether another method could be a faster solver for multi-variable architectural problems.

GAs have been used more than any other method in the field of building design optimization (Rakha and Nassar, 2011; Caldas and Norford, 2003). The GA is a programming technique that also underpins the theory of biological evolution that the fittest is the one that will survive, through natural selection (Modrak et al., 2011). Holland proposed the groundbreaking theory of GAs in 1975 (Holland, 1992). Since then this theory has been developed and has become the predecessor of many other algorithmic theories (Ghosh and Tsutsui, 2012). Particularly, it has been at the frontier of optimization methods in the building industry. David Rutten created Galapagos, a Grasshopper plugin which sets up a ground work for architects to use GAs in design (Rutten, 2010b). The most interesting design research tool developed by this theory is the one that finds the forms or windows sizes based on either daylight or energy performance. GAs have been used to find the optimal shape for louvers, roofs, ceilings, and atriums, based on daylight performance (Sheikh and Gerber, 2011; Gadelhak, 2013; Rakha and Nassar, 2011; Caldas and Norford, 2003). However, many studies shown that the results from GAs are unstable, due to the initial inputs, the size of searched scenarios and the design criteria (fitness functions) (Modrak et al., 2011; Gadelhak, 2013; Rutten, 2010b). The shortcomings of the GA opens a research area for implementation of new mathematical algorithms that are faster and converge with more trustworthy optimal solution(s).

After discussing the energy saving capabilities of daylighting strategies and current optimization methods to find a solution, a question is raised: how is the studied algorithmic platform situated in the bigger picture of sustainable design? It was in 1973 that an increase in energy consumption coincided with the OPEC embargo, ending the era of cheap and endless energy and material resources, causing an energy crisis and generating a public dilemma (Daniels and Hammann, 2009). The increased cost of energy and the growing dissatisfaction with industrial society gave rise to the Brundtland's definition of sustainable design (Daniels and Hammann, 2009). The intent of such a definition was to set out a design guide which encourages solving the problem at hand without endangering the future generation's capability to meet their needs (Berardi, 2013). As discussed above, the use of skylights increase HVAC loads and decreases lighting loads. If the lighting savings of skylights cannot offset the increased HVAC loads, more energy will be pointlessly consumed, compromising the resources available in future. Therefore, skylights should be sized in a way that is environmentally conscious. In other words, skylight solutions are pinned to the sustainable definition of Brundtland's commission.

Environmentalist groups are interested in the impacts of skylights on ecology, because they are concerned about global warming and pollution. The relevant agents/groups are actors who share the same view toward the design challenge and actively exercise their specific interpretations (Bijker and Law, 1992; Moore and Wilson, 2013). But should the algorithmic platform solely target energy, one of the main interests of environmentalists, without considering other ramifications of the effects of daylight in the human well-being and the building industry?

Implementation of toplights enhances the occupants' quality of life, which brings about financial gain. The absence of daylight imposes psychological and physiological effects on employees' bodies (Edwards and Torcellini, 2002; Heerwagen, 2011; Boubekri, 2008; Tregenza and Wilson, 2011); thus, it is their interest to avoid such detrimental impacts. Healthy occupants with enhanced morale and higher levels of consciousness yield productivity which draws the attention of owners/employers (Heschong Mahone Group, 1999; Heschong Mahone Group, 2003; Romm and Browning, 1994; CoolCompanies, CoolCompanies). What makes the owner support the idea of daylight and productivity is whether or not the initial investment will be paid back by increased productivity (Romm and Browning, 1994). While the owner may support daylighting strategies for economic reasons, occupants look for the quality of life provided by daylight strategies.

Productivity is a side effect of enhanced quality of life which, in itself, is influenced by effective daylight. It has been challenging for researchers to measure the qualitative aspects of daylight, including productivity. Researchers have studied the impacts of daylighting strategies on productivity, and they have attributed different values to increased productivity, in a range of $2-40\%$ (Heschong Mahone Group, 1999; Heschong Mahone Group, 2003; Romm and Browning, 1994; CoolCompanies, CoolCompanies). Nevertheless, the findings all agree that increased productivity outstripped energy saving (Heschong Mahone Group, 1999; Heschong Mahone Group, 2003; Romm and Browning, 1994; CoolCompanies, CoolCompanies). This can also be supported by a cost breakdown for a typical office building. In 2000, both the Department of Labor and the Building Owner and Managers Association (BOMA) reported that the cost of salaries represents the biggest slice of office expenses, (63%) while the combined cost of electricity, light and utilities is about 2%. This highlights the role of daylight quality and its subsequent impact on productivity, in creating monetary benefits.

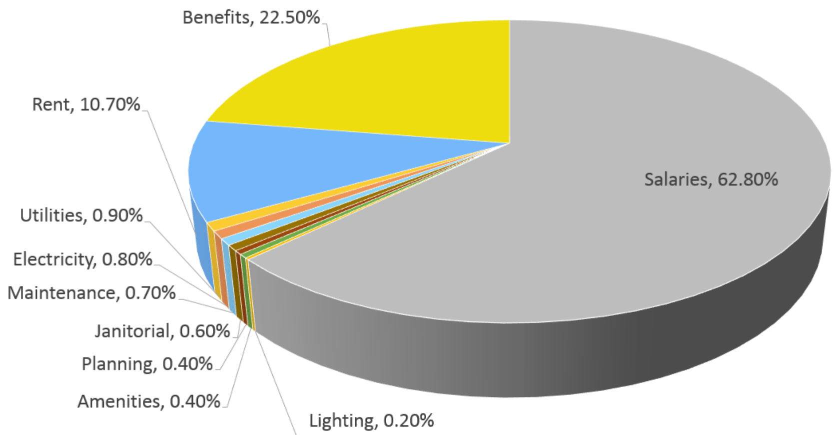

Figure 1.1: Office Expenses Break-down (Steffy, 2008)

Daylight quality cannot be achieved if the space lacks sufficient daylight or suffers from extensive glare. Researchers have been developing metrics for daylight quality mainly through measuring horizontal daylight at desk height or detecting glare spots in an angle of view. (Wymelenberg and Inanici, 2014; Nabil and Mardaljevic, 2006; Suk and Schiler, 2013). With regard to sufficiency of daylight, daylight metrics are evolving from static metrics such as Daylight Factor (DF) and illuminance (lux) to more sophisticated and dynamic ones, such as spatial Daylight Autonomy (sDA) and Useful Daylight Illuminance (UDI). Static metrics are measured at one point in space and time under a specific sky condition while dynamic metrics represents the average performance of daylight over a year for the whole space under real skies reported by a weather file (Nabil and Mardaljevic, 2006; Reinhart and Walkenhorst, 2001). In addition, glare has been measured either through preventing extensive horizontal daylight or detecting high luminance in the field of view, respectively (Wymelenberg and Inanici, 2011). Although UDI, Daylight Glare Probability

(DGP) and Daylight Glare Index (DGI) are the most commonly used glare metric in the industry, researchers have questioned whether or not they can prevent all glare probabilities (Suk, 2014; Wymelenberg and Inanici, 2014). While daylight metrics are undergoing swift progress, the current metrics to assess daylight performance of design scenarios are still widely accepted.

1.2 Statement of the Problem

Although implementation of toplights can improve quality of life and protects the environment, previous studies typically treat these aspects of daylight (quality and quantity) in isolation. A body of literature has been dedicated to showing how daylighting boosts quality of life, via positive impacts on health, well-being and moods, as well as reduction of fatigue (Lawrence and Roth, 2008; Boyce et al., 2006; Heerwagen, 2011). A separate area of knowledge investigates the quantitative side of toplighting, which includes its ability to replace electrical lighting and to decrease energy consumption as well as CO_2 emissions (Motamedi, 2012a; Ghobad et al., 2013a; 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). Architectural design entails solving complex and messy questions where multiple variable and design criteria need to be addressed (Bachman, 2010). As the relevant bodies of knowledge have been investigated in isolation, initially, separate software tools have been developed, for instance Radiance as a daylight engine and EnergyPlus as a thermal engine. Combining both daylight and energy engines, integrative tools such as IES VE and Design Builder provide an opportunity for researchers and designers to study the holistic impacts of daylight on energy consumption. However, the commercial off-the shelf tools, while pushing for integrative design, do not provide free access to a clear road map illustrating how to integrate energy and daylighting engines.

Apart from free access to the integration procedure, the calibration of fenestration has recently received attention from designers and researchers. I diagnose two challenges with the current literature about optimization of fenestration. First, the exhaustive process of Parametric Analysis and the non-deterministic, lengthy and complicated approach of Genetic Algorithms make it challenging to find robust design solutions (Shi and Yang, 2013). Therefore, an opportunity arises to facilitate the process of integration and optimization by developing a new optimization approach. The second challenge is a lack of a holistic approach toward optimization which includes both qualitative and quantitative aspects of daylight.

A review of the existing literature shows two distinct groups of researchers addressing the daylighting issues, which have fragmented daylighting science and the tools by which daylighting strategies are evaluated. One camp is dedicated to discerning the quality aspects of daylighting, associated with higher productivity, lower absenteeism, positive attitudes, reduced fatigue, and reduced eye strain (Edwards and Torcellini, 2002; Heschong Mahone Group, 2003; Heschong Mahone Group, 1999; Boubekri, 2008; Romm and Browning, 1994; Boyce et al., 2006). The other focuses on energy efficient design by minimizing thermal and electrical lighting loads (Yoon et al., 2008; Ghobad et al., 2013a; Motamedi, 2012b; Bodart and Herde, 2002; Superlink, 1993; P. Ihm, 2009; Reinhart and Wienold, 2011). I will describe each group's research, approaches, and findings in the literature review. The methods used in previous studies rarely target all the three design factors, including energy consumption, horizontal daylight availability, and glare. The optimization needs to be more cohesive, including all the design factors, in order to forge (a) solution(s) for a complex design question. Therefore, a major contribution of this dissertation will be to propose methodological approaches to cohesively optimize skylight design which can also be adopted for other design challenges such as window design. Although the proposed methodological approaches can bring about specific ranges of optimal solutions, the resultant skylight sizes will not be the focus of this study.

I hypothesize that a fine line exists that determines whether or not daylighting is "effective." A threshold needs to be set for received daylight to define quality of space while avoiding glare, providing enough daylight, and boosting mood. This threshold also needs to be calibrated for a building's energy consumption, because of the existing trade-offs between electrical lighting and thermal loads. Due to the aforementioned split in building research approaches, in practice, buildings are often one-dimensionally optimized, without considering their situated context. They are either designed for the lowest HVAC loads without considering daylighting quality and glare issues, as well as occupants' well-being and productivity, or designed to provide the most pleasant interior, which may jeopardize energy consumption. Are quantity and quality aspects of daylighting the only forces that influence effective daylighting design?

It is a basic assumption of this research that the context-dependent nature of any design project prevents any universal solution to the use of daylighting. Daylighting design is part of the "culture of building," which Howard Davis refers to as "the coordinated system of knowledge, rules, procedures and habits that surround the building process in any given place and time" (Davis, 1999). Many factors shape the context of a daylighting question in hand, such as building codes, metrics, climates, neighborhood morphologies and their specific shading patterns, materials, available equipment such as lamps and their electric powers, seasons, occupants' age and lighting requirements, cultural acceptance of daylight, environmental concerns, and owners' perspectives toward energy efficiency, a healthy environment, and productivity, as well as economic benefits. The specifications of these human's and non-human's positions create a circumstance in which a particular context emerges. The human (social) and nonhuman actors are "any element which bends space around itself, makes other elements dependent upon itself and translate their will into the language of its own" (Callon and Latour, 1981). In the case of toplights, social actors are residents, architects, engineers and contractors and non-human actors are skylights, buildings, and the environment. Each group of actors shares the same goal and "interest" and perceives a context different than that of the others, while actively motivating others to accept their interest (Callon and Latour, 1981). As a result, any design project comprises actors with different interests, creating a unique, complex context leading to several daylighting solutions. The gap observed in reviewing the literature is the existence of studies that bring together interests of different relevant groups for a question concerning skylights.

1.3 Research Questions

The goal of my dissertation is to initiate an algorithmic platform that is capable of proposing contextualized design solutions for toplights while holding a holistic perspective toward daylighting. The platform proposed and examined in this dissertation accepts flexible inputs and adopts a weighting system to scale different interests, in order to accommodate different contexts. The platform results in energy-efficient skylight sizes that can eventually promote healthy and productive spaces.

Therefore, the main research question is the following: *Can an algorithmic platform be developed to provide effective skylight sizes for single-storey buildings in different climates that considers contexts by weighting qualitative and quantitative aspects of daylighting including daylight availability, glare, energy efficiency and productivity?*

In order to address the major research question, the following research objectives are defined as milestones:

- Propose a road map to integrate daylight and energy engines in order to find solutions with optimal energy performance.
- Develop a methodological framework which can be repeated by others to practice a cohesive skylight design by including qualitative and quantitative aspects of daylight.
- Examine or develop metric(s) for qualitative aspects of daylight or holistic performance, including both daylight and energy factors.
- Set up different multi-objective optimization approaches to find the best effective skylight design and contextualize design solutions.
- Find out impacts of climatic conditions on optimal design solution.

1.4 Overview of Methodology

This dissertation examines three main approaches combining different tools, metrics, and optimization methods in order to propose an inclusive optimal solution for skylight sizes. Each approach in this dissertation employs a wider systematic procedure that includes all variables, design criteria, tools, and optimization methods. However, the methods in this study as the subsets of the approaches are associated with different optimization techniques, which include PA, and Gradient Descent (GD).

Different software tools have been integrated to assess energy and daylight performances and apply optimization methods. I used EnergyPlus and Raidance as daylight and energy engines. Radiance was accessed through its host Ladybug and Honeybee. In addition, Python, a programming language, was used in order to integrate different tools, collect data, and apply optimization methods. All these tools were accessed and simulated in Grasshopper environment, a Rhino Plugin where 3D of geometry can be visualized.

I applied three different approaches to evaluate the role of metrics in the optimization process and compare the optimal solutions resulted by adopting different approaches. The first approach used the GD method, a numeric optimization, and PA to apply unconstrained optimization. This approach did not impose any restriction on the design factors of energy consumption, daylight availability and glare. An aggregated unit was proposed to unify the different metrics of the design factors. In addition, this approach utilized Parametric Analysis to validate the results of the Gradient Descent method. The second and third approaches used Parametric Analysis to find the optimal solution, by imposing a bar for acceptable daylight availability and glare. While the second approach used two sets of metrics for daylight availability and glare, the third approach implemented an aggregated unit of cost by converting "effective daylight" to monetary gains from increased productivity and energy cost savings. Chapter 3, Methods and Methodology, provides a detailed description of my epistemology, methodology, and specific methods for this dissertation.

1.5 Significance

The platform which is examined in this study is anticipated to be significant for the building industry due to its capabilities for integration, contextualization, and optimization. It considers all aspects of daylighting (quality and quantity) by integrating the most trustworthy engines such as Radiance and EnergyPlus. It provides context by including all interests and weighting those interests. Finally, it suggests robust and optimized design solutions based on defined contexts. Thus, it provides an avenue to tackle complex multi-faceted design problems by combining a mathematical theory of optimization, the physics of energy and daylight simulation, social concerns over environment and quality of life, and economic benefits from saving energy and boosting productivity.

Studies have shown that daylighting and toplighting strategies can significantly decrease total energy consumption (Motamedi, 2012a; Ghobad et al., 2013a; 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). These findings are significant because electrical lighting loads account for 20.5% of source energy for commercial buildings, while the commercial building sector contributes as much as 19% of the total energy consumed in the U.S. (EIA, 2003a). Preliminary studies show that electrical lighting loads can be reduced by 20−77% if good daylighting practices are implemented (Motamedi, 2012a; Ghobad et al., 2013a; 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). As a result, any question addressing the challenges of daylighting design in the building sector plays a crucial role in saving energy in the U.S..

Despite promising contribution of toplights in energy savings, the Commercial Building Energy Consumption Survey (CBECS) for 2003, prepared by the U.S. Energy Information Agency (EIA), revealed that less than 1% of all commercial buildings in the United States had any skylights. This low statistics, in fact, show that there is a potential market for toplights. Urban sprawl and low density developments are predominant characteristics of many American cities (Batty et al., 2003). Interestingly EIA's data confirms American urban sprawl by showing that one-storey buildings makes up 67% of the commercial building sector in the U.S. (EIA, 2003b). Since toplights are an essential daylighting strategy for one-storey buildings, toplights as daylighting and energy efficient strategies suit American cities better compared to very dense European cities.

Thus, considering the fact that a one-storey building is a common practice in the U.S. both renovations and new designs can benefit from the positive impacts of toplights. This giant building sector can take advantage of implementing toplighting strategies that bring quality of life and save energy. In addition, many abandoned warehouses, "big boxes", need renovations and functional changes to bring life back to the communities in which they are located via reusing embodied energy. Despite having very dark, deep configurations these vacant fabrics can be opened to the sky through toplights. Six percent of all the commercial buildings in the U.S. are vacant and 67% of these are one-storey (EIA, 2003b). This data demonstrates the importance of recycling vacant buildings and using toplighting strategies. The Livestrong Foundation, designed by Lake | Flato in East Austin, is an exemplary precedent, presenting a transformation of a warehouse to an office building that gets its daylight through the roof (Figure 1.2) (ArchiveInnovation, 2015). Another example is a robust report prepared by the Heschong Mahone Group showing that adding skylights to an average non-skylit one-story retail space would be likely to improve its performance (gross sale) up to 40% (Heschong Mahone Group, 1999). Hence, toplights have a substantial market potential in both renovated and new projects.

Figure 1.2: Implementation of toplighting strategy in a big box, Livestrong Building, Austin, TX (ArchiveInnovation, 2015)

In addition, the algorithmic platform examined in this research offers capabilities to change the culture in the building industry by promoting integration and by educating related professions. As Davis explains, after the Enlightenment and the Industrial Revolution, explicit knowledge forged discrete professions out of "scientific, quantifying and classifying mentalities"

(Davis, 1999). People become more specialized in their occupations and professions became more explicitly defined (Davis, 1999). These changes resulted in "separation of design and building, decreased ability of people to have the responsibility for making decisions on the basis of their knowledge" (Davis, 1999). One of the significant contributions of the platform in this study is to bring together all the related professions and actors in the building industry. Because the platform asks for inputs related to different professions, this motivates users to have a holistic view toward the question of toplighting or to collaborate with related professions to collect the required information. This teaching and learning mechanism informs users that their decisions have an impact on people and professions outside of their own fields.

While many designers' tools are isolated from major energy or daylighting tools used in current practice, the easy access to the proposed tool from design tools motivates architects to consider "effective" daylighting strategies in the early stage of design. The examined platform has plugged into the popular architectural modeling tool, Rhinoceros 3D. This allows the automatic coupling and visualization of daylight, energy consequences, and quality assessment. Its connection to geometry will make the platform powerful because designers will see how formal decisions can be changed by energy use (environmental protection), occupant visual comfort and health (social justice), and owners' financial benefits (economy). As a result, not only can the examined platform help architects to design "effective" daylighting but it also influences design decisions from the preliminary stage of design.

This dissertation can have a great opportunity to be influential in the building industry because the result of this dissertation can be used to evaluate several credits of the dominant sustainability program, LEED - Leadership in

Energy-efficiency and Environmental Design. More than 17.1 billion square feet of building space is LEED-certified (as of January 2017) (LEED, 2017). The examined platform can be used effectively for evaluation of LEED v4 credits, including Energy and Atmosphere credits (EAp2 and EAc2), as well as Indoor Environmental Quality credit (IEQc7). The proposed tool can be used to earn points for the former, which is concerned with minimum and optimized energy efficiency, and the latter, which is about access to daylight.

1.6 Acknowledgment of Limitations and Scope

As the proposed platform with its optimization approaches may be developed into a future tool, it is necessary to consider the significant role of a researcher or designer. The proposed platform is founded on integrating different interests and the basic foundation of its optimization process supports a holistic perspective toward all daylight aspects. However, optimal solutions heavily depend on a researcher or designer who is a mediator, playing the role of modeler, or who assembles the integrative algorithmic platform. This algorithmic platform with different optimization approaches has place holders for weighting factors/multipliers and acceptable thresholds for daylight and glare metrics. The mediator uses judgment, experience and earned knowledge, and defines defaults, metrics and their targets. A supervised third party may be needed to review the inputs and avoid creating a black box. Transparency regarding inputs and outputs as well as the pros and cons of the implemented optimization approach is vital. Such transparency has been practiced in this dissertation and is explained in Chapter 3, Methods and Methodology.

Although this study has devised an algorithmic platform to be inclusive and cohesive, the boundary of the study was defined by several limitations, such as an appropriate analysis of ventilation. Natural ventilation positively or negatively impacts the indoor environment quality and thermal performance (ASHRAEComfort, 2013). The investigated platform lacked any quality assessment of natural ventilation and did not optimize toplighting configurations based on natural ventilation. EnergyPlus, as a thermal engine of the proposed platform, is capable of tackling the impact of natural ventilation on thermal loads (BigLadder, 2016). However, my reasoning for not including natural ventilation in the optimization algorithm is that the quality of natural ventilation depends on many other factors that are beyond the scope of the study, such as occupants' control over openings, outdoor pollution, outdoor noise, and ventilation patterns (Hausladen et al., 2008).

The analysis of embodied energy was another area of scope that was not considered in this study. The proposed platform included utility costs and the economic benefits of productivity. However, embodied energy was excluded from this study to reasonably narrow down the scope of the research. Embodied energy is the energy consumed to create the building, including extraction, processing manufacturing, transportation, and assembly (Garrison and Stout, 2004; Klaus and Hammann, 2009). One may worry about the assumptions buried in the algorithmic platform regarding materials (glass, aluminum, polycarbonate, etc.). Although the material and construction assumptions were built in and fixed across the studied models, these assumptions do not represent a real limitation of the proposed platform because the future user/research can feed different constructions into the platform. In addition to the embodied energy, this study did not include life-cycle analysis. Although one of the optimization approaches was to include productivity and energy gains, such monetary benefits do not reflect the final cost. The final cost should be measured by life-cycle assessments, which is, in itself, a significant topic. This adds another wrinkle to the research question which is beyond the scope and time considered for this PhD research. However, it can be adopted to future multi-objective optimizations.

1.7 Main Definitions

While some of the definitions and acronyms used in this dissertation were borrowed from bodies of literature, I have also introduced some new definitions or redefined the existing ones to fit the subject of dissertation, and I have applied new acronyms (distinguished by asterisks):

- **Fenestration:** It refers to any aperture in buildings allowing for daylight, view and natural ventilation. Fenestration is divided into sidelights and toplights.

- **Sidelights:** These are apertures on vertical surfaces of buildings. It is usually used to refer to windows and introduces natural light into space from sides (LumenhubWebsite, 2015).

- **Toplight:** Apertures admit dayight from above (DeKay and Brown, 2013). They are appropriate daylighting strategies for deep plans and top floors (DeKay and Brown, 2013). Different types of toplights exist, encompassing skylights, sawtooth roofs, and monitor roofs (See Figure 1.3).

- **Skylight:** This is a punched aperture on a flat or tilted roof (Figure 1.4). Skylights are the subject of this dissertation on which the optimization

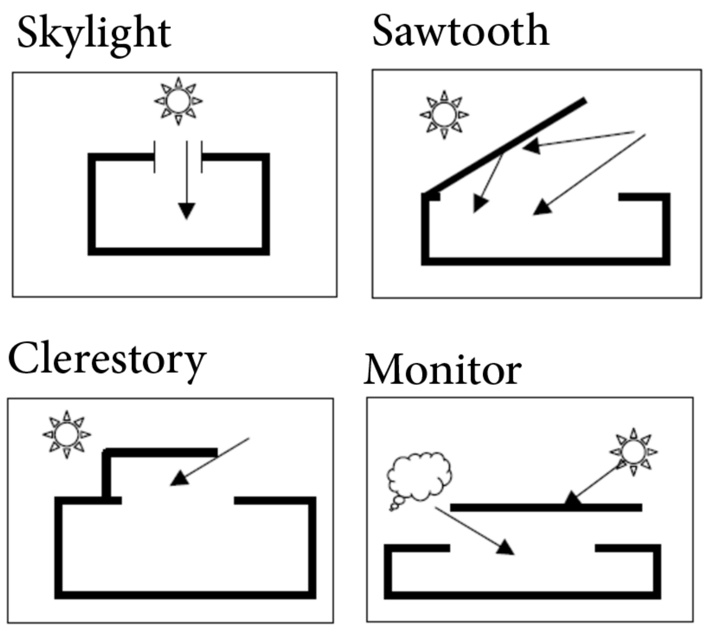

Figure 1.3: Different Toplighting Strategies (LumenhubWebsite, 2015)

process is focused. In this dissertation it is mostly attributed to toplights (Ander, 2003).

- **Skylight to Floor Ratio (SFR):** This is gross area of skylights divided by floor area.

- **Qualitative Aspects of Daylight*:** This refers to the psychological and physiological effects of daylight on employees' bodies. Although it is challenging to directly measure these aspects, in this dissertation they are estimated either by their activators including daylight availability and glare or by their side effect, productivity.

- **Quantitative Aspects of Daylight*:** These represent the energy impacts of daylight, and include electrical lighting and HVAC loads. These

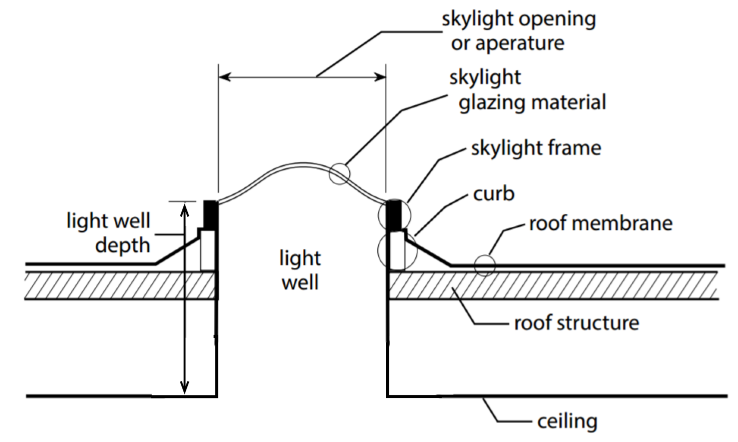

Figure 1.4: Skylight Design (EnergyDesignResources, EnergyDesignResources)

aspects account for decreased internal heat gain, increased solar gain and enhanced conduction rate.

- **Effective Daylight*:** This refers to a daylighting design that provides an even distribution of daylight and an extensive view, limits glare and thermal heat gain, and decreases electrical lighting loads (Boyce et al., 2006). Because the subject of study, skylights, extensive views were eliminated from the optimization process.

- **Toplighting Comfort*:** This refers to visual comfort for a space that daylight admits from above. It is caused by sufficient horizontal daylight with less glare incidence.

- **Multi-Objective Optimization:** This is the process of finding a solution by simultaneously applying more than one objective function or criteria-based decision making (Caramia and Dell'Olmo, 2008).

- **Multi-Variable Optimization:** It finds a solution for different variables fed into a function. In other words, function's value or performance depends on multiple variables. (Caramia and Dell'Olmo, 2008)

- **spatial Daylight Autonomy (sDA):** The percentage of floor area that receives sufficient daylight for at least 50% of the annual occupied hours (Nabil and Mardaljevic, 2006).

- **Useful Daylight Illuminance (UDI):** The percentage of floor area that meets an illuminance range of 100 and 2,000 lux for at least 50% of occupied hours (Nabil and Mardaljevic, 2006). This metric avoids excessive level of daylight and potential glare incidence (Rogers, 2006).

- **Mean Daylight (MD)*:** The percentage of occupied hours that an average node in a daylight grid map receives at minimum 300 lux.

- **Daylight Glare Probability (DGP):** This is a luminance-based glare metrics calculated by a mathematical equation which is derived from daylit on-site studies. The DGP ratings are as follows: 35% is "imperceptible glare," 35−40% is "perceptible glare," 40−45% is "disturbing glare," and above 45% is "intolerable glare" (Wymelenberg and Inanici, 2014).

- **Relevant (social) Group/Actor**: These are active social individuals who share the same goal and interest. They perceive a context of a problem at hand which is different from that perceived by others, while actively motivating others to accept their interest (Callon and Latour, 1981). This dissertation includes the interests of a priori groups in the optimization process. Such groups include: owners, occupants, and environmentalists.

- **mDGP*:** Mean of DGP for occupied hours.
- **DGPi*:** The percentage of annual occupied hours during which DGP is "imperceptible".
- **Gradient Descent Method:** This is an optimization method which starts with an initial guess and iteratively moves the guess toward lower values of a function by taking steps in the direction of the negative gradient (Snyman, 2005).
- **Parametric Analysis:** This is an exhaustive search that examines the behavior of outputs as systematically varies one or more of the variables with constrained resolution (Frost, 2015).

1.8 Summary of Chapter 1

Chapter 1 has introduced qualitative and quantitative aspects of daylight and why daylight design needs to be cohesive and include both aspects. This chapter has presented the goal of this study, which is to join the isolated bodies of knowledge regarding skylight design, bridge different tools, and apply a more integrative and inclusive optimization method. It has been explained that the new rush toward optimization requires a contextualization of design which entails bringing together the interests of different groups. Revealing a number of caveats, I summarized the research project and subsequent research objectives which govern the conduct of the research. The intent of this research is to set up an integrative algorithmic platform that is capable of proposing robust skylight sizes while holding a holistic perspective toward daylighting, by including daylight availability, glare, energy and productivity factors. I have also outlined the significance of the study in the field of design and buildings. Lastly, I defined a few key terms to remember while reading the following chapters.

1.8.1 Structure of the Dissertation

After summarizing chapter 1, here, I outline the structure of this dissertation. Chapter 2 provides a thorough discussion of the literature where I discuss how my perspective toward the daylighting question arose from theories of technology and sustainability. I then review studies related to qualitative and quantitative aspects of daylight. Chapter 3 lays out the methods and methodology of the dissertation, where I explain all the software tools, optimization algorithms, simulation assumptions and metrics that are applied in this study. Chapter 4 illustrates the results of different inclusive approaches and presents consecutive discussions. In Chapter 5 I summarize the main findings of the research and its limitations and suggest future research opportunities.

Chapter 2

Literature Review

This section places my dissertation topic within related scholarly literature, expresses my paradigm and finds gaps that have not previously been examined. The following literature review is organized into several bodies of knowledge that contribute to this study: theories of sustainable design and technologies, qualitative aspects of daylight and their metrics, quantitative aspects of daylight, including thermal and electrical lighting loads as well as optimization methods. First, I discuss the major theories in the field of sustainability, and how these theories mold my perspective toward the issue of daylighting. I explain how this adopted perspective influences my methods of tackling the problem at hand. I then discuss peer-reviewed articles and reports about the impacts of daylighting on the quality of human lives and metrics associated with such daylight qualities. Next, I highlight state-of-the-art papers that investigate how sidelights and toplights influence thermal and electrical loads. The last category of literature concerns methods to optimize fenestration based on energy and daylight performance. Finally, I identify how my dissertation addresses gaps in the existing literature.

2.1 Theories of Sustainable Design and Technologies

While scholarly theories and philosophies draw a bigger picture, they influence how I envision the problem of daylighting and how to address this problem. I divide this section into two parts of theories of sustainable design and theories of technology. In each part, after I delineate the most popular theories, I explain why these theories matter to the subject of this dissertation.

2.1.1 Theories of Sustainable Design

A daylighting design, if protecting environment and enhancing quality of life, can be considered a sustainable solution in building practice. Although sustainable building terminology has been increasingly used in the last three decades, the concept has not codified into a certain single, universal definition (Berardi, 2013). In fact, "sustainable building" has gradually developed new meanings (Berardi, 2013). Sustainability mainly started with the Brundtland commission's simple definition and the term was later divided into different spheres of society, economy, and environment. Finally it developed into an advanced complexity theory that highlights the role of social actors who make solutions to evolve through time and locations (Hopwood et al., 2005). In the following section, I explain these major theories, note how they inform my specific paradigm, and apply them to my research.

While the underlying ideas of sustainable design is very old, this concept has encountered significant changes by different theories over the last few decades (Berardi, 2013). Sustainability did not gain momentum until the 1980s when the Brundtland Commission published the most popular definition (WCED, WCED). It stated, "sustainable development is development which meets the needs of the present without compromising the ability of future generations to meet their own needs" (WCED, WCED). This definition forges the theory of the three pillars of sustainability − environment, society, and economy − while implying their integration is needed for sustainable development

(WSSD, WSSD). Although this theory is depicted for the larger scale of urban development, it has influenced my dissertation in terms of territory belonging to an individual building.

The question concerning daylighting entails a fundamental challenge of balancing among three pillars of society, economy, and environment. Environmental protections include pollution reduction through minimizing footprints and energy-efficient strategies, which may include technological developments (Guy and Farmer, 2001). In this regard daylighting is capable of substituting electrical lighting and reducing buildings' energy consumption and CO_2 emissions. Economy, the second sphere of sustainability, is concerned about the summation of monetary benefits including initial cost, operational cost, and the benefits of increased productivity or sale rate. Studies claim that the aforementioned costs and revenue will be influenced by daylighting; I will expand upon this subject later in this paper. The sphere of society values fair access to high quality of life for every member of a community. Social equity can be defined as improvements to "quality of life" or having "the goal of a better environment for everyone" (Crosbie, 1993). A body of literature is dedicated to how daylighting boosts quality of life via positive impacts on health, well-being, and moods, as well as reduction of fatigue. Since I consider daylighting quality as one of the factors of the proposed tool, my research relates to the sphere of society. As a result, the theory of three pillars suits daylighting design because daylighting has contingencies of environment, economy, and society (as shown in Figure 2.1).

While viewing sustainable solutions as a position at the center of the triangle induces a static and universal solution, some scholars envision sustainability through the paradigm of complexity, which "helps one view sustainable development not as a goal that can be reached through the achievement of balance but as a dynamic process of continuous evaluation, action, and re-evaluation" (McDaniel and Lanham, 2010). In the realm of building design this theory can be interpreted into regenerative architecture, regenerative sustainability, and civic environmentalism. Canizaro's theory of civic environmentalism promotes a design providing "ecological and social justice through democratic and participatory methods" (Canizaro, 2010). This closely aligns with regenerative architecture as proposed by Moore, which "seeks to engage human institutions in the democratic reproduction of life-enhancing place" (Canizaro, 2007). These two theories have the same root as regenerative sustainability as proposed by Robin and Cole. These authors depict this theory as going beyond the maintenance of a socio-ecological balance, adding value and benefits to its context (Robinson and Raymond, 2014). The theory evolves through a process in which agents participate and collectively make a decision (Robinson and Raymond, 2014). The authors conclude that there is not a "right" solution; in fact, "there might be many ways to go about it (Robinson and Raymond, 2014).

A new concept of sustainability that includes different voices and context contingency consolidates my assumptions in terms of how I approached a design problem in my dissertation. I accepted this new concept and proposed an algorithmic platform that incorporates relevant voices in order to sustain the current status quo of an ecosystem and adds value to users' health and quality of life. Instead of considering the sole interest of environmental protection, the platform accounted relevant groups with different interests in daylighting. Solutions lie in the participation of relevant social actors as they are the "key starting point" to understand the social construction of a prob-

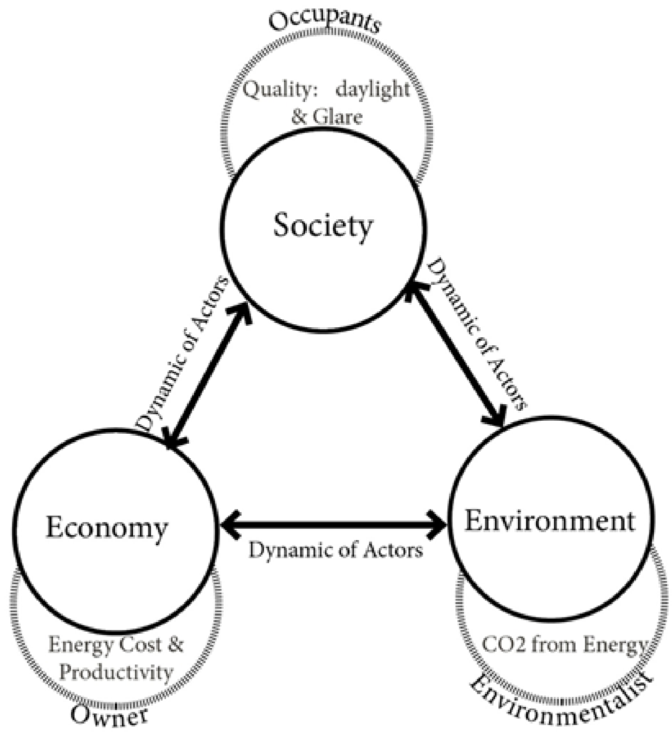

Figure 2.1: Reconstructing the Theory of Three Spheres of Sustainability for Toplights

lem at hand (Bijker and Law, 1992). In other words, relevant groups or agents are actors sharing the same "technological frame," which means inhabiting a common interpretation of a specific technology situated in a specific context (Moore and Wilson, 2013). A toplight is a technology and based on the definition of agents I have concluded that the following social groups, which represent an a priori or idealized selection of actors, are comprised of: owners, occupants, designers and environmentalists. The interests of groups may merge or conflict depending on the context of project at hand (Moore and Wilson, 2013). This conflicting and merging makes a specific interest more influential in a certain project than other projects. This means context matters. As I adopted this concept, I contextualized the solutions proposed by the algorithmic platform. Therefore, I implemented a weighting system assigning different weights to groups' interests. I delineated different interests of the relevant groups in regard to toplighting and the importance of weighting system later in the Sections of 3.2 and 3.5.1.

In conclusion, theories of sustainable design define the paradigm of my research and its resultant platform, which is a technological change. My work was influenced by sustainability regarding the three spheres of environment, society, and economy and how actors with different interests affect a solution. The algorithmic platform, as a final result of this dissertation, is a technology providing formal solutions to the design and changing the tradition of creating a space using solely the minds of architects. As a result, the platform may change the existing dynamic among professions. The setting of the platform may be changed based on different professions' interests. Whether this tool is considered deterministic or not is the question of theories of technology, which are explained in the next section.

2.1.2 Theories of Technology

Since the result of my research is a technological platform offering a method to make design decisions in daylighting, it is imperative to understand whether this platform is supposed to force a change in the building industry or if the building industry − engineers, architects, inhabitants, and contractors − shape the final design as a technology. To do this, I explain popular scholarly definitions of technology, and theories of technology. Then, I provide failed examples related to the topic of daylighting in order to reject a deterministic view toward technology and technology mentality. In addition, I discuss how daylighting criteria is socially constructed. Finally, I conclude why my research is situated in a theory of technological momentum and how it practices such a theory.

Throughout history the word "technology" has been interpreted differently, however Frank Lloyd Wright and Thomas Hughes offer the most apropos definitions for my dissertation. Frank Lloyd Wright never used the word "technology" in his arguments but rather referenced mechanical discoveries, mechanical inventions, and machinery (Wright, 1992; Smith and Marx, 1994). Believing in the "mechanic arts," Wright was convinced that "in the machine lies the only future of art and craft" (Wright, 1992). He persuaded artists to embrace science and the machine in the creation of artifacts (Wright, 1992). Wright's opinion suits the proposal algorithm platform. This setting embraces energy-efficiency science and the statistical research of productivity and daylight quality and helps designers shape the final artistic forms of their buildings. While Wright motivated architects to create the "mechanic arts," Hughes assumed a collective creation of technology.

Because the final platform considers voices of different professions, it represents the concept of collaboration in Hughes' definition of technology. In his work, Hughes affirms that technology is a creative or poetic process involving actions and skills of many actors such as craftsmen, inventors, engineers, designers, scientists, and users (Hughes, 2004). I adopted the anti-heroism of Hughes' interpretation of technology since my proposal platform considers multi-agency. When the platform is used in the design process, new forms of buildings are discovered by collectively sharing different interests of agents (designers, engineers and users). In other words, there is not a "genius" hero who invents forms; rather, there is a collaborative team who discovers forms

(Bachman, 2010). The research resultant is an example of Hughes's definition of technology due to its inviting different but related voices and making a formal decision that concerns all interests. In the scope of the skylight design through the algorithmic platform, who or whatever should be the changing drivers of designs (engineers, architects, or the tool itself) depends on the true understanding of theories of technology. In this section, I explain these theories and their relation to my research and the topic of daylighting.

In the history of technology the question of who defines technological change has been a major, decades-long debate among historians, sociologists, and engineers. The two conflicting theories of technology are technological determinism and social construction of technology. The first presumes that technology is "self-determining and independent of all human intervention" and derives changes in social structures and cultural values (Smith and Marx, 1994). In contrast, the latter emphasizes different interests and power relationships among social groups who actively shape technological developments of a society (Smith and Marx, 1994). In the middle position of these two theories stands technological momentum, proposed by Hughes. He contends that a technological system "can shape and be shaped by society" (Hughes, 2004). He argues that young technological systems develop while being influenced by socio-cultural forces (Hughes, 2004). In contrast, older mature systems gain momentum over time and become more independent and deterministic in nature (Hughes, 2004).

Technological determinism attenuates architects' "knowledge and judgment" giving rise to the design of sealed buildings with limited or tinted fenestrations. This design trend was caused by architects who adopted engineers' frame about HVAC systems and accepted that energy-efficiency solely depends on thermal loads (Yoon et al., 2008). The trend ignores the impact of daylighting on electricity savings as well as its contribution to users' health and thermal loads (Motamedi, 2012b).The trend leads to office rooms with dark working areas or rooms without any windows, both which upset the circadian rhythms of our bodies' clocks and causing SAD symptoms (Tregenza and Wilson, 2011). Architects as designers should have a cohesive perspective toward different social groups with different interests (in this case, toward energy-flow in buildings and toward users' health) to avoid poor judgment.

In addition, the long established use of Daylight Factor (DF) to measure efficient available daylighting illustrates a lack of professionals' reflective understanding in building practice. DF is a mathematical formula coined by a British physicist Trotterto in 1892 and it represents the overall appearance of daylight condition (Addis, 2006). It is a ratio of inside illuminance at a point of interest to the unobstructed, horizontal illumination under the CIE overcast sky (Tregenza and Wilson, 2011). This type of sky is suitable to represent the cloudy skies of Britain but it may not be appropriate for the representation of sunny climates (Tregenza and Wilson, 2011; Reinhart, 2011). However, DF gained such momentum that professionals in the fields of design, engineering, and policy accepted it without questioning its history and definition. DF has been used for more than a century in architectural designs as well as in building codes (Addis, 2006). Even LEED adopted this measure in its earlier versions (LEED v2) and recently replaced this historical metric with another metric (LEED v4) (Overbey, 2014). In addition to DF's sky condition, this method does not consider different climates, complex geometries of interiors, surrounding objects, and windows' orientations (Tregenza and Wilson, 2011; Reinhart, 2011). The failure of DF prompts the question as to whether metrics of a qualitative subject like daylight should be represented by reductive mathematical formulae. In fact, in what follows I argue daylighting criteria are socially-constructed.

Different recommended levels of daylighting in different regularity systems indicate that daylighting criteria – its assessing tools and its subsequent designs – are socially constructed. Just what is the "right" level of light lacks consistency among different countries and even within a country over time (Mills and Nils, 1999). Historical patterns show that daylighting requirements (illuminance levels) increased ten times until the early 1970s (Mills and Nils, 1999). After that, many countries stabilized or declined their levels of illuminance (Mills and Nils, 1999). Mills and Nils justify this socio-technological change through "a combination of economic factors (increasing energy costs), new perspectives on lighting design (increasing light is not necessarily better light), and a pronounced trend toward more precise focusing of light on specific task (task lighting over ambient lighting)" (Mills and Nils, 1999). Daylight criteria and its metric have evolved over the years; this implies daylighting criteria holds contingencies of time, location, and social components. Culture, one social component, can also impact our perceptions toward good design of daylighting. Large windows in western culture may present relationship to the nature and engagement. In Middle Eastern countries, however, that design choice can be perceived as a violation of privacy (Tregenza and Wilson, 2011). In addition, daylighting holds contingencies of location and culture because small tinted windows make a space look gloomy in the cloudy climate of the U.K but safe and cool in the sunny climate of Las Vegas (Tregenza and Wilson, 2011). Thus, there is no universal criterion of daylight quantity. What is found to be satisfactory depends on a complicated context in which economical, cultural, ecological, social, and technological forces are continuously changing and changed via their influence on each other. Such multi-directional dynamics hold the theory of technological momentum.

Switching between macro and micro lenses is an important method of understanding the truth about the driving force of socio-technological changes and the theory of technological momentum (Smith and Marx, 1994). At first glance, when considering my dissertation's algorithmic platform with a macro perspective, it seems that the tool is an autonomous driving force defining the final shape of design, determining a building's footprint and its environmental impacts, as well as shaping how people feel and live in a building. However, with a micro lens, it can be seen that the tool is bi-directional. In the beginning of a project, the platform is influenced and fed by shared concerns and knowledge of relevant agents. In the later design stages, the technological tool with its collected information helps the tool users – designers or consultants – generate more "effective" forms. How this platform has derived appropriate forms and may influence the building industry will be explained in the sections of Methodology and Methods, and Conclusion. The technological platform of my dissertation continuously and dynamically impacts and is impacted by relevant and defined social actors. The explained procedure depicts that if the platform is used in future, it will exercise the theory of technological momentum in each project.

This section expressed how theories of sustainable design and technologies mold my epistemological assumptions with regard to the problem of daylighting. In the following sections I examine literature related to the subject of daylighting, including its role in enhancing quality of life and saving energy as well as the existing methods used to optimize building parameters.

2.2 Qualitative Aspects of Daylight

This section reviews the relevant literature about daylight quality, under three sub-categories: the psychological and physiological effects of daylight on a human body; the economic benefits of such qualitative impacts on human lives and the current metrics to assess daylight performance.

2.2.1 Impacts of Daylight on Humans

Different spectra of light affect humans both physiologically and psychologically (Edwards and Torcellini, 2002). Since these effects are less quantifiable, they are overlooked as benefits of daylighting (Edwards and Torcellini, 2002). Some of the associated benefits include improved mood, enhanced morale, lower fatigue, and reduced eyestrain (Edwards and Torcellini, 2002). Natural light that carries information from the outside world apprises us of time of the day and month and the surrounding location we live in (Edwards and Torcellini, 2002). In addition to this important psychological aspect, many on-site surveys indicate other psychological impacts, such as reducing stress, decreasing anxiety, holding attention, and improving mood (Edwards and Torcellini, 2002; Heerwagen, 2011).

In regard to physiological impacts, the human nervous and hormonal systems are influenced by daylight (Edwards and Torcellini, 2002). Vitamin D production, melatonin hormone release, and the circadian cycle are the most important impacts of daylight on human bodies. For example high melatonin levels cause drowsiness while low levels correspond to an alert state of consciousness (Edwards and Torcellini, 2002). As a result, daylight can adjust sleep hours or internal "clocks" of human bodies (Edwards and Torcellini, 2002; Tregenza and Wilson, 2011). Circadian rhythm is regulated by daily exposure to the full spectrum of natural light and the alternate darkness at night (Edwards and Torcellini, 2002; Tregenza and Wilson, 2011). A major portion of natural light that impacts circadian rhythm is the blue-green spectrum with a wavelength range of 446-447 nm that lies in the spectrum of visible light, which has a wavelength range of 380-700 nm (Ellis et al., 2013) (Figure 2.2). The blue-green spectrum is at its highest intensity during the day, while vanishing in the afternoon. In the late afternoon natural light turns into a red-orange color and goes to darkness at night (Ellis et al., 2013). In addition to visual information from the environment, light provides data on the timing as well as intensity of brightness and darkness in order to regulate biological rhythms of the body (Ellis et al., 2013). Where lack of a proper amount of daylight upsets circadian rhythms, this can consequently increase SAD effects (Edwards and Torcellini, 2002; Tregenza and Wilson, 2011). Because SAD has been one of the most researched areas related to well-being of humans in buildings, researchers have concluded that natural light can play a vital role in preventing and curing SAD (Edwards and Torcellini, 2002; Tregenza and Wilson, 2011).

Many studies argue that people perceive daylight to be more pleasant than electric lighting in terms of their primary source of light (Edwards and Torcellini, 2002). These studies have shown that employees are more productive and happier in daylit than artificial-lit spaces (Ellis et al., 2013). The body of literature presented here confirms the significance of daylight quality and research into daylighting topics. Because of the importance of daylighting, researchers attempt to assign measures to daylighting qualities in order to assess them.

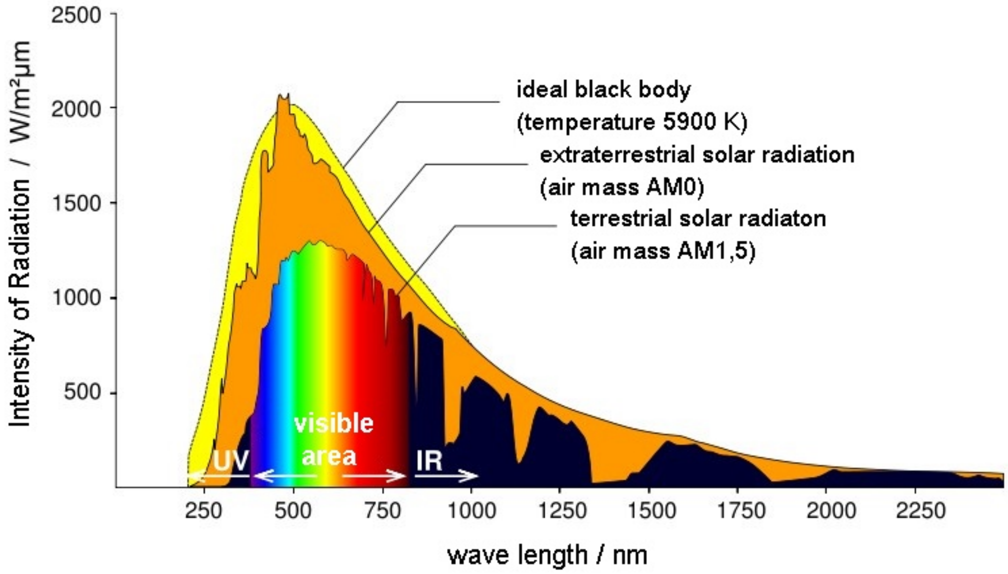

Figure 2.2: Situation of Visible Light in Solar Radiation and Situation of Blue Light in Visible Light Spectrum (Fondriest, 2017)

2.2.2 Financial Gain (Productivity)

Increased performance of occupants brings about financial savings, which motivates owners to invest in daylighting strategies. The quality aspects of daylighting problems can only be measured through experimentation and case studies, such as on-site or online surveys (Boyce et al., 2006; Heschong Mahone Group, 1999). The following paragraphs present a variety of case studies prepared by different agencies.

The Heschong Mahone Group conducted several studies on daylight and its impact on productivity for different building types. They studied the impacts of windows in two offices, considering view, daylight, and glare. Glare potential from windows was found to have the worst influence on employees' performance, lowering it by 15% to 21% (Heschong Mahone Group, 2003). In contrast, views were shown to improve mental and memory function by

10% to 25%. Horizontal daylight illuminance resulted in inconsistent impacts on the different performance metrics. However, it was reported that daylight boosted the performance metrics of attention span and short-term memory (Heschong Mahone Group, 2003). Considering the overall impacts of windows Heschong Mahone Group concluded that windows improve workers' productivity by 2−5%. The group also analyzed the impacts of skylights on sales performance of retails. One hundred eighty stores were studied out of which two thirds had skylights and the rest did not. A typical store without skylights would increase sales by 40% with the addition of skylights (Heschong Mahone Group, 2003).

Table 2.1: Different Productivity Rated in Different Projects Where Daylighting Was One of Energy Efficient Strategies

Projects	**Increased Productivity (%)**	**Reported by**
Offices	2-5%	Heschong Mahone Group
Retails	40%	Heschong Mahone Group
Walmart	NA	Cool Companies and Romm and Browning Report
Pennsylvania Power and Light	13.2%	Romm and Browning Report
VeriFone, Inc.	5%	Cool Companies
Lockheed Martin	15%	Romm and Browning Report
Schools	14%	Cool Companies
Prince Street Technologies	$100,000 to $200,000	Cool Companies

The Non-Profit Center for Energy & Climate Solutions' Cool Companies reported on several case studies considering daylight on productivity. For renovation, a series of skylights were added to VeriFone, a subsidiary of Hewlett-Packard in Costa Mesa, Calif. Employees reported less complaints about headaches or sluggishness. The study shows that absenteeism was reduced by 40−45% and productivity increased by 5%. In another project, 32 skylights were added to Prince Street Technologies, a subsidiary of Interface Carpet, in Cartersville, Georgia. The company reported a significant drop in workers' compensation cases. It changed from 20 cases per year to under one case per year resulted in savings of $100,000 to $200,000 a year. In addition, the presence of daylight in classrooms has been appreciated for years. Cool companies reported that students performed 14% better on standardized tests in day-lit than non-daylit schools in North Carolina (CoolCompanies, CoolCompanies).

Increased productivity has also been reported for cases where daylighting was one of the implemented efficient strategies. Romm and Browning, in 1994, documented several projects in which energy efficient strategies, including lighting, also increased the productivity of employees. In one case, Lockheed office building in Sunnyvale, California approached energy efficiency by implementing several daylighting strategies. Fifteen foot-high windows with sloped ceilings brought daylight deep into the space. In addition, the building took advantage of daylighting through a central atrium and poured daylight deeper into the space by implementing light shelves on south windows. These daylighting strategies saved 75% on lighting bill. The energy savings in this project were nearly $500,000 a year, which would have covered the $2 million energy-efficient improvements in about four years. In fact, the company also reported that absenteeism dropped by 15% and productivity increased by 15%, and this lower absenteeism and higher productivity paid off the extra cost of energy-efficient improvements in the first year (Romm and Browning, 1994).

Pennsylvania Power & Light is another project reported by Romm and Browning, where daylighting strategies were implemented for the building's renovation. The company reported absenteeism rates dropped by 25%, productivity increased 13.2% and energy costs declined by 69%. Energy savings were primarily estimated for a four year payback. However, after productivity and absenteeism were factored in, the renovation paid for itself in 69 days.

Walmart also installed skylights in half of on its store in Lawrence, Kansas. Using a real-time inventory system, it was found that sales skyrocketed in the daylit half of the store (Romm and Browning, 1994).

Although all these case studies confirmed that daylight availability increases the occupants' performance, the increased productivity rate varied over a wide range. Productivity is a multi-faceted subject that depends directly and indirectly on many factors, including time of the year, personal mood, thermal and visual comfort, social settings and the environment (Heerwagen, 2011). In studying daylight impacts on employees' performance, it is challenging to isolate the impacts of daylight from other relevant factors, and take into account the ramifications of the apertures' presence, including view, glare and natural ventilation. In addition to the multi-faceted nature of the problem, the methods used to measure performance were different case by case, which led the productivity results to differ. Therefore, these studies do not point to a specific value as an indicator of productivity rate but they all agree that the presence of daylight improves workers' performance.

This increased productivity rate is associated with different absolute values, depending on annual revenues of offices. In other words, the weight of productivity depends on the context where daylighting strategies are implemented. In many case studies the energy savings were outstripped by the reward of boosted productivity (Edwards and Torcellini, 2002). Yet, in spite of the proven financial benefits of daylighting, this aspect does not play any role in design decisions in current practice. Therefore, this dissertation applies productivity rate as one of several motivating factors that can shift our decisions from one design alternative to another in the preliminary stage of design. However, studies demonstrate that "simply providing daylight is not a guarantee of success" (Boyce et al., 2006). Too much daylight can increase thermal heat gain and glare, which eventually disrupts the performance of occupants. Whether daylight effects are positive or negative depends on how they are delivered (Boyce et al., 2006). Effective daylighting provides an even distribution of daylight and a view to the outside (especially one featuring greenery), and limits glare and thermal heat gain (Edwards and Torcellini, 2002). Appropriate metrics can address the question as to how much daylight is enough. These are explained in the following sub-section.

2.2.3 Daylight Metrics

Over the past decade, the architecture industry has experimented with many metrics. The main reason why metrics and their thresholds have changed is because daylighting satisfaction is a sensation. As a result, the daylight metric and its threshold have been verified by on-site experimentation. Daylighting design depends on factors such as location, climate, building orientation, reflection, materials, space arrangements, and age of occupants. These factors show that daylight metrics should consider context. Common daylight metrics such as DF are independent of contextualized factors like the age of occupants. Studies show that older people need more lighting and are less sensitive toward brightness contrast (Wienold, 2009). However, this factor has rarely been addressed in daylight metrics. Although such context dependency makes it challenging to evaluate daylighting, in practice, common daylight criteria are regulated by institutions such as Illuminating Engineering Society of North America (IESNA), International Commission in Illumination (CIE) and LEED.

The existing practice and research has divided daylight measurements into two major categories: horizontal light, as the received "amount" of light on the desk, and visual "comfort", such as lack of glare. In recent years the profession has moved toward dynamic illuminance metrics, which are location-based (using actual weather data similar to energy modeling tools) and annualized (summarizing performance over the entire year) (Nabil and Mardaljevic, 2006). The following list summarizes horizontal daylight metrics that are commonly used.

- **Illuminance (lux):** The amount of light (luminous flux, lumens) divided by the area on which it falls (lux) (Hausladen et al., 2008) (Figure 2.3).
- **Daylight Factor (DF):** The ratio of inside illuminance at a point of interest to the unobstructed, horizontal illumination under the CIE overcast sky (Tregenza and Wilson, 2011).
- **DA:** The percentage of annual occupied hours when daylight meets a minimum illuminance threshold (Reinhart and Walkenhorst, 2001).
- **DA$_{\mathbf{max}}$:** The percentage of annual occupied hours when the illuminance level of daylight is 10 times higher than the required light level. The intent is to estimate overall hours with potential glare incidents (Rogers, 2006).
- **Continuous Daylight Autonomy (CDA):** A variation of DA that takes into account spaces that are not fully saturated but contribute to daylight availability. It assigns partial credit in a linear fashion to values below required daylight threshold (Rogers, 2006).

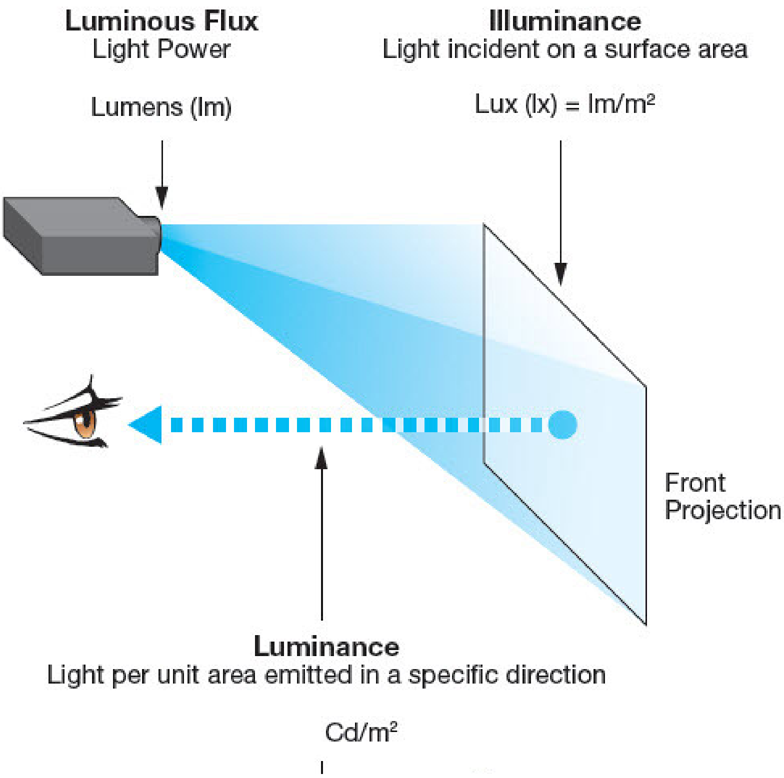

Figure 2.3: Illuminance and luminance (ExtronElectronics, 2003)

- **spatial Daylight Autonomy (sDA):** The percentage of floor area that receives sufficient daylight for at least 50% of the annual occupied hours (Nabil and Mardaljevic, 2006).

- **Useful Daylight Illuminance (UDI):** The percentage of floor area that meets an illuminance range of 100 and 2,000 lux for at least 50% of occupied hours (Nabil and Mardaljevic, 2006).

- **annual Sunlight Exposure (aSE):** The percentage of floor area that receives at least 1,000 lux for at least 250 occupied hours per year. The intent is to estimate how much of space receives excessive sunlight, which can entail visual discomfort (glare) (Heschong and Wymelenberg, 2012).

The threshold of each metric has also been changed because different functions and modern equipment like computers require different light levels. Different functions need different thresholds; the light level necessary in a classroom is different from that in a corridor. In addition, one of the many socio-technological reasons that building codes are changing their lighting requirements is because new types of equipment have been added to rooms that needed different light settings. For example, IESNA's office substituted light levels of 300-500 lux for 750-1,000 lux (Dilaura et al., 2011). One of the reasons for such a change is because current office operations primarily involve computers, which lead to a reduction of overhead lighting due to the self-luminosity of computer screens (Tregenza and Wilson, 2011). Another example is the inclusion of adaptive lighting technologies in California's Title 24 building standards in 2013. This new technology provides lighting comfort for different users or requirements by automatically dimming or shutting off light when it is not needed (Siminovitch, Siminovitch). In addition, although all of the metrics and thresholds mentioned so far are related to horizontal lighting, many state that horizontal lighting is not a good predictor of lighting quality (WGBC, 2016).

Effective design of daylighting depends on a lower incidence glare in the field of view, which is optical noise masking information (Tregenza and Wilson, 2011). Glare is a subjective human sensation describing the situation where the eye cannot adapt the brightness distribution (Hausladen et al., 2008). Since glare is based on human sensations, it has been very difficult to define an indicator or formula to predict glare discomfort.

In current practice, glare potential has been estimated by horizontal illuminance and luminance. The upper limit for horizontal illuminance level has been a subject of scholarly debate, as 2,000 lux is suggested by Nabil and Mardaljevic and also by Olbina and Beliveau (Nabil and Mardaljevic, 2006; Olbina and Beliveau, 2009), while Mardaljevic and Heschong suggest 2,500 lux (Mardaljevic et al., 2009); however, David et al. propose a much higher limit of 8,000 lux (David et al., 2011). Recently Wymelenberga and Inanicib found that some individuals become accustomed to or even prefer illuminance as high as 5,000 lux (Wymelenberg and Inanici, 2014). They found that glare is more probable in scenes with more than 5,000 lux (Wymelenberg and Inanici, 2014). The common practice currently applies 2,000 lux as the horizontal upper bound of illuminance; however, the current scholarly research is developing a more appropriate illuminance-based metric with a threshold that confidently predicts uncomfortable glare.

Although horizontal lighting has been used for glare prediction due to its ease of calculation and measurement, glare, is, in fact, a function of the luminance (brightness), which is a distribution of light in a very specific view direction (Hopkinson, 1972) (Figure 2.3). Glare metrics related to brightness in the field of view are called luminance-based metrics. The most commonly-used luminance-based metrics are Daylight Glare Index (DGI), Daylight Glare Probability (DGP) and luminance ratios, which are explained as follows:

- **Daylight Glare Index (DGI):** DGI was developed in 1972 by Hopkinson based on on-site studies in daylit interiors and is a function of the visible sky brightness and its size (Jakubiec and Reinhart, 2012). DGI sums the glare contribution of each bright source as shown in the following equation:

$$DGI = 10\log_{10} 0.478 \sum_{i=1}^{n} \frac{L_{s,i}^{1.5}\Omega_{s,i}^{0.8}}{L_b + 0.07\omega_{s,i}^{0.5} L_{s,i}} \tag{2.1}$$

where: L_s is luminance of source, ω_s is solid angle of source, L_b is background luminance and P is the position index.

The thresholds of glare sensibility for DGI are defined in the following table:

Table 2.2: DGI Subjective Ratings

Subjective Rating	DGI Range
Imperceptible Glare (%)	< 18
Perceptible Glare (%)	$18 - 24$
Disturbing Glare (%)	$24 - 31$
Intolerable Glare (%)	> 31

- **Daylight Glare Probability (DGP):** Proposed in 2006 by Wienold, it is a modified version of DGI developed based on on-site tests. The main modification is that DGP includes vertical illuminance at the eye (Jakubiec and Reinhart, 2012).

$$DGP = c_1 E_v + c_2 \log\left(1 + \sum_{i=1} n \frac{L_{s,i}^2 \omega_{s,i}}{E_v^{a_1} P_i^2}\right) + c_3 \tag{2.2}$$

where: L_s is luminance of source, ω_s is solid angle of source, E_v is vertical Eye illuminance, P is the position index, C_1 is 5.87×10^{-5}, C_2 is 9.18×10^{-2}, C_3 is 0.16, and a_1 is 1.87.

The thresholds of glare sensibility for DGP are defined in Table 2.3:

- **Luminance Ratios:** Glare can be identified through luminance assessment of source, task area, and contrast of task and source (Suk, 2014).

Table 2.3: DGP Subjective Ratings

Subjective Rating	DGP Range
Imperceptible Glare (%)	$< 35\%$
Perceptible Glare (%)	$35 - 40\%$
Disturbing Glare (%)	$40 - 45\%$
Intolerable Glare (%)	$> 45\%$

Many institutions and researchers, including NUTEK (the Swedish National Board for Industrial and Technical Development), suggest conflicting thresholds for luminance in a field of view and in a background, such as the luminance contrast ratio between a task/source and background (Suk, 2014). While the most recognizable suggestion is a 1:3:10 ratio among task, immediate surroundings, and remote surfaces, Suk claims that glare is a function of both the luminance ratio of task and glare source as well as the luminance range of the glare source. Based on his on-site analysis and simulation results, he found that when the occupants have a writing task, the imperceptible and disturbing levels of glare occur if the luminance values of the glare source are below 1,921 and above 5,014 (cd/m2), respectively. In addition, he also noticed that the ratio of task and glare source matters. The glare is imperceptible when the glare-luminance ratio of task and glare source is 1:12 and disturbing glare occurs when this ratio is 1:22 (Suk, 2014). Suk proposed an equation for glare mixing the two factors of absolute luminance and ratio of glare source as follows:

$$GlareLevel_{typingtask} = 0.496 + 0.000244 \times L_s - 0.0310 \times R_t \qquad (2.3)$$

where: L_s is glare source luminance, R_t is the ratio between task mean luminance and glare source luminance (Suk, 2014).

Table 2.4: Subjective Ratings for Suk's Glare Metric

Subjective Rating	Glare Range
Imperceptible Glare (%)	< 0.59
Perceptible Glare (%)	$0.59 - 1.03$
Disturbing Glare (%)	$1.03 - 2.36$
Intolerable Glare (%)	> 2.36

Table 2.4 shows the thresholds for the glare metric proposed by Suk. Although luminance ratio and the new glare metrics seem promising, currently there is not yet a software tool to automatically detect all glare spots based on luminance ratios.

Although two commonly-used metrics of glare are DGI and DGP, studies show that even these cannot predict all glare incidents in different scenes (Suk and Schiler, 2013). DGI is not considered to be reliable in the presence of direct light or specular reflections (Jakubiec and Reinhart, 2012). In contrast, DGP not only covers the gap error of DGI, it also considers vertical illuminance at the eye (Jakubiec and Reinhart, 2012). Many studies have reported that DGP outperforms DGI and it is perhaps considered to be the most robust and reliable luminance-based metric for predicting glare; yet it still suffers from some disadvantages. DGP lacks differentiation between a large source with low luminance and a small source with high luminance, since both represent the same vertical illuminace at the eye (Suk and Schiler, 2013). In addition, Wymelenberga and Inanicib point out that DGP results in low values, which underestimates glare incidence in scenes (Wymelenberg and Inanici, 2014). Finally, it was found that DGP can not accurately estimate glare probabilities, especially if the sun appears in the task region of view (Wymelenberg and

Inanici, 2014). A new study shows that the 40° horizontal band is the best view region to study glare based on luminance assessment (Wymelenberg and Inanici, 2014). Due to the conflicting results and shortcomings of illuminance- and luminance-based methods, more empirical research is needed to establish appropriate metrics to assess glare in day-lit buildings.

While glare metrics are under investigation in research institutions, glare does not yet play any significant role in design, despite the fact that glare causes visual discomfort, decreases the well-being and health of occupants, and lowers their productivity (Edwards and Torcellini, 2002). Although current metrics are not robust, DGP and UDI are considered the most trustworthy glare metrics that are currently available in software tools. These metrics cannot predict all possible instances of uncomfortable glare but they can diagnose designs that suffer from seemingly excessively glaring scenarios or excessive daylight that increases the probability of glare. As a result, glare analysis with the current metrics can help to design space without extreme glare possibilities and thus, consideration of glare should be part of the preliminary stage of design.

In addition to quality and metrics, daylighting influences a building's electrical lighting, heating, and cooling loads. In the following section I explain the recent research in this area and the current gap in this body of literature.

2.3 Quantitative Aspects of Daylight (Energy Consumption)

Moving toward minimizing an environmental footprint, researchers have conducted studies related to daylight and energy efficiency which can be subdivided into two major categories: studies of sidelights and individual case studies of toplights. The first subsection summarizes the studies of sidelights, including windows and their impacts on lighting and HVAC loads. The second subsection reviews toplights and their energy performance. Both categories include studies regarding integration between daylighting and energy simulation tools for a specific case with a pre-defined location, function and form.

2.3.1 Sidelights and Energy Efficiency

Development of new integrative simulation tools entails studies of sidelights and their impacts on electrical lighting and HVAC loads (Bodart and Herde, 2002; Superlink, 1993; P. Ihm, 2009; Li and Wong, 2007; Yangi et al., 2010; Reinhart and Wienold, 2011; Li et al., 2008). These studies have estimated lighting savings in a range of 20−77% (Bodart and Herde, 2002; Superlink, 1993; P. Ihm, 2009). Li and Wong used EnergyPlus and its embedded Radiosity lighting tool to evaluate energy performance of an existing building in Hong Kong (Li and Wong, 2007). It was found that if a lighting control system was applied, 25% of electrical lighting consumption could be saved, which is 8.6% of total building energy consumption (Li and Wong, 2007). This saving would be lower if the nearby buildings and their shading were considered (Li and Wong, 2007). In another study, Li et al. used the same tool to build a regression model and estimate the annual lighting energy for the following variables: Window to Wall Ratio (WWR), light transmittance of the window, and the width of overhangs and fines (Li et al., 2008). In addition, Yangi and Nam used a combination of 3D Max 8.0 Radiosity and DOE-2.1 E to predict daylight performance and study an application of an on/off lighting control system in energy consumption for an existing office building in Seoul (Yangi et al., 2010). The result showed that electrical lighting loads could be reduced by 32.9%, 31% and 27.5% for WWRs of 100%, 80% and 60%, respectively (Yangi et al., 2010). In a very comprehensive analysis Reinhart and Wienold developed a daylighting dashboard that integrated Ecotect and DesignBuilder simulation tools and analyzed the impact of south facing windows in a Boston climate for an office room (Reinhart and Wienold, 2011). The energy and glare performance were studied in addition to the occupants' behavior. The results of energy performance measurements showed that external blinds lowered the electric lighting and cooling loads while significantly increasing the heating load (Reinhart and Wienold, 2011).

2.3.2 Toplights and Energy Efficiency

The second category of literature focuses on studies on toplights, using a range of different methods, tools, and functions while carried out in different climates. In 2008 the U.S. Department of Energy conducted a report on energy efficiency of different toplighting configurations in different climates (Yoon et al., 2008). This report coupled a lighting rendering software tool (Radiance) with building energy simulation software DOE 2.1E (Yoon et al., 2008). However, the research was based on a problematic assumption: they sized the glazing area to meet 2% Daylight Factor (DF), the requirement of LEED at that time (v2) (Yoon et al., 2008). However, DF is an incorrect metric for an 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).

Instead of using DF, other toplight studies have considered horizontal illuminance [lux] as a daylighting metric. In 2012, Motamedi analyzed the energy efficiency of different toplights (sawtooth, skylight and monitor roofs) via IES-VE PRO - an integrative tool of Radiance and Apache - for offices in Austin (Motamedi, 2012a). She concluded that regarding the site energy a proper toplighting strategy could save electrical lighting loads by up to 70% over the course of a year, with a smaller impact on heating and cooling loads. This study did not calibrate the shapes of toplights in order to optimize energy efficiency, nor did it consider different climates (Motamedi, 2012a). In 2013, as reported in several publications, Ghobad et al. studied monitor-roofs and skylights for offices in the climates of Boston, Miami and Charlotte (Ghobad et al., 2013a,b). They applied Diva software - an integrative tool of Radiance and EnergyPlus - and defined the illuminance target as 300 lux. Compared to other studies, Ghobad et al. simulated a larger, but still limited cases of toplighting configurations in a few climates. In addition, Chen et al. used EnergyPlus and its embedded Radiosity tool to consider the impact of skylights. They also studied the effect of different lighting control systems, including on/off and dimming systems, on energy consumption for an industrial building in Tianjin, China (Chen et al., 2014). The results showed that skylights could decrease the total energy consumption by up to 36% and 41.5% for the on/off and dimming control systems, respectively (Chen et al., 2014). The extant literature about toplights has confirmed the significant role of toplights in saving energy; however, its result cannot be applied to other cases with different contexts, having various building shapes, climates and functions.

In 2014 Energy Design Resources published a comprehensive report, “Skylighting Design Guidelines”, which explains how to integrate skylight design with other building elements, including glazing types, roof structure, insulation, shading devices and daylight control systems. It also applied *Skycal* to estimate potential energy savings. It implemented Parametric Analysis for an SFR range of 0−12% and calculated energy savings for an office building in San Bernardino, California (EnergyDesignResources, EnergyDesignResources). The model consumed a lighting power density of 0.75 watt/sqft with a target illuminance level of 500 lux and it applied a dimming control system (EnergyDesignResources, EnergyDesignResources). The study also considered different climates, glazing types and control systems. The final result showed that the most energy efficient optimal solution shifts from 2.5% to 4% if climate is changed from San Bernardino to San Francisco (EnergyDesignResources, EnergyDesignResources). While this report provides significant applicable information about skylight design, its result is based on total energy performance excluding daylight and glare performance. *Skycal* is a simple spreadsheet in Microsoft Excel tool which facilitates skylight design decisions. Its energy engine is DOE-2.1E which applies the Split-flux method for daylight performance. The DOE-2.1E hast its own shortcomings when it comes to simulating daylight performance. It only uses CIE overcast and clear skylights which do not represent real sky conditions (Kota and Haberl, 1969). It considers all surfaces as perfectly diffuse reflectors and lacks the ability to consider different optical surfaces (Kota and Haberl, 1969). Due to these limitations, DOE-2E cannot properly simulate reflective surfaces such as light shelves and reflection from adjacent buildings, complex fenestration systems or an atrium (Kota and Haberl, 1969).

While all studies in both the first and second categories agree that even distribution of daylight can save electrical lighting loads beyond its possible negative impacts on thermal loads (Motamedi, 2012a; Ghobad et al., 2013a; Yoon et al., 2008; Ghobad et al., 2013b), the extant literature shows different thermal load changes. Heating loads can be increased by admitting daylight

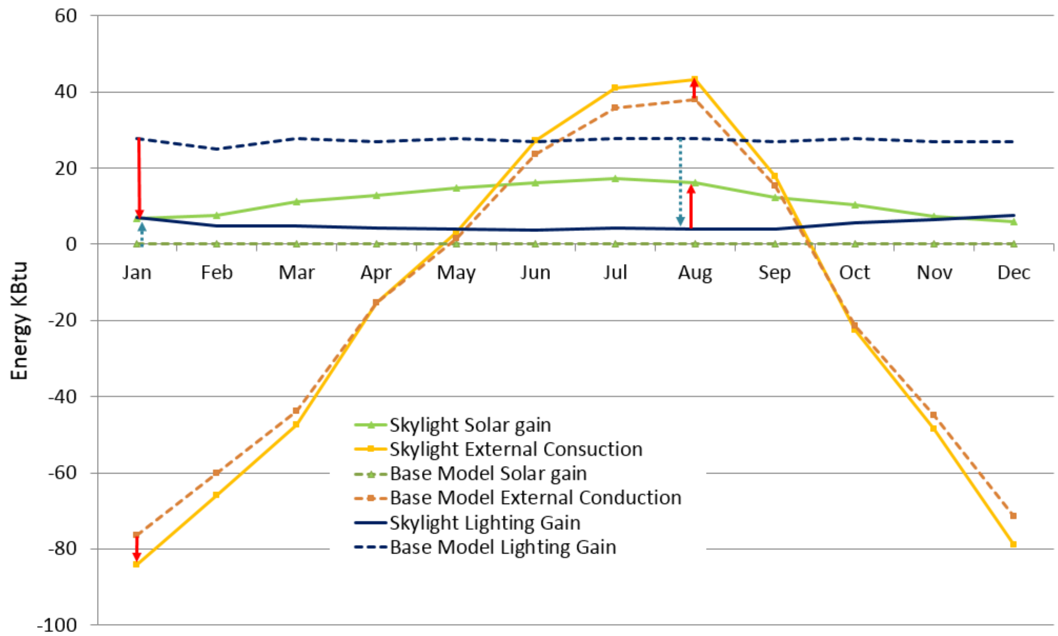

Figure 2.4: Comparison of Solar Heat Gain, External Conductance and Electrical Heat Gain between Skylight and Base Models. Solid Red and Dashed Blue Arrows Indicate Increase and Decrease in Building Energy, Respectively (Motamedi, 2012a)

into a space and its subsequent reduction of electrical lighting (Motamedi, 2012a; Yoon et al., 2008; Ghobad et al., 2013b); however, it may or may not increase cooling loads. Motamedi and Ghobad et al. studied the dynamics between daylighting through toplights as well as thermal and lighting loads in different climates (Motamedi, 2012a; Ghobad et al., 2013b). Compared to a base model with no skylights Motamedi concluded that 5% SFR does not change cooling loads in a hot climate like Austin (Motamedi, 2012a). In addition, Ghobad et al. showed that any SFR smaller than 3.5% decreases cooling loads in Miami and Boston while SFRs above 3.5% increase cooling loads in these climates (Ghobad et al., 2013b). In addition to the impacts of toplights on cooling loads, the studies mentioned in this section illustrate that heating loads are increased regardless of SFR (Motamedi, 2012a; Ghobad et al., 2013b). To explain the impacts of adding skylights on HVAC loads, Motamedi prepared Figure 2.4 to study the monthly internal heat gain of electrical lighting, external conductance and solar gain, the sum of which defines heating and cooling requirements (Motamedi, 2012a). In Figure 2.4 red arrows show the negative impacts of changes on HVAC loads while blue arrows represent the positive impacts for heating and cooling seasons. Toplighting strategies with dimming control systems decrease electrical lighting loads, which subsequently reduces internal heat gain (Motamedi, 2012a). However, adding skylights increases solar heat gain and external conductance. In winter, the positive impact of increased solar heat gain cannot outweigh the negative impacts of the reduced internal heat gain and increased external conductance (Motamedi, 2012a) (Figure 2.4). Hence, heating loads are increased by adding any skylight. In summer, depending on the climate and SFR, the positive impact of reduced internal heat gain may be offset by negative impacts of increased solar heat gain and external conductance (Motamedi, 2012a) (Figure 2.4). As a result, cooling loads can only be reduced up to a certain SFR threshold. Whether or not cooling loads are increased, the adverse effects of skylights on HVAC loads can be compensated by significant savings in electrical lighting loads (Motamedi, 2012a; Ghobad et al., 2013a; Yoon et al., 2008; Ghobad et al., 2013b). To what extent SFR can be increased to still save total energy consumption needs a further study of the trade-offs between electrical lighting and thermal loads.

2.4 Optimization Methods

The fourth category of literature includes recent attempts to optimize building parameters which provide methods and inputs for the interest of this study. Inclusive optimization of fenestration calibrates configurations of fenestration in order to minimize thermal and lighting loads and maximize daylight performance. The most common methods used to optimize fenestration have been GA and Parametric Analysis. In the following sections I present state-of-the-art studies in regard to optimization.

2.4.1 Parametric Analysis

Parametric Analysis is an exhaustive search that considers all possible fenestration sizes with constrained resolution. Goi et al. conducted research to optimize WWR for a typical two-storey office building in a temperate oceanic climate (Goia et al., 2013). They used EnergyPlus for estimating both thermal and daylighting performances. They conducted a Parametric Analysis simulating several WWRs and compared them based on their total energy performances. This paper concludes that while an optimal WWR is in the range of 35-45%, WWR has a low impact on the total energy performance of a building (Rakha and Nassar, 2011).

In another Parametric Analysis, Ochoa et al. applied multi-objective optimization to narrow down WWR for an office building in Amsterdam, the Netherlands (Ochoa et al., 2012). They simulated both daylight and energy performance via EnergyPlus. They included total energy performance (kWh/sqm), daylight uniformity, DGI for 50% of occupied hours and DA with a 500 lux target for 50% of occupied hours. The WWRs were studied in a range of $0-100\%$, with 10% resolution (0, 10, 20, ..., 100). More than one possible solution was proposed. However, the authors raised a concern about the weight of each design criterion, as they did not apply the weighting technique (Ochoa et al., 2012). Moreover, the study did not offer any guide as to how to implement scaling in the optimization process, leaving the subject for future studies. There were also some major shortcomings with the method of this research. EnergyPlus is a trustworthy tool to assess energy performance; however, EnergyPlus embeds Radiosity as a daylgith engine, which cannot outperform its competitor tool Radiance. Radisoity only considers perfectly diffuse reflectors and cannot fully simulate bounces of light from surfaces. This subject is covered in section 3.3.5. Moreover, DGI as a glare metric is not the best metric available in the profession, because studies have shown that DGI performs worse than DGP as a luminance-based metric of glare. In addition, the applied Parametric Analysis has a very low resolution in finding the optimal WWR (10%). This Parametric Analysis only coarsely assessed optimal solutions.

2.4.2 Genetic Algorithm (GA)

Recently researchers have optimized design parameters and energy performance of fenestration by implementing different optimization algorithms. Genetic Algorithms (GAs) have been used more than any other method in the field of building design optimization (Rakha and Nassar, 2011; Caldas and Norford, 2003). GAs find the fittest solution through principles of evolution by randomly selecting its initial population, evaluating its performance by fitness functions, reselecting the successive generation population by mating the predecessor individuals or randomly modified predecessor individuals (Caldas and Norford, 2003).

Rakha et al. applied GA as a performance-driven method in order to find the appropriate shape of a ceiling regarding optimizing daylight performance (Rakha and Nassar, 2011). The proposed method in this paper considered reflective and diffusive impacts of the ceiling on interior illuminance (Rakha and Nassar, 2011). While Rakha et al. only used a GA for daylight performance, Caldas et al. implemented this algorithm for optimization of fenestrations, building forms and HVAC systems in order to minimize energy consumption (Caldas and Norford, 2003). In their study both lighting and thermal simulations were simulated by DOE2.1E, which calculates daylighting based on the DF method (Caldas and Norford, 2003). As mentioned at the beginning of this section, DF is not an appropriate metric for annualized and climate-based daylight simulations. In 2013 Trubiano et al. applied a GA to perform single-objective optimization and to find the optimal atrium based on total energy consumption. The GA was scripted in Matlab to integrate Grasshopper with Radiance and EnergyPlus (Trubiano et al., 2013a).

Although use of GAs 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 a GA, is a Grasshopper plug-in component, which was proposed by David Rutten (Rutten, 2010a). It uses the same theory as GAs but it offers a user-friendly interface which facilitates its application among professionals who may not have extensive programming and mathematical knowledge.

Sheikh and Gerber applied Galapagos to optimize louver positions in front of windows, based on daylight performance. Diva was used with Galapagos. Three main design criteria were applied: 75% of the space achieves useful illuminance range (200-1,500); the highest and lowest luminance values in the field of view should not exceed a 1:10 ratio and the area deep in the room should receive an acceptable illuminance range (Sheikh and Gerber, 2011). Their study was one of the initial attempts to optimize design based on daylight performance by incorporating an optimization algorithm into the design decisions. It should be noted 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 target of 500 lux for 50% of the time. Two cases were 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 showed that the near optimal solution(s) was found for case one which represented better daylight performance. However, the researcher speculated that in the second case Galapagos proposed optimal solutions that may not provide better daylight performance compared to other solutions (Gadelhak, 2013). It was pointed out that Galapagos needs to be fed with limited variables to provide more precise and robust optimal solutions (Gadelhak, 2013).

Another study using Galapagos was performed by Gonzlez and Fiorito, where they optimized external solar shadings and defined the target daylight level as 320 lux. The result of Diva was fed into Galapagos for GA optimization. Diva embeds EnergyPlus and Radiance as its thermal and daylight engines (Gonzlez and Fiorito, 2015). As the fitness function of the GA was to minimize CO_2 emissions, the optimization process in the study was not set to maximize daylight performance. In a more extensive study, Shi and Yang developed three Grasshopper components as plugin tools for Ecotect, Radiance and EnergyPlus. Integrative methodologies were proposed to run Ecotect, Radiance and EnergyPlus whithin the Grasshopper environment. The researchers intended to plug the analyzing tools into the Grasshopper environment and to feed their results into Galapagos for optimization (Shi and Yang, 2013).

They studied three separate cases: an optimal complex geometry of a roof to maximize insolation, an optimal window design to maximize daylight performance, and an optimal window design to minimize energy consumption (Shi and Yang, 2013). They stated that they studied single-objective optimization and concluded that integration between different software tools within Grasshopper is needed to solve complex and multi-faceted design questions. This task requires an extensive knowledge about programming (Shi and Yang, 2013). They highlighted the gap between architecture and coding, which slows down integration of many tools. This gap raises challenges of assessing performance of more design variables to find more highly informative decisions (Shi and Yang, 2013).

2.4.3 New Approaches

Besides GAs and other algorithmic platforms embedding GAs, Futrell et al. recently applied the GenOpt[1] tool and its different embedded algorithms to allow for integration of Radiance and EnergyPlus as well as optimization of fenestrations (Futrell et al., 2015; Genopt, 2017). They investigated the performance of fenestrations including a clerestory type with a strip of window for a classroom in Charlotte's specific climate (Futrell et al., 2015). Futrell et al. used Radiance in conjunction with EnergyPlus to compute daylight and energy performance. They first optimized the size of fenestrations, based on daylighting performance, and then minimized the thermal loads of the best daylighting scenario by adding longer overhangs and lowering Solar Heat Gain Coefficients (SHGC) (Futrell et al., 2015). These strategies to decrease

[1]GenOptis an optimization program for the minimization of a cost function that is evaluated by an external simulation program, such as EnergyPlus, TRNSYS, Dymola, IDA-ICE or DOE-2.

thermal loads are parameters of design, which can subsequently impact both electrical lighting and thermal loads. However, in this study the influence of these parameters on electrical lighting loads was ignored. Thus, this study was not able to address a cohesively integrated optimization of fenestration because the daylighting and energy simulations were studied in isolation.

2.5 Literature Review Conclusion

Although GAs and Parametric Analysis have been adopted by many researchers to optimize building parameters, they have some shortcomings for the holistic optimization of skylights. Parametric Analysis is the easiest method, as it considers all the possible scenarios, but this means it is time consuming and computationally expensive. In addition to Parametric Analysis, the GA, more than any other method, has been used in the field of building design optimization (Rakha and Nassar, 2011; Caldas and Norford, 2003). The solving time is also one of the GA's shortcomings, since for a good quality solution a GA needs a decent sized population. The 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). This is backed up by some studies showing that Galapagos needs to be fed with limited variables (Gonzlez and Fiorito, 2015; Gadelhak, 2013). This highlights the limitation of the GA method in optimization of building parameters.

Currently, the previously mentioned studies on toplights or fenestration optimization do not provide a sound algorithmic platform that can tease out the feasibility of holistic toplighting optimization. A proportion of the existing studies have investigated toplights as individual case studies, by using integrative tools such as IES-VE PRO and Diva. Their results have context-dependency and are not applicable to other cases with different lighting powers, materials, climates, footprints, fenestration forms, or daylighting thresholds. Some studies exist that provide an algorithm to be applicable for future cases; however, the algorithm was only designed for single-objective optimization by optimizing either energy or daylight performance. Another deficiency was that most existing studies neglected glare as a design parameter. They did not combine the glare factor with other design criteria, including daylight availability and energy performance. The very limited number of studies that offered a role to glare applied an inappropriate metric, such as DGI, which has been shown in many studies to be not the best luminance-based glare metric. In regard to integration, the current studies lack a clear road map, laid out step by step, to incorporate daylight and energy engines which can be repeated by other researchers. Such an open source platform is necessary to advance academic research and invite participation of more professions across different fields in the building industry, which will eventually enhance the development of that platform. Although Diva and IES-VE Pro tools embed daylight and energy engines and are able to couple the results of daylight and energy engines, they are commercial packages which do not offer a free platform.

This study, however, has developed an algorithmic platform that is integrative and can find a robust skylight solution for any design and climate. One of the goals of this study is to provide a free resource while revealing the integrative algorithm and optimization approaches. This dissertation has examined different approaches to optimize skylights considering daylight availability, energy consumption, glare and productivity. These approaches utilized Parametric Analysis and the gradient descent optimization method, which has been used for the first time in optimizing fenestration. The next chapter explains the methods and methodology that have been used in this study.

Chapter 3

Methodology and Methods

Before establishing any system of methods to produce knowledge, in this chapter I first explain the hybrid paradigm, or the "basic set of beliefs" and approaches upon which this study is founded (Guba and Lincoln, 1994). I, then, describe why the ontology of this paradigm suits my dissertation. I explain the way in which the research methodology entails the inclusion of different voices. This involves establishing an algorithmic platform by applying three approaches in order to include the interests of different groups such as glare, energy, daylight availability and productivity. The platform was thus designed to be dynamic by including and scaling the mentioned interests, as well as requiring minimum qualities and meeting performance targets. This dynamic platform differs from the static approach suggested by ASHRAE[1] standards, which only focus on energy consumption. In this research, three different approaches are applied to ensure the interests of these voices play their roles in finding a solution. The first approach is a weighting system that assigns different importance to each interest, based on the project at hand. The second approach is a conditional hierarchy that searches for a solution by satisfying minimum requirements. The third approach considers the monetary benefits from installing skylights. I will support the applied methodology proposed in this research by comparing daylighting designs for a high-tech

[1] American Society of Heating, Refrigerating and Air-Conditioning Engineers

company and a storage space. After outlining the methodology platform of my research, I consider the quantitative methods required to tackle the question of toplighting, including a literature review, simulation and coding.

3.1 Methodology

For this dissertation, I have adopted a constructivist ontological position while implementing post-positivist methods to propose contextualized solutions for the design problem at hand. Since a constructivist paradigm does not necessarily preclude the use of scientific research and quantitative methods, I applied a hybrid ontological and methodological setting to address the complex question of daylighting. Thus, while the ontology of constructivism defines my basic set of beliefs toward the research question, I implemented quantitative methods such as simulations and coding to provide a context and solve the problem at hand. Based on this ontology, there is not an absolute reality (solution) that a researcher should discover; rather, there exist multiple realities that are socially and locally constructed (Guba and Lincoln, 1994). and the investigator unfolds these realities as the investigation proceeds (Guba and Lincoln, 1994). This paradigm practices a dialectic interchange as its methodology (Guba and Lincoln, 1994). In conclusion, the paradigm of constructivism refers to multiple interpretations and the context-dependency of phenomena (Guba and Lincoln, 1994). My research includes topics of energy simulation, different interests of relevant actors, productivity and human comfort. This complex set-up will not result in a universal solution (reality). As a result, the ontology of the constructivism paradigm set my "frame of perception" toward this research, classified the entities of my research into spheres of being, and highlighted the need for a context. By adopting this ontology, I have included all relevant actors and their interests in the design decisions. I defined the context by including and scaling different interests, as well as requiring minimum qualities and meeting performance targets. The requirements and scales were applied to create a context matching the project at hand. Finally, with the ontology of constructivism I adopted a wider perspective and was able to thoroughly make sense of the question of daylighting.

3.2 Different Interests Defined by Literature Review

While extant case studies have discussed the benefits of energy efficient and daylighting strategies in offices, they also reveal different interests playing crucial roles in design decisions. In this section, first, I present a Walmart case study to highlight the roles of different actors. Then, I identify and describe the assumed actors and their interests in this research. Finally, I explain the context dependency of toplighting design by comparing the scenarios of a high-tech company and a storage space unit.

Several case studies have shown that major renovations were initiated due to the drive for energy saving and the subsequent reduction in utility bills (Romm and Browning, 1994). However, the project owners of those renovation projects were surprised by some unforeseen and irrefutable side effects of energy efficiency and daylighting strategies, including high morale, low absenteeism, and higher productivity among employees in the office (Romm and Browning, 1994). The lessons learned from these renovations motivated the owners to implement energy efficient and daylighting strategies in other projects. Walmart in Lawrence, Kansas is one of those influential case studies. In June 1993, Walmart decided to implement environmentally responsive design strategies and technologies to build a so-called "Eco-Mart" (Romm and

Browning, 1994). The sustainablity team, which consisted of architects and sustainability consultants, proposed strategies such as an efficient lighting system, ice-storage for the HVAC system and light monitoring skylights. The skylights were only installed on a half of the roof while the other half of the roof was left without skylights. According to Walmart's Vice President for Real Estate, Tom Seay, sales per square foot skyrocketed for daylit departments, while employees in non-daylit areas argued to be transferred to the daylit area (Romm and Browning, 1994). Based on this experiment, Walmart then considered "Eco-Mart" measures in both new and renovated stores (Romm and Browning, 1994). The eco-movement set up by the Walmart owners was instigated by environmental concerns, as well as incentives of utility saving; however, it was the unexpected improvement in the comfort of the employees and customers that led to higher sales. Therefore, not only the owner and design team, but also the occupants (employees and customers) played roles in the future development of the "Eco-Mart" project. The impact of energy efficient and daylighting strategies on productivity has been examined and discussed in more detail, in Literature Review in section 2.2.2.

Knowing the importance of social groups, four *a priori* groups holding different interests were assumed: owners, occupants, designers and environmentalists. I derived these a priori groups from extant studies that have been conducted based on interviews and on-site studies (Heerwagen and Zagreus, 2005; Heerwagen, 2011; Heschong Mahone Group, 2003; Heschong Mahone Group, 1999; Romm and Browning, 1994) rather than through personal action research. Here, I assume owners to be corporations or individual clients who expect to be compensated for the cost of design projects by financial reward in the future. This group owns the project financially and is in favor of lowering initial or operational costs and maximizing productivity or sale rates. Occupants are the inhabitants of the design projects who desire quality of daylighting design, including access to daylight with lower glare issues. Designers are architects designing the space, who care about the quality of design, especially the image and what it conveys. The environmentalist group is presumed to include any members related to design projects concerned about global warming, climate change, pollution, and ozone layer depletion which shapes their global viewpoint toward the environment (Guba and Lincoln, 1994). In the building industry members of this group implement quantitative strategies such as energy efficiency to tackle the environmental crisis, such as CO_2 emissions (Guba and Lincoln, 1994). In this study the members of this group are from diverse professions, depending on the project at hand, including designers, engineers, and even owners and occupants who are advocates of environmental protection.

Figure 3.1 depicts the assumed relevant groups and their interests, while positioning me as the current researcher and a future design team and illustrating different actors who have influenced or are influencing daylighting design decisions. As shown in Figure 3.1, different groups present different interests in the quantitative fields of loads, and the qualitative fields of well-being, comfort, productivity and aesthetic. The proposed position of the researcher enables him/her to mediate among these interests and define minimum quality performance and scales in order to create an appropriate context for a proper skylight design.

Google offices versus a storage space are two extreme, opposite examples that provide a context showing why all qualitative and quantitative aspects need to be considered. Google invests more in the productivity of

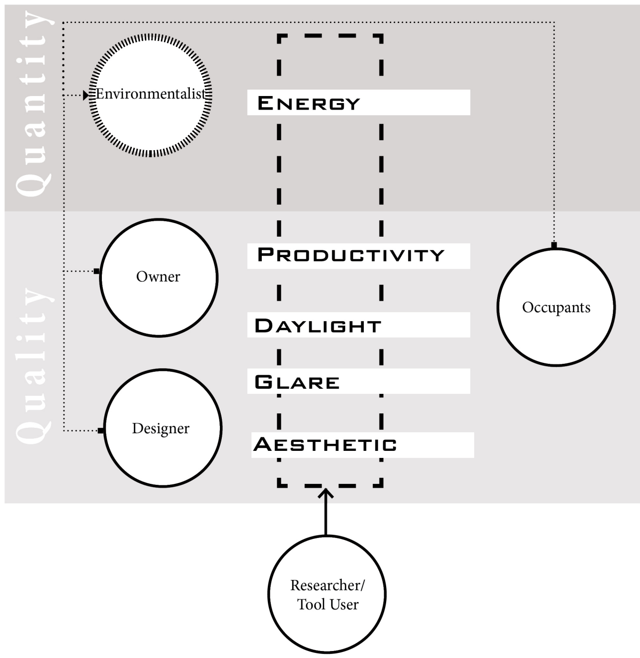

Figure 3.1: A Methodological Platform Showing Different Actors with Different Interests

their employees because Google's employees are mostly highly paid electronic and computer engineers (Kuntze and Matulich, 2010). As a result, an increase in productivity would benefit this company more than a focus on energy incentives. In this example the owner's perspective is aligned with the occupants' perspective, which necessitates allocating more weight to the quality of daylighting than to the role of daylighting in energy savings. In contrast, in a storage unit where there are infrequent occupants, an owner invests in reduction of utility costs. The owner is willing to apply toplights in order to save energy and lower the operational cost. In this example the owner's perspective is aligned with the environmentalist's view, which is to reduce energy and protect the environment.

Finally, as the main platform of this research is the inclusion of different interests and integration of both quantitative and quality aspects of daylight, the ontolgy of constructivism provides a better understanding of this multidimensional complexity. In the following subsections I investigate two approaches to find a robust skylight design by creating a context and considering the interests of all the actors. First, I define optimization and discuss the three approaches to optimize skylight apertures while maintaining context dependency.

3.3 Optimization

In this section, after mathematically explaining optimization, I define different facets of skylight optimization, the methods, simulation engines, software tools and different optimization approaches to tackle the question of skylight design. The interests of different actors, including environmentalists, owners, occupants and designers, impose specific design criteria which may be conflicting and synchronized with each other or be independent from each other. In the realms of mathematics and engineering, multiple criteria decision making is known as multi-objective optimization (Caramia and Dell'Olmo, 2008). Different numeric mathematical solvers have been offered to find a solution by simultaneously optimizing more than one objective function (Caramia and Dell'Olmo, 2008). As illustrated in Figure 3.2, the function, $f(x)$ receives an input of x as a variable, applies different criteria in decision making and results in y as an output and a solution. In addition to multi-objective optimization, the problems exist that different variables feed the function, $f(x)$.

In this case, the optimization is called multi-variable optimization (Caramia and Dell'Olmo, 2008). In a more complex problem, the function, $f(x)$ is fed with several variables while applying different criteria to find a solution(s) (see Figure 3.2).

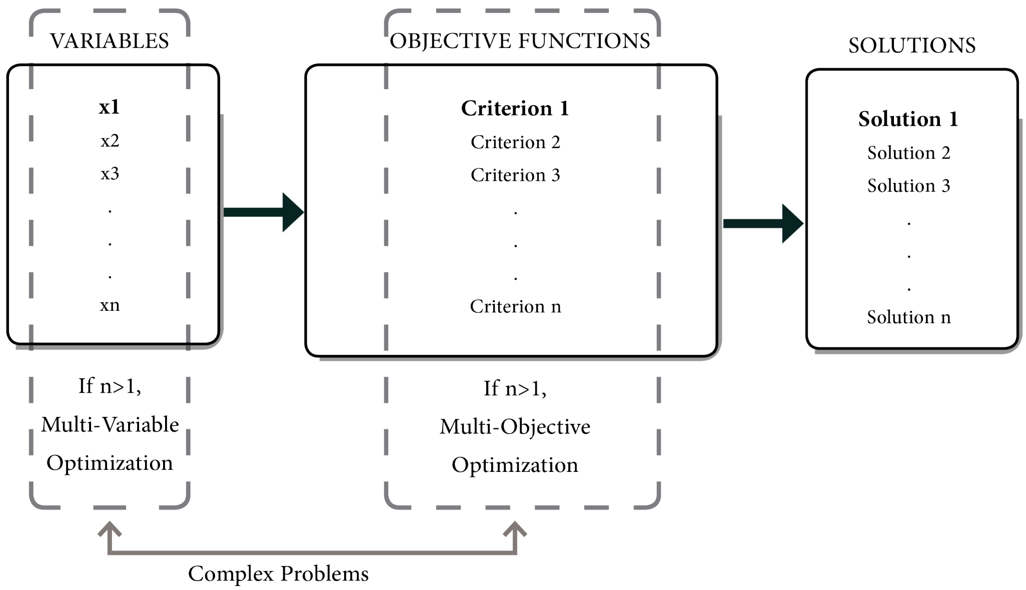

Figure 3.2: Multi-variable and Multi-Objective Optimization

In some complex optimization problems, a single solution cannot be found to simultaneously optimize each objective (Caramia and Dell'Olmo, 2008) (see Figure 3.2). In these problems, some or all of the criteria defining the objective functions are conflicting. In other words, it is impossible to optimize one objective function without worsening another objective function (Caramia and Dell'Olmo, 2008). In these cases a single solution cannot be found to simultaneously optimize all objectives. Thus, there exists multiple solutions which will be defined by design/solver criteria or objective functions (Figure 3.2). For instance, Figure 3.3 shows a relation between environmental impacts and cost of applying energy efficient strategies (Robinson, 2017). A Pareto Front curve visualizes a trade-off between different objective functions (Caramia and Dell'Olmo, 2008). Figure 3.3 shows how lowering environmental impacts increases initial costs. All the points on the Pareto Front curve are solutions while the acceptable solutions are the ones that represent a trade-off defined by a decision maker. After explaining the nature of multi-variable and objective optimization, the following section presents multi-objective optimization for the skylight design in this research.

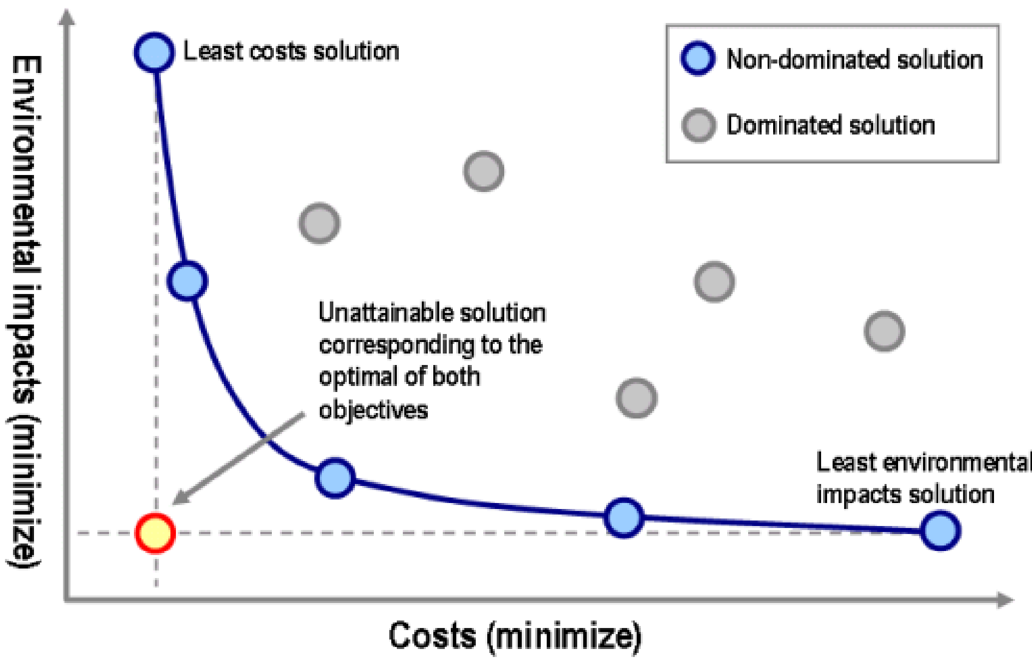

Figure 3.3: Pareto Front Curve (Robinson, 2017)

3.3.1 Optimization of Skylights

There are many variables and criteria (objective functions) that create a context for skylight design. An optimal skylight design may change in different contexts which are defined by the following variables: different climate conditions, building types, the existence of shading device, visible transmittance of glazing, building and neighborhood geometries, volume to floor ratios, illuminance targets, skylight sizes (SFR), lighting power density and HVAC systems. In this study, I propose methods to optimize skylight energy and daylight performance with a single variable of SFR. In addition, I investigated the sensitivity of the Optimal SFR in conjunction with different variables, including several different climates, illuminance targets and power densities. However, the properties of the envelope, including the glass (VT[2], SHGC[3] and U-value[4]), were held constant throughout the different scenarios.

In the case of skylight design, qualitative and quantitative aspects of daylighting define the objective functions, which include avoiding glare and providing enough daylight as well as saving energy. As shown in Figure 3.1, different actors hold different interests which sway the design decisions and mold the design criteria or objective functions of skylight optimization (Figure 3.2). As illustrated in Figure3.1, while energy is a quantitative aspect of daylight design, productivity, glare, daylight and aesthetic are qualitative aspects of daylight design. In this study the aesthetic criteria of skylight design have been ignored because skylights installed on a roof are not primary visible elements of buildings as facades are. In addition, in the scope of skylight design, a productivity rate only improves in cases where daylight is present while minimum glare incidents occur. Although establishing the criteria for productivity by itself is a complex multi-dimensional question and productivity can be adversely impacted by other factors such as thermal discomfort, for

[2]Visible Transmission
[3]Solar Heat Gain Coefficient
[4]Thermal transmittance

the sake of simplicity, this study considers productivity as a function of daylight availability with the minimum of glare incidents. My intent to include the subject of productivity in this study is to discuss the state-of-the-art case studies and shed light on its importance as a decision making criterion while confirming that this field is currently developing.

Finally, the question of skylight design in this study entails solving multi-objective optimization with its single variable (skylight sizes). The intricate relations between different objectives lead to different approaches to tackle the challenge of skylight design. Maximizing daylight availability often leads to larger windows, while minimizing energy consumption entails smaller windows. Moreover, visual comfort is provided if excessive daylight and glare are avoided. The glare challenge adds another wrinkle to the question of daylight design and aperture sizing because of its complex relationship with daylight availability, energy consumption and window sizing. Therefore, the goal is to organize a multi-objective optimization which leads to understanding how qualitative and quantitative aspects of effective daylighting interact in designing skylights. In addition, I study how climatic conditions, lighting power and illuminance targets strengthen or weaken the roles of energy consumption, glare, and daylight availability in optimizing skylight sizes. In subsequent paragraphs I will explain the major methods that were applied to achieve effective daylighting through toplights.

3.3.2 Methods

The methods used to tackle the qualitative and quantitative aspects of daylighting include a literature review, simulations, and coding. Both data mining and triangulation of data were necessary to review the literature with regard to the qualititaive aspects of daylighting, whereas scientific research was needed to simulate the quantitative aspects of daylighting. In addition, to collect all qualitative and quantitative data and process them into a meaningful result, I relied on programming as well. What follows describes these methods in more detail.

3.3.2.1 Literature review

Data was collected from peer-reviewed state-of-the-art reports and papers concerning productivity rate and occupants' comfort regarding amount of available daylight and glare problems. While I did not perform on-site experimentations, surveys, and interviews, I took advantage of reports that applied these methods and were verified by professionals in the field. I then used triangulation as a "method of cross-checking data from multiple sources to search for regularities in the research data" (ODonoghue and Punch, 2003). The triangulation was used to define an appropriate productivity rate for the high-quality daylight design. In addition, the literature review was used to establish the daylight metrics that have been commonly used in industry and acceptable thresholds for each metric.

3.3.2.2 Simulation and Coding

Integration between different tools is needed in order to take into account the impacts of daylight on the overall energy consumption as well as incorporating qualitative aspects of daylight into decision-making criteria. There has been an increasing effort to improve the capabilities of tools by coupling them to examine the impact of daylight on electrical lighting loads, as well as heating and cooling loads (Reinhart and Wienold, 2011; Trubiano et al., 2013b; Konstantoglou and Tsangrassoulis, 2016). As natural light is being used as a free source, it replaces electrical lighting loads. The decreased number of electrical lights will influence electrical utility and internal heat gained from electrical light. Such a change in internal heat gain impacts heating and cooling loads. In addition, natural light increases the amount of solar gain and the aperture itself increases the conductance transmission, because of the low resistance of skylight glass. The decreased internal gain should be simulated by a daylight engine. However, energy balance must combine conductivity, solar gain, and internal gain, all of which should be handled by a thermal engine. Therefore, integration between different engines is required in order to cohesively include the impacts of daylight on the overall energy consumption.

A daylight engine was used not only for energy performance but also for daylight performance. A more holistic approach requires the qualitative aspects of daylight to be included in optimizing skylight design. Thus, I simulated daylight performance through a daylight engine in order to evaluate horizontal daylight availability and glare incidents as qualitative aspects of daylight.

Simulating different scenarios with different tools required data management, which was handled by scripting and coding. Data management in this research required automating simulation, feeding data back and forth between tools, storing data, organizing data, applying optimization functions, interpolating data and deriving a solution(s). In subsequent paragraphs I describe the tools and integration processes that were applied to achieve effective daylighting through toplights.

3.3.3 Daylight and Thermal Engines

In this study I applied Radiance and EnergyPlus as daylight and thermal engines which are embedded in the Ladybug and Honeybee tool. 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 (EnergyPlus, 2016). EnergyPlus is also capable of daylighting simulation by its embedded daylight engine, Radiosity. However, in this study I used Radiance as a daylight engine which is a state-of-the art illuminance prediction (Radiance, Radiance). The type of engine used in the research impacts assessment of daylight performance because each engine applied different mathematical algorithms to predict daylight performance. In addition, sky models embedded in daylight engines influences assessment of daylight performance. In the following subsection I will expand on different sky models and different daylight engines.

3.3.4 Sky Models

Prediction of daylight performance significantly relates to how sky is modeled in a daylight engine. The solar flux depends on the sky condition, including the position of the sun in the sky and weather conditions (Darula and Kittler, 2002). The position of the sun in the sky is a function of its latitude, while weather conditions contain information about water vapor, pollution, and also direct and diffuse sunlight. Direct sun means incident light, which is defined by the geometric position of the sun in the sky, while diffuse light means light scattered by clouds, molecules of different gases, concentration of pollution particles and nature of ground or other surfaces (Darula and Kittler, 2002). Daylight performance in a space heavily depends on the ratio of direct and diffuse light in that location and various climates have different ratios of direct and diffuse light. Therefore, an accurate daylight engine considers different climatic conditions in its embedded sky models.

Sky models represent sky luminance distribution by mathematical formula (Darula and Kittler, 2002). Sky luminance distribution is calculated by the amount of light radiated from different patches of the celestial hemisphere (Reinhart, 2011). The state-of-the-art sky model is one that is a good representation of a sky condition for a specific location, while holding a range of sky conditions from an overcast sky to sunny sky, as proposed by CIE (Commission Internationale de lclairage) (Darula and Kittler, 2002). The most well-known CIE sky models are the overcast, clear and intermediate ones. The CIE overcast sky represents a completely clouded sky in which the sun and its position are not visible (Figure 3.4) (Darula and Kittler, 2002). As illustrated in Figure 3.4 (Mardaljevic, 2000), the zenith shows three times more sky luminance than the horizon. This sky model is appropriate for cloudy skies of cities like London. This sky model is often used to simulate a worst case scenario to predict the daylight quality of interior spaces (Reinhart, 2011).

The CIE clear sky model assumes that the sun shines in the sky without the presence of any clouds (Reinhart, 2011). Figure 3.4 illustrates a clear sky model that has non-uniform sky luminance distribution, while the location of the sun and its surroundings are brighter. This model is more appropriate for sunny locations like Phoenix. The combination of the clear and overcast skies results in the CIE intermediate sky model, representing partly cloudy skies (Reinhart, 2011).

While CIE sky models are commonly implemented in the building industry to evaluate daylight performance, some simulation tools such as Energy

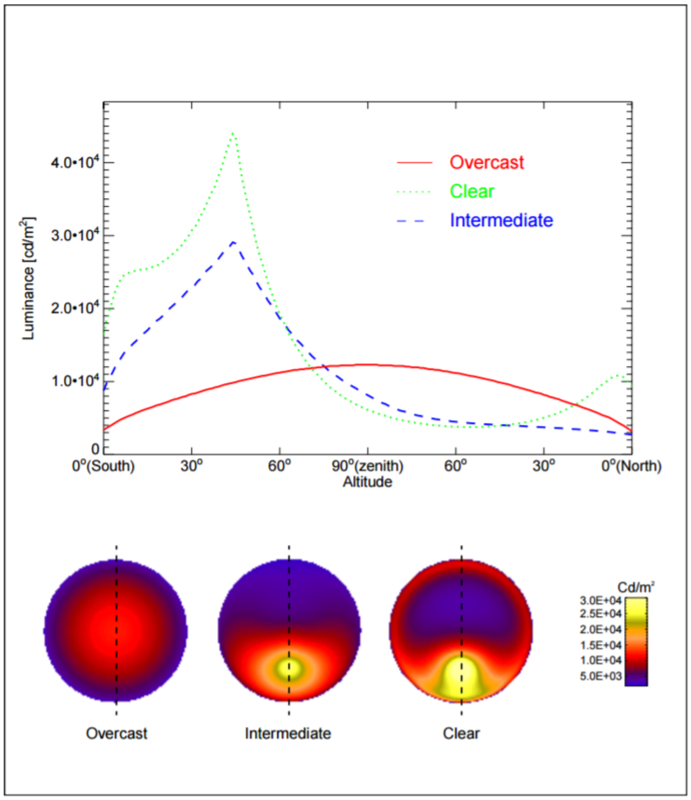

Figure 3.4: Different CIE Skies (Mardaljevic, 2000)

Plus and Ladybug and Honeybee use the Prez sky model (Reinhart, 2011). This model contains hourly information regarding the sky condition, while its direct and diffuse illuminance are continuously changing (Reinhart, 2011). The previously mentioned tools apply the Prez sky model for simulating both daylight and energy performance (Reinhart, 2011). The results of this approach are more consistent and coherent.

Recently, a digital camera with a fish eye and a luminance meter has been applied to carry out High Dynamic Range (HDR) photography and capture information about the sky for each location. Should the HDR photography of the skies replace mathematical sky models, the results for daylight simulation will be more accurate. In this research the Prez sky model is used in Radiance and EnergyPlus to be consistent. In the following subsection I explain why Radiance outperforms its competitor, Radiosity, for daylight analysis.

3.3.5 Radiance versus Radiosity

The most powerful tool for daylighting is Radiance, which is able to use a ray tracing technique. Ray tracing is a computer graphics rendering technique that attempts to simulate the physical behavior of light as closely as possible (Durand and Cutler, 2017a,b). It traces rays from the virtual camera through several bounces on or through objects. The Radiance forward method is able to trace the light traveling from sources, hitting surfaces and being distributed based on the reflectivity of surfaces (Tregenza and Wilson, 2011; Reinhart, 2011). In the backward method, Radiance is able to trace light rays emitted from the sensors' positions and trace them backwards until they hit a light source or other objects (Tregenza and Wilson, 2011; Reinhart, 2011). Ray tracing is capable of simulating a wide variety of optical effects, such as reflection and refraction, scattering, and dispersion phenomena (Tregenza and Wilson, 2011; Reinhart, 2011). The backward ray tracing technique hunts the light from eye to light sources; therefore, its result is very view dependent (RadiositySolution, 2017). This means that each run of Radiance simulation can be used for a specific view (or perspective). It is usually associated with a longer simulation time compared to Radiosity (Figure 3.5) (RadiositySolution, 2017).

Radiosity was originally developed to calculate radiative heat transfer, based on interreflections between finite surfaces and their view factors (Tregenza and Wilson, 2011; Reinhart, 2011). The light passing from openings creates the lighting flux within the space. This method considers all surfaces as perfectly diffuse reflectors, so-called Lambertian surfaces (Tregenza and Wilson, 2011; Reinhart, 2011). Radiosity cannot consider different optical aspects such as reflection, refraction, scattering and transparency; however, this can be simulated by its competitor tool, Radiance (Tregenza and Wilson, 2011; Reinhart, 2011), which follows the light from the source to the surfaces. Therefore, Radiosity simulation results in the total luminance distribution, independent of the point of view (Reinhart, 2011; RadiositySolution, 2017). It is associated with a shorter simulation time compared to Radiance (Figure 3.5).

In conclusion, Radiance's overall performance excels its competitor's, Radiosity's, because of its unique capability. As mentioned above, Radiance is able to simulate different optical materials. In addition, Radiance's rendered image is closer to what eyes perceive and therefore, its rendered luminance image is more accurate for glare diagnosis. Although simulation time is usually longer with Radiance than Radiosity, Radiance's simulation takes less computation time than Radiosity if the geometry is complex containing different surfaces (Reinhart, 2011). In the next subsection I subscribe the specific simulation tools that apply these engines.

3.3.6 Simulation Tools

I used Radiance through its host, Ladybug and Honeybee. This tool is an environmental plugin for Grasshopper, which is a graphic programming language accessed within Rhino (Ladybug, 2015). The Ladybug and Honeybee tool was chosen because it is an open source and it is able to visualize

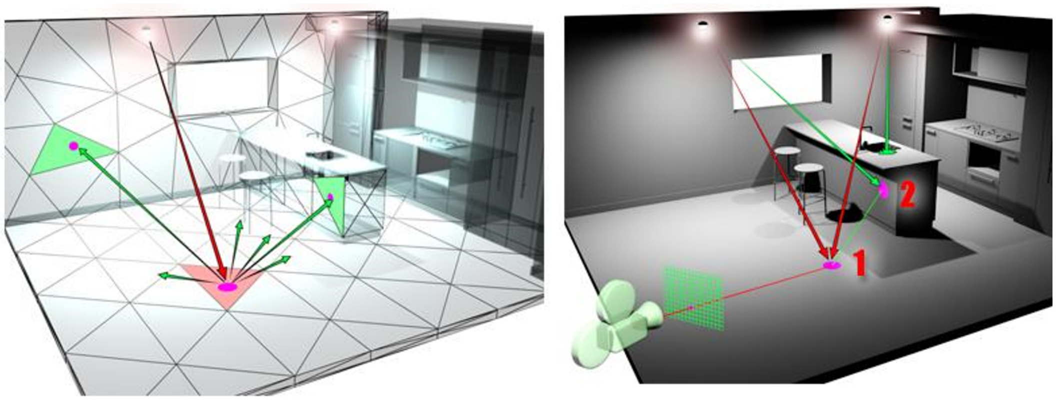

Figure 3.5: Radiance (Right Picture) and Radiosity (Left Picture) (RadiositySolution, 2017)

geometries and results as well as to read EnergyPlus models, IDFs. The availability of source code helps software developers for modification or enhancement, which was needed in this study for integration between tools and optimization. Visualization is another capability of this tool for displaying 3D geometry and daylighting illuminance layout. The final advantage of this tool includes its easy access to IDF models. It reads geometries, materials, constructions and HVAC systems of IDF models. Although it can prepare IDF models for Radiance simulations, the version of Ladybug and Honeybee used in this research, released in Feb-02-2015, is incapable of feeding data back and forth between EnergyPlus and Radiance. This tool can separately calculate daylight and thermal performances; however, it is unable to consider the impacts of daylighting strategies on electrical lighting loads and thermal loads. Thus, it cannot deliver reduced electrical lighting loads to EnergyPlus for further thermal simulations. I filled the gap of disconnection between daylight and thermal engines by Python scripts.

While Grasshopper was used to present results and to manipulate 3D geometries, I applied Python to handle intricate tasks of integration and optimization. Python as a plugin component of Grasshopper was used to generate different skylight ratios, prepare 3D geometry, optimize SFR, run EnergyPlus within Grasshopper and manage data between EnergyPlus and Radiance engines of Ladybug and Honeybee. For integration between EnergyPlus and Radiance engines, a Python script was written to embed a reduced electrical lighting load generated by Radiance in EnergyPlus. While Ladybug and Honeybee implements Radiance for daylighting simulation, it uses Daysim to specify electric lighting systems, such as the type of dimming system and an illumination target for dimming lights. Daysim is another validated Radiance-based daylighting analysis software. By running Daysim and Radiance in the background, Ladybug and Honeybee generates "intgain.csv" which is an internal heat gain file showing annual hourly lighting loads. This internal heat gain file is calculated based on available daylight, a defined illuminance target and an occupancy schedule. This file is the key for coupling EnergyPlus and Radiance. After discussing all the tools and their implications, I parse the integration process to predict energy consumption while considering the holistic impact of daylight on energy.

3.4 Integration Process to Calculate Energy Consumption while Considering Daylight

The "intgain.csv" file carrying information from Radiance and Daysim simulation needs to be fed into EnergyPlus. The significant step of integration is EnergyPlus adopting "intgain.csv" as its new electrical lighting schedule, which should be defined under the subcategory of "schedule: file" object. Before feeding this file into EnergyPlus, modification of hourly data is necessary, because EnergyPlus and Daysim implement different assumptions for lighting

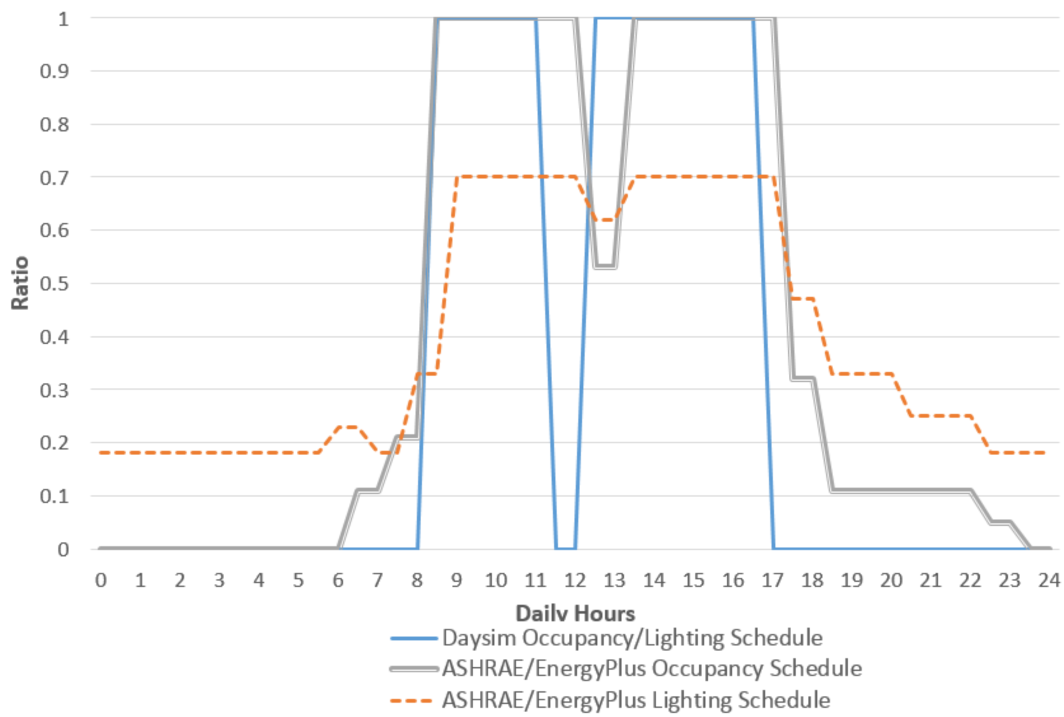

Figure 3.6: Lighting and Occupancy Schedules of Daysim and EnergyPlus

schedules. Lighting schedules in Daysim use binary values of 0 and 1 for each time step, where 1 represents the presence of people and turned-on lights and 0 indicates lacks of occupancy and use of lights. Figure 3.6 demonstrates the use of binary values for a 9am-5pm default schedule in Daysim. This is different from the ASHRAE electrical schedule used in the EnergyPlus model. ASHRAE uses real numbers (any number between 0 and 1) to represent the fraction of lights that are turned on during a day. Figure 3.6 shows a default schedule of 9am-5pm in Daysim, which assigns 0 to unoccupied hours between 5 pm and 9 am. As illustrated in Figure 3.6, ASHRAE uses 0.2 for uncrowded hours, which are between 11 pm to 6 am. To remove this discrepancy between

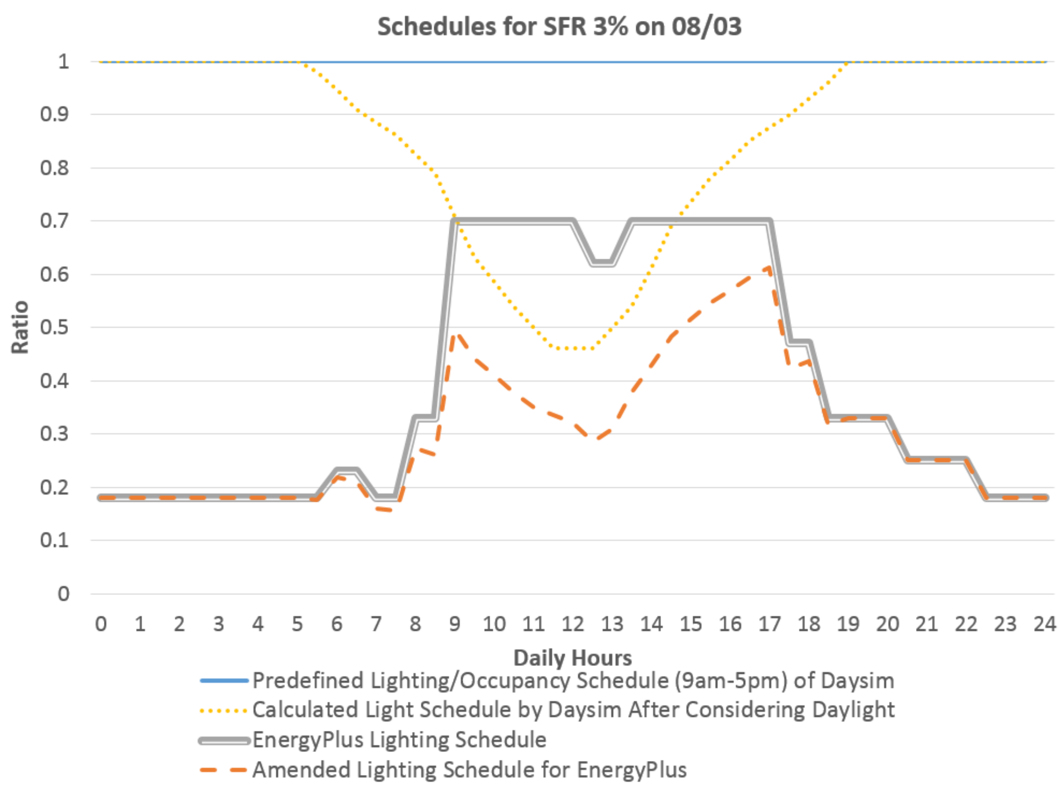

Figure 3.7: Lighting Schedules of Daysim and EnergyPlus before and after Considering Daylight Impacts

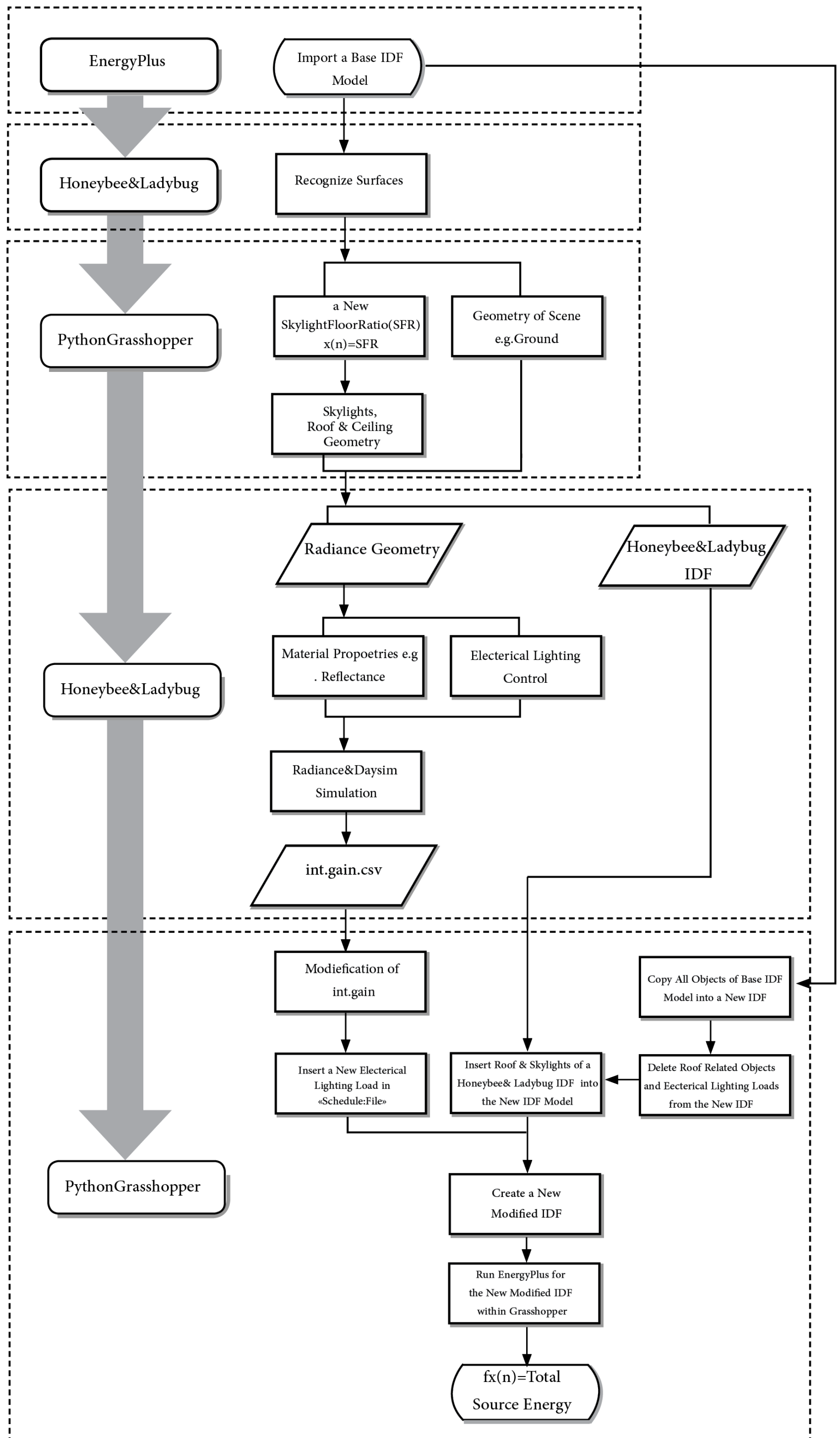

Figure 3.8: Flowchart Showing the Process of Integration between Different Tools

Daysim and ASHRAE, another Python script was written to alter Daysim lighting loads ("intgain.csv"), based on the ASHRAE lighting schedule (Figure 3.7). For the Daysim model I considered the 24-hour default schedule in order to consider the impact of daylighting on electrical lighting loads for all hours of the EnergyPlus lighting schedule. As Figure 3.7 shows, the hourly data of Daysim indicated a dent in lighting loads after considering daylight. I proportionally projected the same reduction to the EnergyPlus lighting schedule. This shows it is imperative to understand tool assumptions; otherwise simulation may result in wrong outputs.

The flowchart of Figure 3.8 outlines a procedure of integration between EnergyPlus and Ladybug and Honeybee used in this study in order to consider daylighting impacts of a skylight model on thermal performance. The integrative process starts by having an IDF model as a base model, which will be described the base model in the section "Experiment". Ladybug and Honeybee imports the IDF model and reads its geometry, such as its surfaces. The tools of Python and Grasshopper define SFR as well as geometries of the building and scenery. These two tools add skylight geometries to the roof of the base model and attach a vertical wall and a dropped ceiling to the geometry. In addition, a ground plane - three times bigger than a floor plane - should be drawn as part of the scenery. Next, Ladybug and Honeybee generates a Radiance geometry, as well as another IDF model that includes the new roof with its skylight geometries, which is called a Ladybug and Honeybee IDF model. The material properties and a lighting control system should be then set up for the Radiance geometry, which will be explained later in the "Case Study" section.

After Daysim and Radiance simulating on the background of Ladybug and Honeybee, Python modifies its resultant internal heat gain based on the ASHRAE schedules and feeds the modified results into a new IDF. The new IDF file is a copy of all objects of the base IDF model, except the roof geometry and electrical lighting loads, because the base IDF model does not have skylights and its electrical lighting loads do not include the impacts of daylight. A Python script is written to borrow the new roof structure with its skylight geometries from the Ladybug and Honeybee IDF model and insert them in the new IDF model. Finally, Python generates the new modified IDF model, simulates EnergyPlus from the Grasshopper environment and reads the total source energy consumption of the new modified IDF model. The flowchart in Figure 3.8 depicts all the mentioned process of integration, step by step. It illustrates an Integrative Algorithm (IA) for coupling daylighting and energy performances. After this discussion of how to integrate different tools, in the next subsection I will present different optimization approaches I took to find robust skylight design solutions.

3.5 Optimization Approaches

Since the goal of this study is to perform multi-objective optimization while including different interests, I propose three major optimization approaches to provide effective daylighting through skylights. It should be noted that the main intended contribution of this study is the set-up of these optimization approaches, rather than the actual results emerging from these approaches. The multi-objective functions contain all the qualitative and quantitative aspects of daylight, including glare, daylight availability and energy consumption criteria. The inclusion of these objective functions or interests in design decision making creates a context dependency. The imperative part of

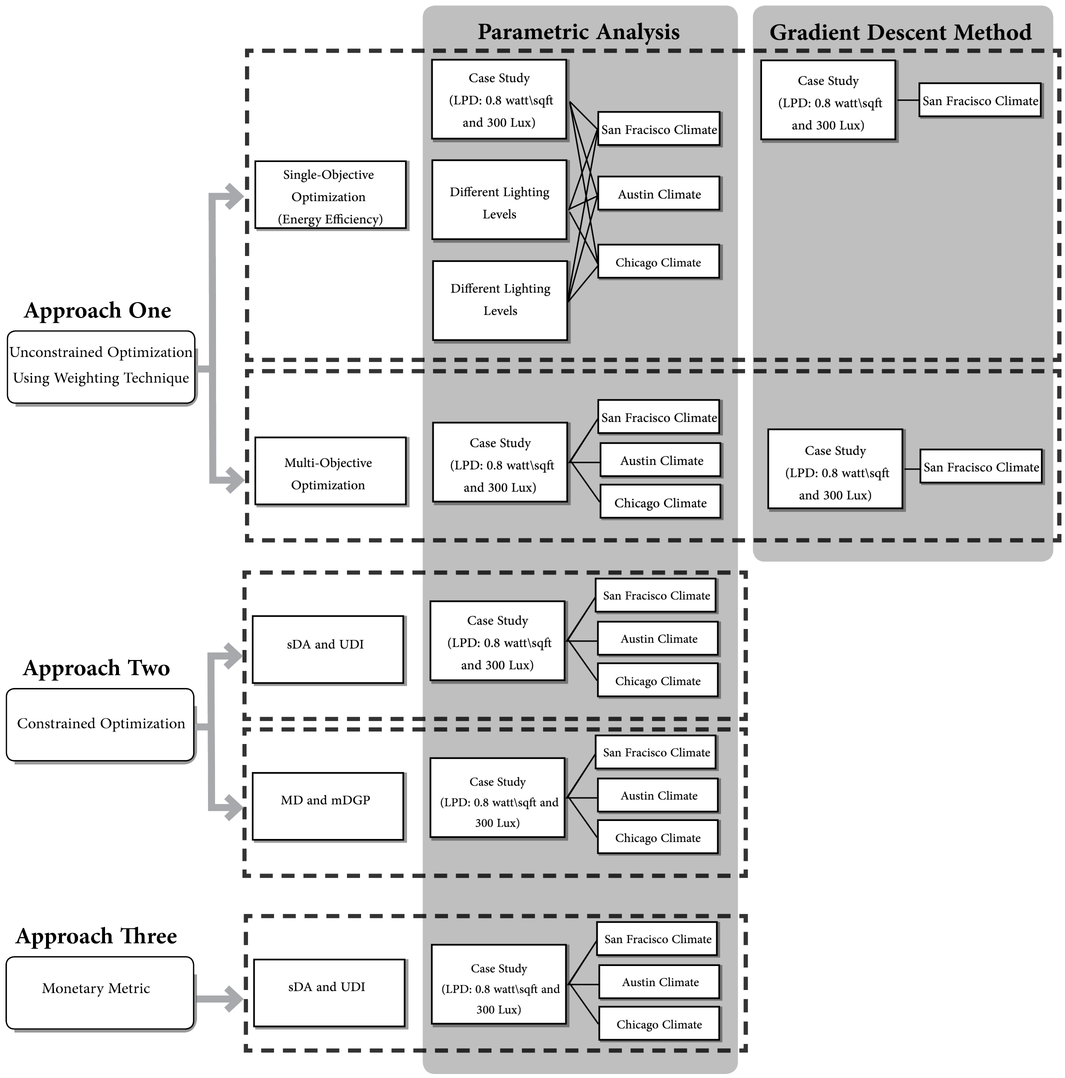

Figure 3.9: Different Applied Optimization Approaches

any multi-objective optimization is how to aggregate different criteria or how to build up a selection process system. Definition of the metrics for each objective and their acceptable thresholds also plays a role in final results. One of the proposed multi-objective optimizations is unconstrained optimization, developing a weighting system to scale different objective functions or interests.

The other approach I have investigated is constrained optimization, which is a conditional selecting system to meet the minimum daylight performance target while saving energy. This approach assigns appropriate thresholds to each objective function or interest. The third approach is based on the collective monetary benefits from energy savings and increased productivity. In the following subsection I explain each approach. Figure 3.9 illustrates all the three approaches with its subsequent case studies and applied methods.

3.5.1 Unconstrained Optimization

I implemented the idea of contextualization in this approach by unifying units of different interests regarding glare, energy and daylight and assigning different weights to each interest. I implemented two methods of numeric optimization (Gradient Descent) and exhaustive search (Parametric Analysis) in order to validate the final result of this optimization method. In the following subsections I discuss different metrics of qualitative and quantitative aspects of daylight, I explain the unifying process of metrics and expand on the two methods of Gradient Descent and Parametric Analysis.

3.5.1.1 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 electrical lighting loads. The reduction of electrical lighting loads decreases internal heat gain generated by lights. 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, I applied total source energy, including lighting and HVAC loads (kWh), in order to consider the holistic impact of daylight on energy consumption and to encompass the importance of the energy source.

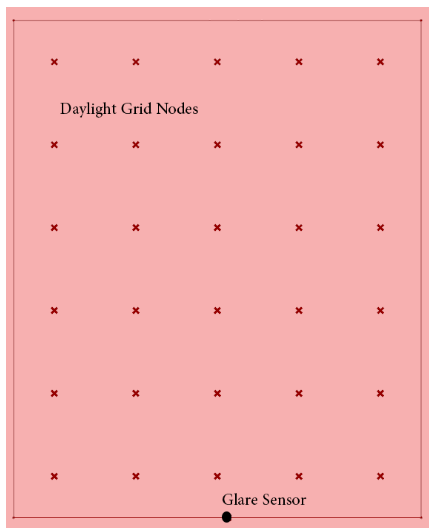

Figure 3.10: Daylight Grid Map and Glare Sensor

For daylight assessment, I 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 (Figure 3.10). This view was chosen since it represents the worst case scenario while looking over all the skylights (probable glare sources) down the room (Figure 3.13). The mean DGP was calculated for all the occupied hours in a year for the mentioned sensor. In addition to mean DGP, I 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. Figure 3.11 illustrates the calculation of DGPi. In addition, for the daylight availability, I applied a mean annual illuminance. I calculated the percentage of occupied hours that an average node in a daylight grid map receives at minimum 300 lux. This percentage is called Mean Daylight (MD) in this study. Figure 3.12 illustrates how MD was calculated in this optimization approach, while Figure 3.10 shows daylight grid sensors.

The 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), I 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. I aggregated energy and daylight performance and represented these with an average performance $f(x)_{avg}$ by using the above equation (Eq. 3.1).

TIME			GLARE	STATUS	
Month	Day	Hour	DGP	tn	
1	1	1	0	t1	Not Occupied
1	1	2	0	t2	Not Occupied
1	1	3	0	t3	Not Occupied
1	1	4	0	t4	Not Occupied
1	1	5	0	t5	Not Occupied
1	1	6	0	t6	Not Occupied
1	1	7	0	t7	Not Occupied
1	1	8	0.251	t8	Occupied
1	1	9	0.334	t9	Occupied
1	1	10	0.55	t10	Occupied
1	1	11	1	t11	Occupied
1	1	12	1	t12	Occupied
1	1	13	1	t13	Occupied
1	1	14	0.678	t14	Occupied
1	1	15	0.543	t15	Occupied
1	1	16	0.326	t16	Occupied
1	1	17	0.217	t17	Occupied
1	1	18	0	t18	Occupied
1	1	19	0	t19	After Sunset
1	1	20	0	t20	After Sunset
1	1	21	0	t21	After Sunset
1	1	22	0	t22	After Sunset
1	1	23	0	t23	Not Occupied
1	1	24	.	t24	Not Occupied
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.		.	.

Continue for the whole year

```
Annual Hours = 8760
DGP_hr = 0 (#occupied hours that DGP passes the threshold)
Occupied Hours = 0
DGP_limit = 0.35 (#DGP of imperceptible threshold)

For i in range (0, Annual Hours):
        if t_n is "Occupied" ;
                Occupied Hours = Occuped Hours + 1
                if DGP [i] =< DGP_limit:
                        DGP_hr = DGP_hr + 1

DGPi = DGP_hr /Occupied Hours
```

Figure 3.11: DGPi Calculation for Occupied Hours

TIME			ILLUMINANCE ON THE GRID					STATUS	
Month	Day	Hour	x1	x2	x3	...	xn		
1	1	1	0	0	0		0	t1	Not Occupied
1	1	2	0	0	0		0	t2	Not Occupied
1	1	3	0	0	0		0	t3	Not Occupied
1	1	4	0	0	0		0	t4	Not Occupied
1	1	5	0	0	0		0	t5	Not Occupied
1	1	6	0	0	0		0	t6	Not Occupied
1	1	7	0	0	0		0	t7	Not Occupied
1	1	8	7	9	8		10	t8	Occupied
1	1	9	50	72	64		72	t9	Occupied
1	1	10	78	156	133		147	t10	Occupied
1	1	11	110	300	209		223	t11	Occupied
1	1	12	142	334	275		300	t12	Occupied
1	1	13	165	354	359		370	t13	Occupied
1	1	14	163	300	390		400	t14	Occupied
1	1	15	140	201	145		450	t15	Occupied
1	1	16	92	116	84		300	t16	Occupied
1	1	17	42	48	39		200	t17	Occupied
1	1	18	10	11	10		100	t18	Occupied
1	1	19	0	0	0		0	t19	After Sunset
1	1	20	0	0	0		0	t20	After Sunset
1	1	21	0	0	0		0	t21	After Sunset
1	1	22	0	0	0		0	t22	After Sunset
1	1	23	0	0	0		0	t23	Not Occupied
1	1	24	0	0	0		0	t24	Not Occupied
.	.	.	.	.	.		.	.	.
.	.	.	.	.	.		.	.	.
.	.	.	.	.	.		.	.	.

Continue for the whole year

```
Annual Hours = 8760
ill_occupied = 0
Occupied Hours = 0
sensors = [x1, x2, x3, ... , xn]
number of sensors = n
ill_limit = 300

For i in range (0, Annual Hours):
    if t_n [i] is "Occupied" :
        Occupied Hours = Occupied Hours + 1
        for j in range (0, number of sensor):
            if x[j]>= ill_limit:
                ill_occupied = ill_occupied + 1

MD = ill_occupied/Occupied Hours
```

Figure 3.12: Mean Daylight (MD) Calculation for Occupied Hours

$$f(x)_{avg} = \frac{\alpha MD + \beta DGPi + \gamma EnergySaving}{\alpha + \beta + \gamma} \tag{3.1}$$

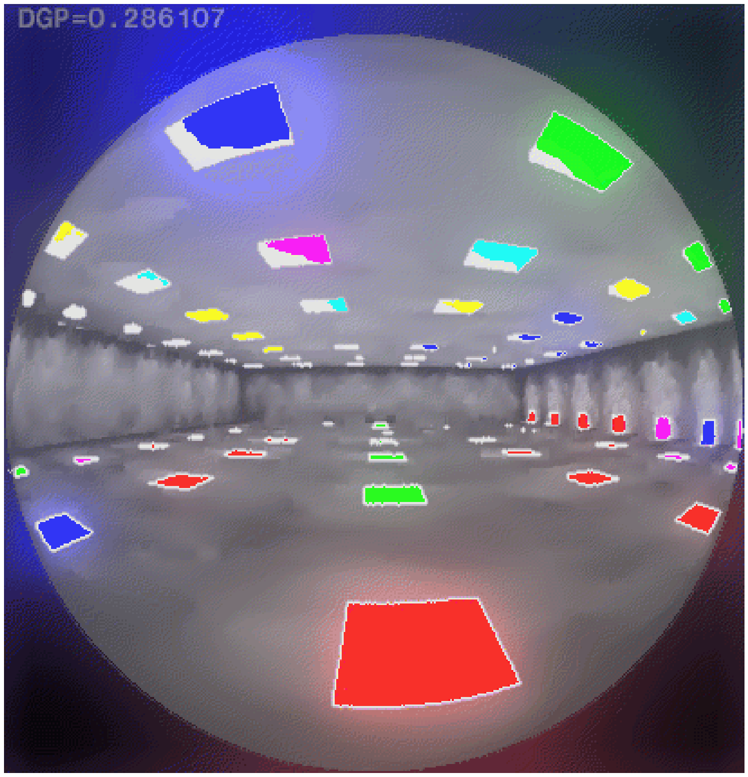

Figure 3.13: False Color Image Shows Glare Incidents based on DGP calculation

in this approach $0 \leq \alpha$, β, and $\gamma \leq 1$.

To contextualize the question concerning skylight design, the proposed unconstrained optimization applies a weighting technique, where different interests concerning glare, energy and daylight are scaled by assigning different multipliers to each interest. α, β, and γ can be any number between zero and one. Two scenarios have been investigated for the multipliers. In the first scenario α and β were zero and γ was one. These assumptions for the multipliers indicate the energy factor as the only design criterion which can be applicable for spaces such as storage areas. In the second investigated scenario one was assigned to all multipliers in order to equally include all the interests in the equation. The multipliers in the second scenario are more suitable for daylight design in Google office spaces, where daylight quality, productivity of employees and energy consumption all matter.

The intent of this study is not to idealize any specific numbers for the multipliers but rather to prepare a platform that is capable of examining the weighting technique which allows inclusion of all interests with different levels of importance. The platform is intended to be dynamic, empowering active groups to decide on the multipliers, based on a context of a future design at hand. While this unconstrained optimization with weighting technique allows for the dynamic exchange among the groups, this approach differs from the static top-down approach suggested by ASHRAE standards that only focuses on energy consumption and does not expand its boundary to allow for the specific challenges arising in each project. In other words, this study avoids the static approach of ASHRAE standards which lacks context-dependency.

3.5.1.2 Comprehensive Integration Process of Energy, Glare and Daylight

The proposed IA for energy (Figure 3.8) needs to be integrated by glare and daylight analysis in order to comprehensively take into account the qualitative and quantitative impacts of daylight. Therefore, Ladybug and Honeybee not only generates internal heat gained from lights in the presence of daylight, but it is also used to simulate daylight performance. I calculated daylight performance by considering the daylight metrics of MD and DGPi. Finally, I stored the data and calculated $f(x)_{avg}$ for each scenario, through another Python script.

Figure 3.14 outlines the Inclusive Integrative Algorithm (IIA), which

1. Input model from EnergyPlus (EnergyPlus)
2. Define x_n (x_n represents SFR which is a random number in the first iteration and for the second iteration it is x_1 - 0.1; otherwise it is generated in step 8)(PythonGrasshopper)
3. Run Radiance/daylight simulation (Ladybug and Honeybee)
4. Calculate and store all the daylight metrics (e.g. MD and DGPi) (PythonGrasshopper)
5. Feed lighting schedule (int.gain) from Radiance to EnergyPlus (PythonGrasshopper)
6. Run energy simulation and generate total source energy consumption (EnergyPlus)
7. Aggregate all daylight and energy metrics and calculate an average performance (Eq.1)
8. Apply the Gradient Descent optimization method (Eq.2) and generate x_{n+1} and $f'x_n$ (PythonGrasshoper)
9. if $f'x_n$ >0.0001 then repreat steps 2 through 9. Otherwise, the model is converged and read x_n (PythonGrasshoper)

Figure 3.14: Inclusive Integrative Algorithm (IIA) to Find an Optimal SFR by Providing Effective Daylight

Figure 3.15: Interior perspective from Grasshopper Model SFR 20%

integrates the proposed IA shown in Figure 3.8 to estimate total source energy consumption. Figure 3.14 shows the steps from 1 to 6, which are to couple EnergyPlus and Ladybug and Honeybee, while steps from 7 to 9 represent the optimization process by scripting in Grasshopper Python. In addition, Figure 3.15 shows the geometry generated by Honeybee and Ladybug from reading the EnergyPlus model and SFR.

3.5.1.3 Gradient Descent Optimization

As well as being used for the integration process, Python was also used to optimize total energy performance based on the Gradient Descent method. In the optimization process, the goal was either to find a robust SFR while minimizing energy consumption or to find an inclusive optimal SFR while maximizing the average performance ($f(x)_{avg}$). The Gradient Descent method is 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 3.16. In this study, a closed-form equation for the function was unknown; however, the proposed IIA was simulated to get an average performance, $f(x)_{avg}$, for each SFR, x. The optimization algorithm starts by generating a random SFR, a number between 0.1 and 1 standing for 10% and 100% SFR, respectively. Then, the IIA uses the SFR, x, as an input, runs daylight and thermal engines, generates a total source energy consumption, DGPi and MD, and aggregates them into an average performance $f(x)_{avg}$ as an output. These initial inputs and outputs define a first node on the function. To find a second node, another random SFR is generated. Again, the IIA runs for the second SFR, x, and subsequently it generates the second average performance, $f(x)_{avg}$. The gradient is then calculated based on the two found nodes. The following formula (Eq. 3.2) is used to define the next SFR, x_{n+1}, which leads to finding its subsequent average performance, $f(x_{n+1})_{avg}$ and Gradient Descent, $f'(x_{n+1})$:

$$x_{n+1} = x_n - \gamma f'(x_n), \tag{3.2}$$

where γ is case dependent; in this study, it is 10^{-7} for optimizing energy consumption and it is -10^{-4} for optimizing average performance.

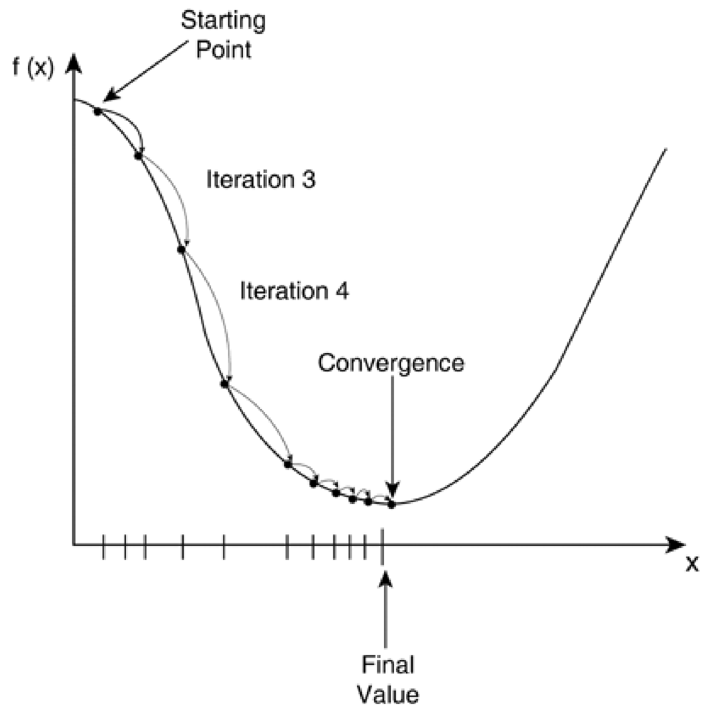

Figure 3.16: Gradient Descent Optimization (CoolJavaScript, 2015)

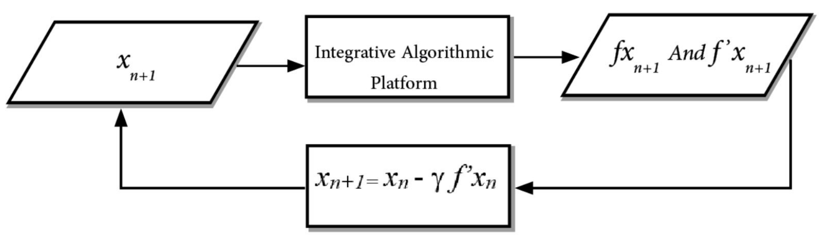

Figure 3.17: Gradient Descent Optimization Process

The process of running IIA to calculate average performance (f), estimate the gradient (f') and generate 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 optimal average performance. Figure 3.17 illustrates the optimization process of the Gradient Descent method.

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 SFR resolution of 0.01%.

Although the Gradient Descent method is supposed to be fast and find solutions with higher resolution, tuning the algorithm and setting the right value for γ require 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 should be carried out by looking into two or three iterations and verifying that the gradients lead to the appropriate next steps. In the case of energy 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 (Figure 3.18). Even though Gradient Descent is fast, resulting in accurate solutions with higher resolution, as mentioned, its implementation needs diligence.

3.5.1.4 Parametric Analysis

To find an optimal SFR with minimum energy consumption, the simplest method was to carry out a Parametric Analysis where all the possible SFRs were simulated and compared based on their average performance, including glare, daylight availability and total energy consumption. A Parametric Analysis considers all possible scenarios for a specific domain and range of variables (SFR in this study). The Parametric Analysis in this research was assumed to have SFR resolution of 1%. If the Parametric Analysis had

GRADIENT DESCENT INITIALIZATION

Iteration	x	fx	$fx_{(N+1)} - fx_{(N)}$	Proportional Step	x_{new}
1	0.2	140,263	-19,431		
2	0.1	120,832		0.0019431	0.098
3	0.098	120,172			
Condition: fx_3 (120,172) < fx_2 (120,832)					

Proportional Step = dfx/dx (Gradient) / 100,000,000 = $[(fx_2 - fx_1)-(x_2 - x_1)]$/ 100,000,000

$x_{new} = x_2$ - Proportional Step

Figure 3.18: Gradient Descent Initialization and Proportional Steps

the same accuracy as the optimization method (0.01), more than 10,000 alternatives would have been necessary. As the reason to undertake Parametric Analysis was to evaluate the result of the unconstrained optimization approach with Gradient Descent method, I coarsened the SFR resolution of Parametric Analysis to 1%. This decreased the number of alternatives to 100. I narrowed down the alternatives even more by handling the Parametric Analysis in two major steps. The first step was to simulate only 11 alternatives, with SFR resolution of 10% (0%, 10%, ..., 90%, 100%) in order to roughly map the optimal solution. After comparing the source energy of these alternatives, it was found that the optimal SFR was 10%, with SFR resolution of 10%. This indicated that the optimal SFR with the highest resolution would be between 0% and 20%. In the second step, 19 SFR alternatives were simulated with 1% resolution in the range of 1−19%. By adopting this approach I ran 30 iterations for Parametric Analysis to find the optimal SFR and to evaluate the result of Gradient Descent method.

3.5.2 Constrained Optimization

In this approach, the context was defined by including different interests of glare, energy and daylight while applying minimum performance targets onto daylight and glare objectives. The proposed IA for energy (Figure 3.8) was coupled with the daylight performance results of Ladybug and Honeybee in order to include qualitative and quantitative impacts of daylight in finding an optimal solution. Like the unconstrained approach, the constrained approach implemented Ladybug and Honeybee to generate internal heat gain while considering daylight, as well as calculating daylight performance by considering daylight metrics for glare and daylight availability. Therefore, steps 1-6 from IIA (Figure 3.14) were applied for this approach as well. However, as steps 7-9, which define the gradient optimization, do not apply to the constrained optimization approach, I implemented Parametric Analysis to find a robust skylight design. The accuracy of SFR in the Parametric Analysis is 1%. The following subsections describe the optimization process to select the effective skylight design and two sets of combined metrics used for this approach.

3.5.2.1 Metrics

While the total source energy consumption (kWh) plays the role of a quantity indicator, there is choice of different daylight metrics which could be identified as quality indicators. For the constrained approach, like the unconstrained one, the energy performance is estimated as total source energy consumption (kWh) in order to value the sources of different loads. In addition, the total energy consumption included HVAC and lighting loads, to comprehensively consider daylight impacts on energy consumption. However, for daylight performance I proposed two sets of combined metrics, horizontal daylight availability and glare. Each set of combined metrics is explained as follows:

- **sDA and UDI:** spatial Daylight Autonomy (sDA) indicates horizontal daylight availability at a desk level (2.6 ft). In addition to sDA, I applied UDI to be an indicator of glare, because it refers to useful daylight (100-2000 lux), in order to avoid excessive daylight and probable glare. Both of these daylight metrics are illuminance based. For more details about the definitions of sDA and UDI, please refer to the subsection 2.2.3.

- **MD and mDGP:** Mean Daylight which is explained in section 3.5.1.1 was used for horizontal daylight availability. In this set of metrics, I used an illuminance based metric to predict daylight availability, whereas I applied a luminance based metric for glare analysis. I applied mean Daylight Glare Probability (mDGP), which is the mean of DGP for all the occupied hours in a year for the installed sensor (Figure 3.10). Figure 3.19 shows how mDGP was calculated.

3.5.2.2 Optimization Process of Conditional Selecting System

For each SFR of the Parametric Analysis, I coupled IA algorithm with daylight performance of Ladybug and Honeybee. After EnergyPlus and Radiance engines were simulated for each SFR, all the metrics of daylight (MD, SDA) and glare (UDI, mDGP) as well as total source energy consumption were calculated and stored for each scenario by a Python script. If the daylight metrics calculated for each SFR, including MD, mDGP, sDA and UDI, did not outperform their defined minimum thresholds, that SFR would be flagged and

TIME			GLARE	STATUS	
Month	Day	Hour	DGP		
1	1	1	0	t1	Not Occupied
1	1	2	0	t2	Not Occupied
1	1	3	0	t3	Not Occupied
1	1	4	0	t4	Not Occupied
1	1	5	0	t5	Not Occupied
1	1	6	0	t6	Not Occupied
1	1	7	0	t7	Not Occupied
1	1	8	0.7682	t8	Occupied
1	1	9	1	t9	Occupied
1	1	10	1	t10	Occupied
1	1	11	1	t11	Occupied
1	1	12	1	t12	Occupied
1	1	13	1	t13	Occupied
1	1	14	1	t14	Occupied
1	1	15	1	t15	Occupied
1	1	16	1	t16	Occupied
1	1	17	1	t17	Occupied
1	1	18	0.4731	t18	Occupied
1	1	19	0	t19	After Sunset
1	1	20	0	t20	After Sunset
1	1	21	0	t21	After Sunset
1	1	22	0	t22	After Sunset
1	1	23	0	t23	Not Occupied
1	1	24	0	t24	Not Occupied
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.

Continue for the whole year

```
Annual Hours = 8760
DGP_occupied hrs= []
Occupeid Hours = 0

For i in range (0, Annual Hours):
        if t_n is "Occupied" ;
                Occupied Hours = Occupeid Hours + 1
                DGP_occupied hrs . append(DGP)
sum_dgp = 0
for each in DGP_occupied hrs:
        sum_dgp = sum_dgp +  each

mDGP = SUM(DGPoccu)/Occupied Hours
```

Figure 3.19: Mean Daylight Glare Probability (mDGP) Calculation for Occupied Hours

would not be accepted as an optimal SFR solution. The following shows the conditional statement for each combined metric set:

- If MD> 50% and mDGP< 35% then find a minimum total source energy consumption (kWh) (DGP$<$ 35% is "imperceptible glare" and the total source energy consumption includes both HVAC and Lighting Loads).

- If sDA$>$ 50% and UDI$=$ 100% then find a minimum Total Source Energy Consumption (kWh).

3.5.3 Optimization Based on Monetary Metric

As improving productivity is a multi-faceted challenge, this study incorporates the monetary benefits of increased productivity with monetary gains from energy efficiency strategies. As discussed in the "Literature Review" section, productivity depends on many factors, including thermal and lighting comfort, views to the outside, the interactive social atmosphere, the nature of the jobs, seasons, weather, etc. Toplighting comfort in this study is defined as the presence of sufficient daylight availability for the whole space, while lowering the probability of glare issues. Although toplighting comfort does not guarantee productivity, as it depends on so many other factors, the lack of toplighting comfort definitely does not increase productivity. In other words, adequate horizontal daylight but with abundant glare issues does not improve productivity. In addition, lack of daylight increases SAD effects and upsets the circadian rhythm, which does not boost productivity either. As the focus of this study is skylight design, toplighting comfort - daylight availability with less glare probability- became the main reason for increasing employees' efficiency. This optimization approach is founded based on the monetary benefits from energy saving and boosted productivity.

As the price of energy is defined based on its source, a heating load is categorized as a gas source while fan and cooling loads have an electricity source. According to EIA, the prices of electricity and gas differ in various locations. I referred to EIA to estimate the price of energy as follows: the gas prices are 0.7, 0.8, 0.7 \$/therm while the electricity prices are 0.13, 0.1, 0.11 \$/kWh for San Francisco, Chicago and Austin, respectively (EIA, 2014, 2017). Different loads were multiplied by their corresponding price rates in order to estimate utility and convert to a dollar metric. The sum of utilities for each SFR was then compared to the baseline of 0% SFR in order to calculate the energy cost saving. The goal is to unify all the metrics to dollar form, in order to compare different scenarios in regard to energy as well as daylight performance.

As the increased productivity rates reported in literature review varied significantly, the minimum increased productivity rate was considered for the monetary benefits from toplighting comfort. The minimum rate of 1% was adopted in order to predict the lowest possible cost savings through enhanced productivity, while avoiding overestimating the monetary benefits of a boosted productivity rate. However, the average productivity rate is 11%, based on the current reports from different case studies. Table 2.1 in the " Literature Review" in section 2.2.2 summarizes all the different case studies and their increased productivity rates by installing advanced lighting and daylighting systems. As shown in this table, productivity rates vary over a wide range (5-16%). According to the BOMA[5], national survey of office buildings, the ratio of area to employees is 310 (sqft/people) (BOMA, 2016). Considering a small office building with 5,500 sqft, the total number of employees is about 18. According to the U.S. Census Bureau real median household income averaged \$50,781 from 1964-2013 (Census, 2013). If \$50,000 is assumed an average

[5]Building Owners and Managers Association

annual salary for each employee, the total payroll for the small office building is \$900,000. Therefore, a minimum increased productivity rate of 1% results in savings of about \$9,000 per annum.

In this monetary optimization, sDA as a daylight availability metric and UDI as a glare metric were utilized to identify scenarios that meet toplighting comfort. The targets for sDA and UDI were defined as 100%. The \$9,000 gain from boosted productivity was only applied to SFR ranges that achieved toplighting comfort. Finally, the optimal solution in this monetary optimization approach is the one that has the highest cost saving considering both energy and productivity aspects.

After discussing the proposed integration and optimization methods and the applied tools, in the next section I will explain the case study which I used to experimentally validate the proposed methods.

3.6 Experiment

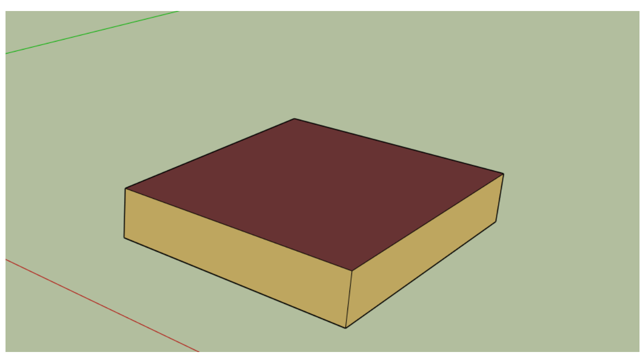

Figure 3.20: Baseline Model

As the goal of this study was to set up an algorithm that could be applicable for any design project, I simulated a base model and proposed models to

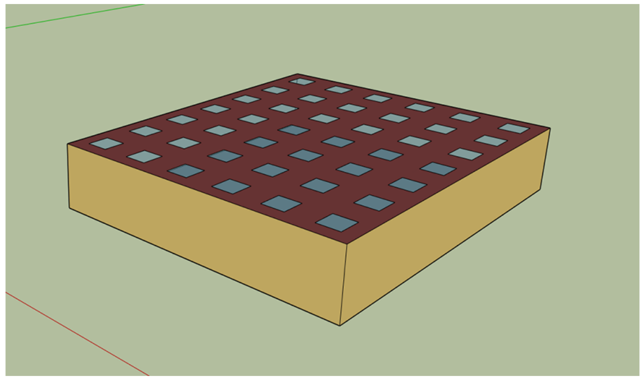

Figure 3.21: Proposed Model with 20% SFR

validate the proposed integration method and optimization approaches. While the base model was developed following ASHRAE standards, benchmarks for daylight performance had not been developed at the time of doing this research. However, daylight parameters for Radiance were mostly borrowed from the Lawrence Berkeley National Laboratory (LBNL).

The base model is a simple box representing a one-storey office building. The base model lacked any sidelight, because in this study I was concerned only with the impacts of skylights on energy performance (Figure 3.20). The proposed models were built on the base model with different SFRs while containing the same construction (Figure 3.21). Given a fixed percentage of the roof area devoted to skylights, many small skylights were uniformly distributed across the roof of the proposed model. The distance between the skylights in the middle of the roof was twice the distance between the last skylights and the walls, in order to avoid dark edges and to create a more even daylit space. I built the base model based on ANSI/ASHRAE/IES Standard 90.1 Prototype Building Model Package (U.S.DOE, 2016), which was published by the Department Of Energy (DOE). The chosen prototype was a small office located in a San Francisco climate zone. 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 this model such as R-value, SHGC, schedules and construction comply with ASHRAE standard $90.1 - 2013$. The most important parameters are listed in Table 3.1. After explaining the construction assumptions and the source for energy simulation, next I explain the assumptions of Radiance simulation.

Table 3.1: 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	5,490 ft2 (90ft*61ft)		**R of Floor Carpet (h.ft2.F/Btu)**	1.2
Number of Floors	1	**Skylights**	**Fraction**	(0%*, 1%, 2%, ...,100%)
Floor to Roof	14.5 ft		**VT**	0.44
Floor to Ceiling	11.5 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.

3.6.1 Radiance Parameters

Table 3.2 presents the significant assumptions for Radiance and Daysim, including reflectance properties, illuminance target and a sensor control system. The quality of Radiance studies depends on several parameters such as -ab, -ad, etc. Here, I define the Radiance parameters I assumed and why I adopted them by citing the sources I used.

- **-ab:** It is the number of ambient bounces, which defines diffuse distribution of light in the space (Antonutto and McNeil, 2016). Two bounces for skylight models means that daylight will reach the task level from the direct sun's ray, from the diffuse sky and from the first and second bounces of daylight reflecting from interior surfaces. In the skylight model the task area receives direct daylight from skylight and diffuse

Table 3.2: Radiance and Daysim parameters.

SURFACE REFLECTION		ELECTERIC LIGHTING CONTROL SYSTEMS	
Wall	0.5	**Control Types**	Auto dimming with switch off occupancy sensor
Ceiling	0.8	**Sensor Points**	30 Points (5*6)
Floor	0.2	**Target Illuminance for the Space**	300 Lux
Site Ground	0.2	**Minimum Dimming Level in Percentages**	20
RADIANCE PARAMATERD			
_ab_	2	**_ar_**	128
_ad_	1,500	**_aa_**	0.1
_as_	256	**Quality of Rendering**	0*-low

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

daylight from the interior side of the roof or the walls. The geometry of the skylight model is quite simple: a box with windows on the roof and no interior furniture. Considering this geometry, -ab of 2 is appropriate. If the geometry had been more complex such as venetian blinds or light shelves, maximum -ab (8) would have been more reasonable. However, according to the Radiance website(RadianceParameters, 2016), -ab of 2 is accurate especially for this simple model.

- **-ad:** This decreases the error in the Monte Carlo calculation of indirect illuminance, which is used in Radiance (Antonutto and McNeil, 2016). The inverse of its square root is propositional to the error (Antonutto and McNeil, 2016). As a result, the higher the number the lower the noise in the calculation (Antonutto and McNeil, 2016). According to LBNL, -ad of 512 produces accurate results (RadianceParameters, 2016). However, -ad of 1500 was chosen for this study, which is three times higher than the number recommended by LBNL (RadianceParameters, 2016). Again, if a more complex scene had been tested, a higher number of -ad should have been adopted in order to test more rays for each point.

- **-quality** Since I did not have to consider preparing a client-ready rendering, I adopted a low quality of image in order to generate the images faster.

It is time-consuming and computationally expensive to run a large number of iterations for different optimization approaches with different variable settings. Considering the simplicity of the geometry and many iterations to run, the Radiance parameters were carefully chosen to provide reasonably fast but accurate results. In addition, this study is a comparative analysis between different SFRs. Since Radiance parameters were fixed for all the scenarios, a higher number of Radiance parameters would not change the final result. However, it would heavily increase the computation time.

3.6.2 Different Variables

Different variables may sway the result of the optimization algorithm including different climates, lighting powers and daylight thresholds. Although the main variable is skylight size and glass and envelope properties were held constant, in this research I considered sensitivity analysis for a few variables in which I studied the impact of different values of an independent variable on the solution under a given set of assumptions (Vanderbei, 2001).

- **Climates:** I simulated the baseline and proposed models within different climates, including San Francisco, Austin and Chicago. According to the EnergyPlus weather file (.epw), the ASHRAE climate zone of San Francisco is 3c, which is Mediterranean climate with a dry warm summer and a mild winter. The ASHRAE climate zone of Austin is 2a which is humid subtropical, having mild with no dry seasons and a hot summer. Chicago has the ASHRAE climate zone of 5a, which is cool with a humid continental and warm summer.

- **Different lighting power density:** In this research a range of Lighting

Power Densities (LPD) was studied for an office building in Chicago, Austin, and San Francisco, respectively. Lighting power densities were considered as 1.2, 1, 0.8, 0.6 and 0.4 w/sq.ft, while optimizing SFR in regard to effective daylighting. As 1.2 w/sf stands for inefficient lighting power, 0.4 w/sf is the minimum lighting power density that can provide sufficient light (lumens) using an advanced efficient lighting system such as LED.

- **Different lighting target levels:** According to the IESNA [6] Lighting Handbook, different spaces require different lighting levels based on the nature of the work or activity that is done in those spaces. General spaces in an office, an open office and a private/closed office need 200-300, 300-500 and 300-500 lux, respectively (IESNA, 2015). However, if an office space is dedicated to drafting or is a workshop, the illuminance required is increased to 750 lux (IESNA, 2015). Therefore, in order to study the sensitivity of the optimization algorithm in terms of required lighting levels, I analyzed a range of lighting target levels, including 200, 300, 400, 500, 600 and 700 lux.

[6] IESNA stands for Illuminating Engineering Society of North America

Chapter 4

Results and Discussion

As the purpose of this study is to find an optimal solution(s) for skylight sizes regarding energy and daylight performances, I have adopted different optimization approaches, methods and metrics. In this section I present and interpret the results of those approaches, followed in each case by a discussion. This chapter is divided into three major sections: unconstrained, constrained and monetary optimization results.

As environmental concerns have motivated researchers to focus on studies regarding energy efficiency and CO_2 emissions, I first present a comprehensive account of the holistic energy impacts of daylight. This energy analysis discusses the results of the single-objective unconstrained optimization approach for the different climates of San Francisco, Austin and Chicago, as well as different LPDs and lighting level targets. I compare the results of GD and PA methods for the energy optimization. I then expand single-objective to multi-objective unconstrained optimization by including both daylight and energy performances and applying the PA method.

After reviewing the results of the unconstrained optimization, I present the results of the constrained optimization for the three examined climates, where I only applied the PA method. Finally, I discuss the results of the PA method, where the financial benefits from both energy efficiency and productivity were utilized to find the optimal solution(s) for the three climates.

4.1 Unconstrained Optimization

The current section compares the application of the Gradient Descent method with a subsequent Parametric Analysis and application of a weighting system. In the first subsection, I present the results of the proposed Gradient Descent method for skylight design, where energy efficiency is the only objective of the optimization. This method was applied for an office building located in San Francisco, and the results then, verified with a Parametric Analysis. This procedure was then repeated for two different climates: Austin and Chicago. After evaluating the single-objective optimization of energy efficiency for different climates, and various Lighting Density Power (LPD) and lighting levels, I present the results of multi-objective optimization, where both qualitative and quantitative factors of energy, glare and daylight were taken into account.

4.1.1 Single-Objective Optimization Concerning Energy Efficiency

While a weighting system considers different scales for the roles of glare, daylight and energy, there exist some contexts in which energy, as the quantitative aspect of daylight, plays the sole role in designing skylights. In a storage area, for instance, the only motive to install skylights is to save energy and lower the utility cost. In this kind of problem where energy is the only design decision criteria, $f(x)_{avg}$ equals to RES, the ratio of energy saving compared to the scenario with maximum energy consumption (SFR 100%). The following equation (Eq. 4.1) illustrates a redefined equation of Eq. 4.2 where the energy factor is the only player in the design:

$$f(x)_{avg} = \frac{\alpha MD + \beta DGPi + \gamma EnergySaving}{\alpha + \beta + \gamma} \tag{4.1}$$

where α, and β is 0, and γ is 1.

For Eq. 4.1 α and β both equal zero, which means that daylight availability and glare, as qualitative aspects of daylight, do not matter in the design of skylights. However, γ is considered equal to one, which imposes energy consumption as the design decision criterion for the optimization. In the following subsection I present the results for the cases where the design decision criterion is solely energy efficiency, while both Gradient Descent and Parametric Analysis were applied to find and verify the optimal SFRs for different climatic conditions.

4.1.1.1 Comparison of Gradient Descent and Parametric Analysis Methods for Design of Energy Efficient Skylights in San Francisco

In the case of the San Francisco climate, although the methods of Gradient Descent and Parametric Analysis reached the same optimal SFR, both required different numbers of iterations. Figure 4.1 shows the energy performance of nine alternatives generated by Gradient Descent. Starting with the random first SFR of 30%, it took nine alternatives for the optimization algorithm to converge on 6.22% SFR as the optimal ratio. Figure 4.2 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 GD, both methods reasonably agree on the same optimal SFR, 6-6.22%. The Parametric Analysis required 30 iterations to discover the optimal SFR with a resolution of 1%, compared to nine iterations of the optimization 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.

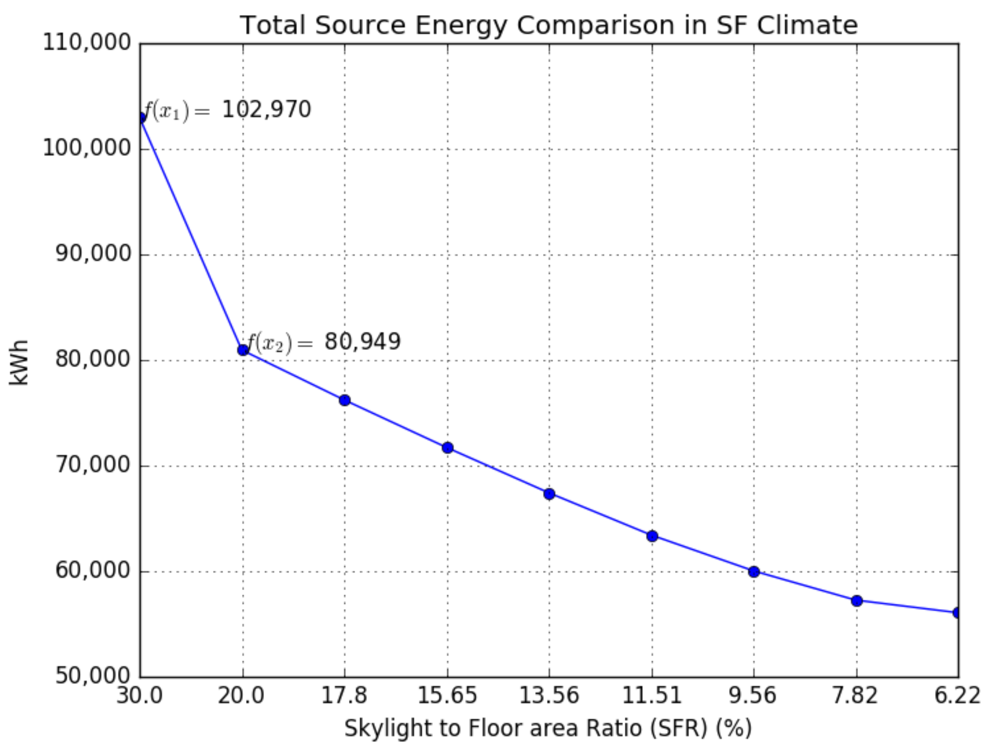

Figure 4.1: Different Alternatives Generated by Gradient Optimization Method

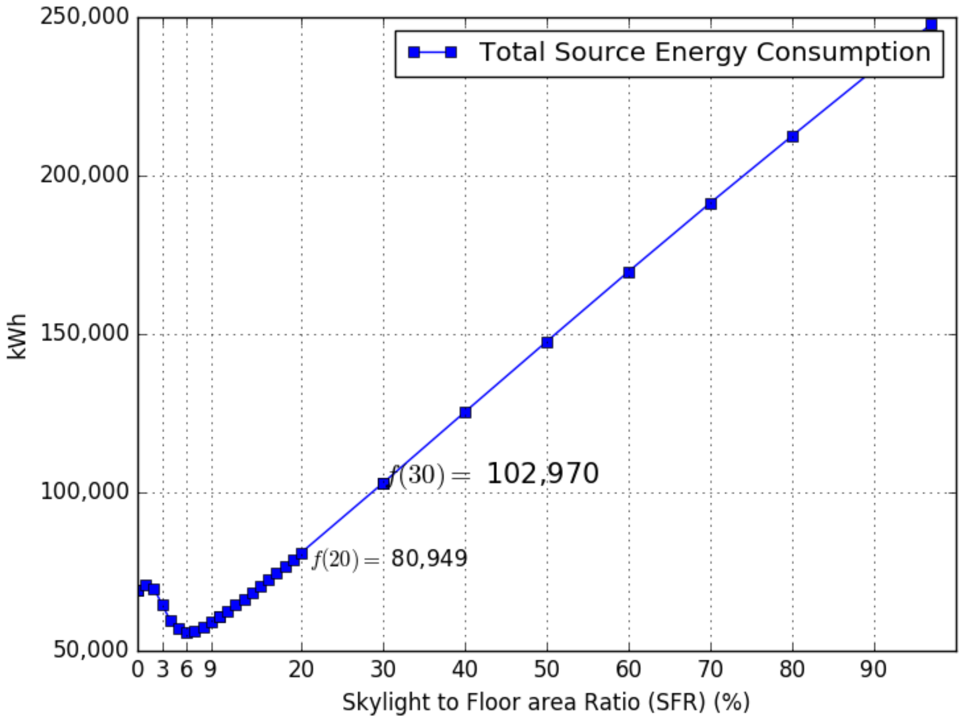

Figure 4.2: Different Alternatives Using Parametric Analysis in San Francisco Climate

4.1.1.2 Detailed Results of Parametric Analysis for Design of Energy Efficient Skylights in San Francisco

As daylight influences both electrical lighting and HVAC loads, I analyze their impacts for the SFRs between 0% and 20%. In Figure 4.3, 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 4.3, 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

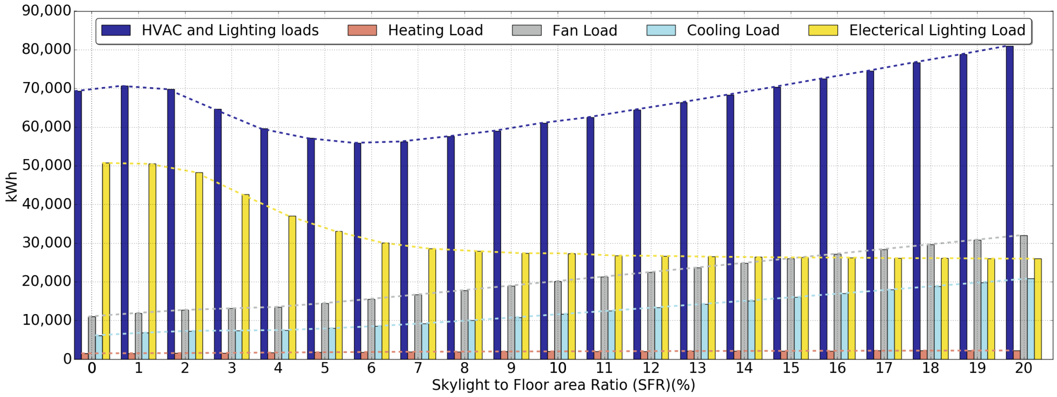

Figure 4.3: Breakdown of Total Source Energy into Electrical Lighting, Cooling, Heating and Fan Loads in San Francisco Climate

reaches its minimum, at 6% SFR. Compared with 0% SFR, 6% SFR saves up to 41% of the source energy of lighting loads, while heating, cooling, fan and total HVAC loads are increased respectively by 23%, 39%, 41% and 39%. In addition, the sum of lighting and HVAC loads is reduced by 19.30% in regard to source energy. After 6% SFR, the total energy consumption increases by adding more skylights. However, any SFR between 3% and 14% is more energy efficient than either 0% SFR (base model) or any SFR larger than 14%. This implies that if the skylight area is expanded to up to 14% of its roof area, the model still saves energy.

As shown in Figure 4.3, adding skylights starts to minimally increase cooling and fan loads until SFR reaches 5%. For SFRs greater than 5%, cooling and fan loads increase linearly but more conspicuously. The consistent increase in cooling loads found in this study is different from what was found in previous ones (Motamedi, 2012a; Ghobad et al., 2013b). In regard to cooling loads, Ghobad et al. showed savings for SFRs below 3.5% in Boston and Miami climates (Ghobad et al., 2013b) while Motamedi demonstrated that

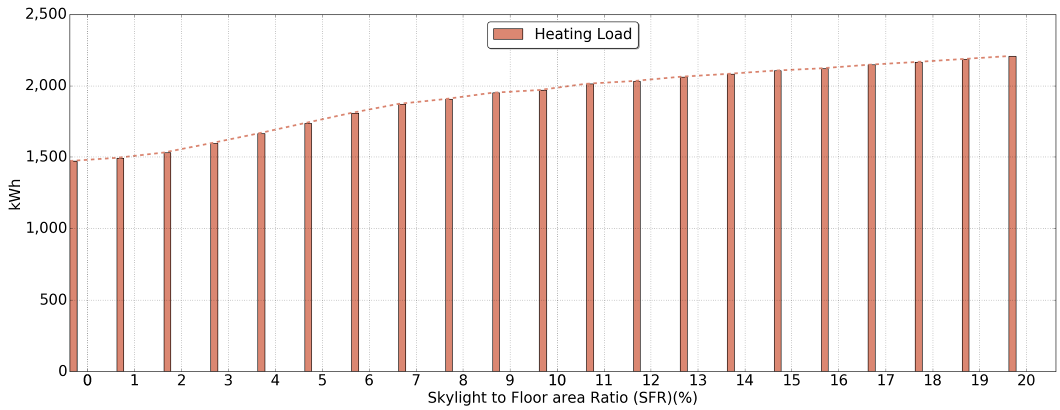

Figure 4.4: Source Energy of Heating for Different Alternatives

cooling loads were not changed by 5% SFR in the Austin climate (Motamedi, 2012a). The previous studies (Motamedi, 2012a; Ghobad et al., 2013b) and this dissertation maintain that the impact of daylighting on cooling loads strongly depends on assumptions regarding the HVAC system, LPD, SHGG and VT properties of skylights and illuminance targets.

While 4.3 shows steady heating loads, Figure 4.4 magnifies the impact of SFRs on heating loads. As illustrated in Figure 4.4, heating loads rise with increasing SFRs. Such an increase has a minor impact on the total energy consumption, because the heating load contributes little to the total energy load in a climate like San Francisco. As a result, its change is not noticeable in Figure 4.3. While the increase in heating load may be insignificant, my result is in agreement with those of Ghobad et al. and Motamedi, that the heating loads are increased by adding skylights (Motamedi, 2012a; Ghobad et al., 2013b). In regard to electrical lighting loads, the decrease is negligible for 1% and 2% SFRs (Figure 4.3). However, such a decrease becomes exponential for SFRs of 3% and more until SFR reaches 7%. For skylight ratios of 7% and more electrical lighting loads linearly and slowly decline.

Another significant point about Figure 4.3 is the specific behavior of its total energy curve. While the curve shows a narrow concave with a maximum at 1%, it also shows a wider convex with a minimum at 6%. The concave part represents the slight increase in total energy consumption (Figure 4.3) for 1% and 2% SFRs. This is mainly because 1% and 2% SFRs do not provide enough daylight to significantly decrease electrical lighting loads. In these two scenarios, the decline of electrical lighting loads cannot offset the increases of heating, cooling and fan loads. As a result, the total HVAC and electrical lighting loads of 1% and 2% SFRs are slightly bigger than the ones of the base model. In contrast, the SFR alternatives represented by the convex curve are between 3% and 14%, for which the decrease in electrical lighting loads always offsets the increase in HVAC loads.

4.1.1.3 Comparison of the Optimal Energy Efficient SFRs for Different Climates

Climatic conditions impact lighting and HVAC loads, which subsequently change the energy saving of the optimal energy efficient SFR. I applied a Parametric Analysis and compared total source energy consumption, including lighting and HVAC loads and I specified the HVAC loads by considering heating, cooling and fan loads. Figure 4.5 shows total source energy consumption in the climates of San Francisco, Austin and Chicago. As shown in Figure 4.5, different SFRs in San Francisco consume less energy compared to the corresponding SFRs in other climates because the other two cities are located in harsher climates, while San Francisco has a much more temperate climate. Austin and Chicago are located in cooling and heating dominated locations, respectively. The scenarios, where SFR is less than 15%, require less energy consumption in the Austin climate than in the Chicago climate. However,

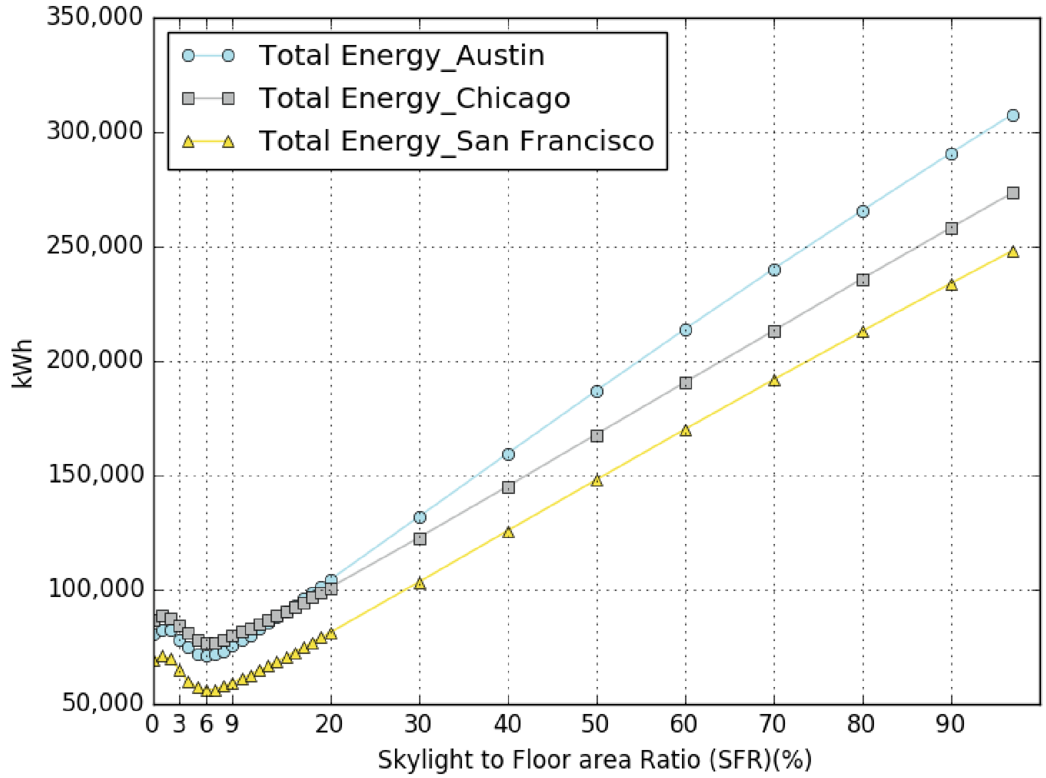

Figure 4.5: Total Source Energy Consumption, including HVAC and Lighting, for Austin, Chicago and San Francisco Climates

scenarios where SFR is above 15% consume more energy in the Austin than Chicago climate. This is mainly because, in the Austin climate, SFRs greater than 15% overlight the space and the reduction of electrical lighting cannot offset the intensive direct solar gain. Moreover, Figure 4.5 shows that different climate curves follow the same behavior as the energy consumption in all climates, presenting a subtle concave at 1% and a wider convex with a minimum at 6%. Interestingly, the optimal energy efficient SFR for all climates is 6%, while the savings over the baseline of 0% are different: 19.30% for San Francisco, 11.80% for Austin, and 11.72% for Chicago. The optimal SFR in

San Francisco has a higher rate of savings because San Franciscos milder climate requires lower HVAC loads, which leads the electrical lighting load to represent a higher proportion of total source energy consumption. Therefore, it appears that daylight can play a more influential role in saving energy in milder climates such as San Francisco. In addition, the energy efficient range of SFR is the widest (3-14%) in San Francisco,while the energy efficient SFR range is 3-11% for Austin and 3-13% for Chicago.

Figures 4.6 and 4.7 break down energy consumption for the Austin and Chicago climates. For Austin, up to 40% of the source energy of lighting loads is saved, while heating, cooling, fan and total HVAC loads are respectively increased by 19%, 30%, 49% and 37%. However, the sum of lighting and HVAC loads is reduced by up 11.80%. For the Chicago climate, although 38% of the lighting load is saved, the other loads are increased, by 16% for heating, 25% for cooling, 38% for fans and 25% for total HVAC. However, the sum of all these loads still leads to 11.72% of savings with regard to total energy consumption.

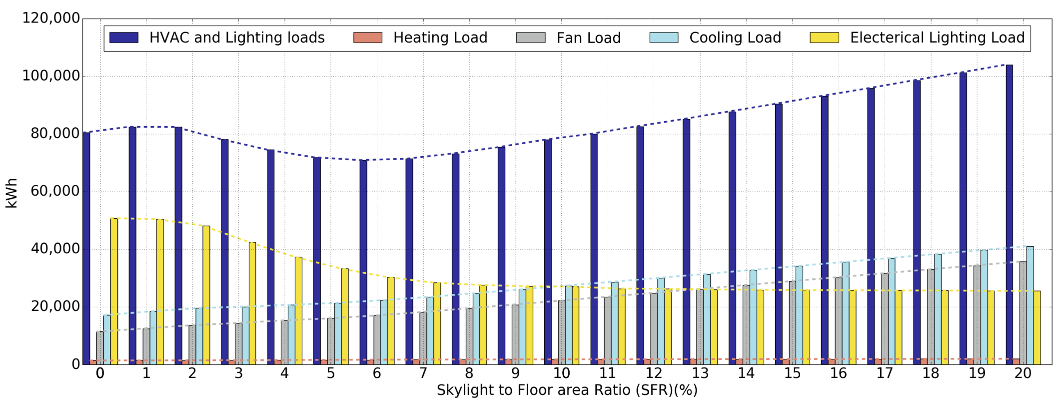

Figure 4.6: Breakdown of Total Source Energy into Electrical Lighting, Cooling, Heating and Fan Loads in Austin Climate

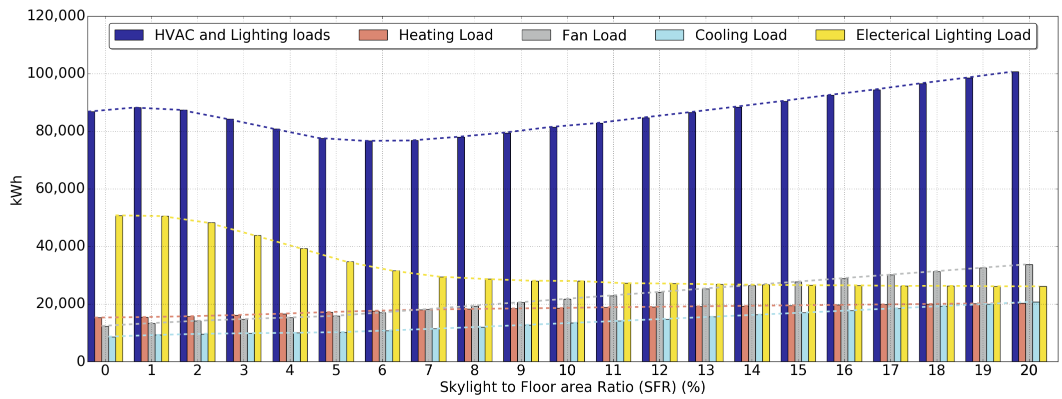

Figure 4.7: Breakdown of Total Source Energy into Electrical Lighting, Cooling, Heating and Fan Loads in Chicago Climate

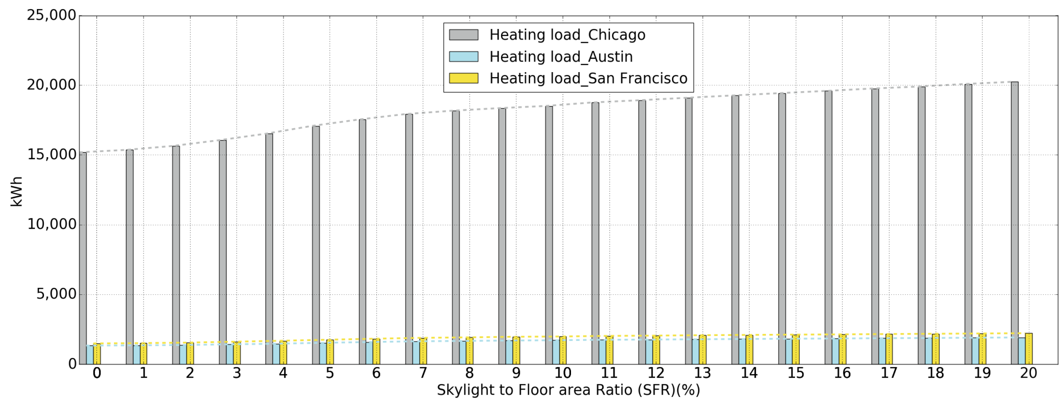

Figure 4.8: Comparing Heating Loads of Different Climates for an SFR Range of 0-20%

Figure 4.8 compares heating loads of different climates for the first 21 SFRs. It can be seen that the heating load in Chicago is significantly higher than in the other climates, whereas Figure 4.9 shows that the cooling loads in Austin are much greater than those in San Francisco and Chicago. According to Figure 4.10 the fan load is smaller in San Francisco than in the climates of Austin or Chicago. Figure 4.11 also shows smaller HVAC loads, including heating, cooling and fan loads, in San Francisco compared to the other two cities, due to its milder climate. However, the reduction of electrical lighting

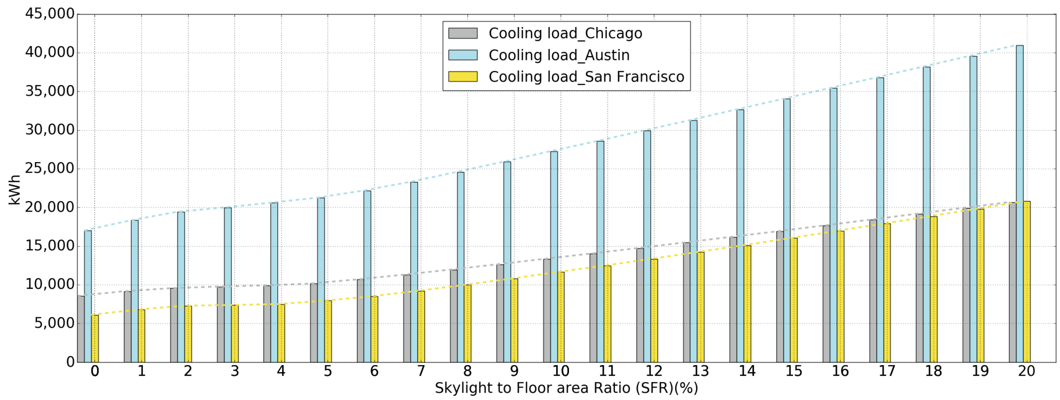

Figure 4.9: Comparison of Cooling Loads of Different Climates for an SFR Range of 0-20%

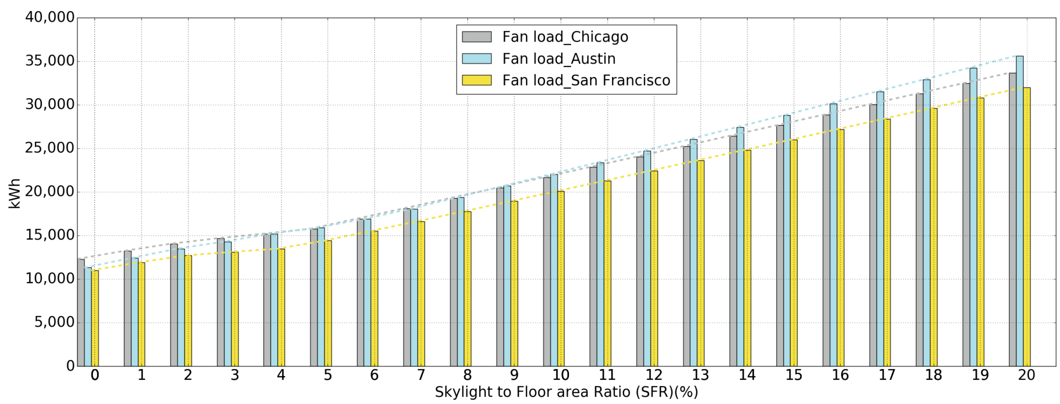

Figure 4.10: Comparison of Fan Loads of Different Climates for an SFR Range of 0-20%

loads mainly follows the same magnitude and behavior for all three climates (Figure 4.12). The electrical lighting loads are noticeably decreased up to 7% SFR; however, the reduction is insignificant for SFRs greater than 7%. In addition, differences in the electrical lighting requirements between various climates for each SFR are subtle.

Generally the electrical lighting load is a function of how much electrical lighting is needed to illuminate the space considering climate, daylight, lighting levels and LPDs. In three studied case studies lighting loads depend on LPD

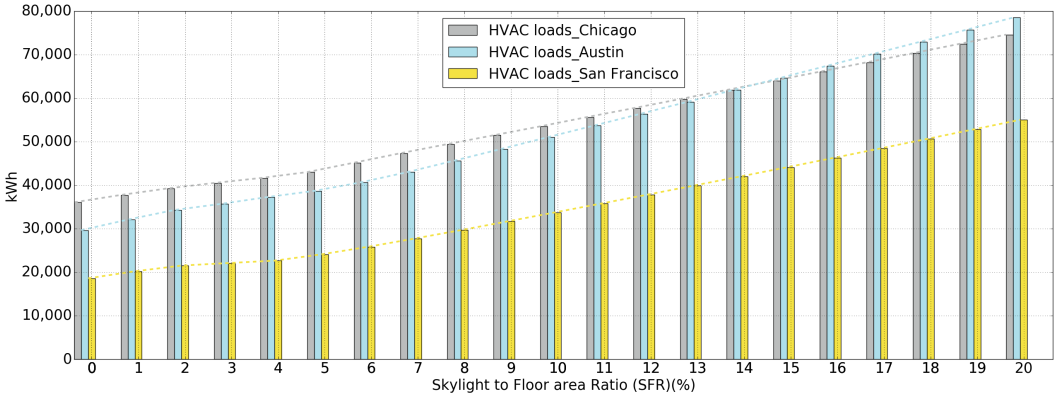

Figure 4.11: Comparison of HVAC Loads of Different Climates for an SFR Range of 0-20%

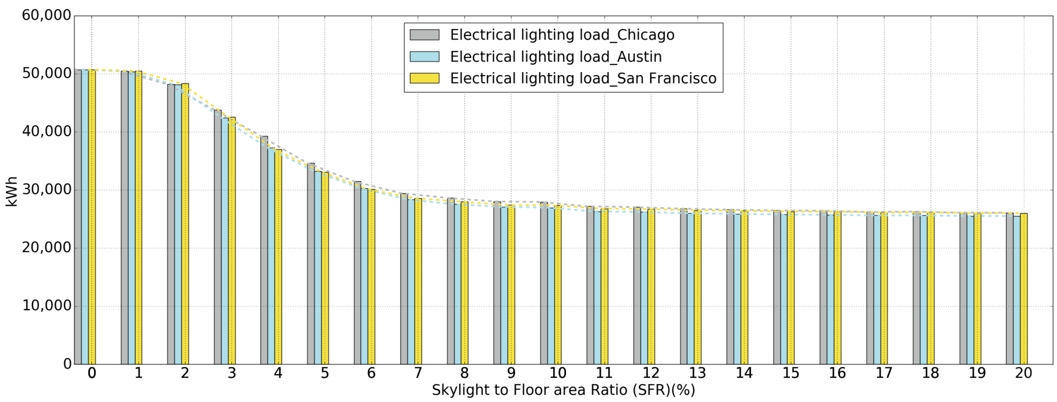

Figure 4.12: Comparison of Electrical Lighting Loads of Different Climates for an SFR Range of 0-20%

of 0.8 watt/sqft, lighting level of 300 lux, the sun position and sky cloud cover. The sun position and sky cloud cover are functions of location. In this research the importance of sun position is reduced because the daylight strategy is through skylights. As skylights are installed on the roof, they receive more sun than any sidelight. If the design problems had involved north or south facing windows, the sun position, and as a result, the locations (latitudes), would have played a more significant role in reducing electrical lighting loads.

4.1.1.4 Comparison of the Optimal Energy Efficient SFR for Different Lighting Levels

Each space requires different target illuminance which influences lighting and HVAC loads. Based on the nature of the work done in an office, a room needs illuminance in a range of 200-700 lux. Here, I present results of a Parametric Analysis by adopting different lighting target levels (200, 300, 400, 500, 600, and 700 lux) for the examined climates of San Francisco, Austin and Chicago, while keeping electrical lighting consumption constant at 0.8 watt/sqft. Figure 4.13 compares total energy consumption of scenarios with different illuminance targets in the San Francisco climate. As shown in Figure 4.13, for target illuminance of 200 lux, the total energy consumptions of SFRs 5% and 6% are very close and show the minimum total energy consumption within the SFR range of $0-20\%$. For a target level of 300 lux, the optimal SFR is 6%. However, at target illuminance levels of 300 to 400 lux the optimal SFR rises to 7% and remains the optimal solution for illuminance targets of 500, 600 and 700 lux. Specifically for 700 lux target illuminance the difference in energy performance between 7% and 8% is negligible. Thus, based on lighting level targets the optimal SFR in regard to energy efficiency ranges from 58%.

A 3% difference in SFR may seem an insignificant variation, but a 3% difference from an optimal SFR of 5% represents a 60% change. Moreover, the significance of SFR differences depends on how big the area of the roof is. The small office type adopted in this research has an area of 5,500 sqft; thus a 3% difference in SFR for this case would equal 165 sqft of skylights. The three-storey medium-sized office proposed by the Department of Energy as a reference building has a total area of 53,628 sqft. If skylights are assumed to be installed on the top floor, with 17,876 sqft area, a 3% difference in SFR for

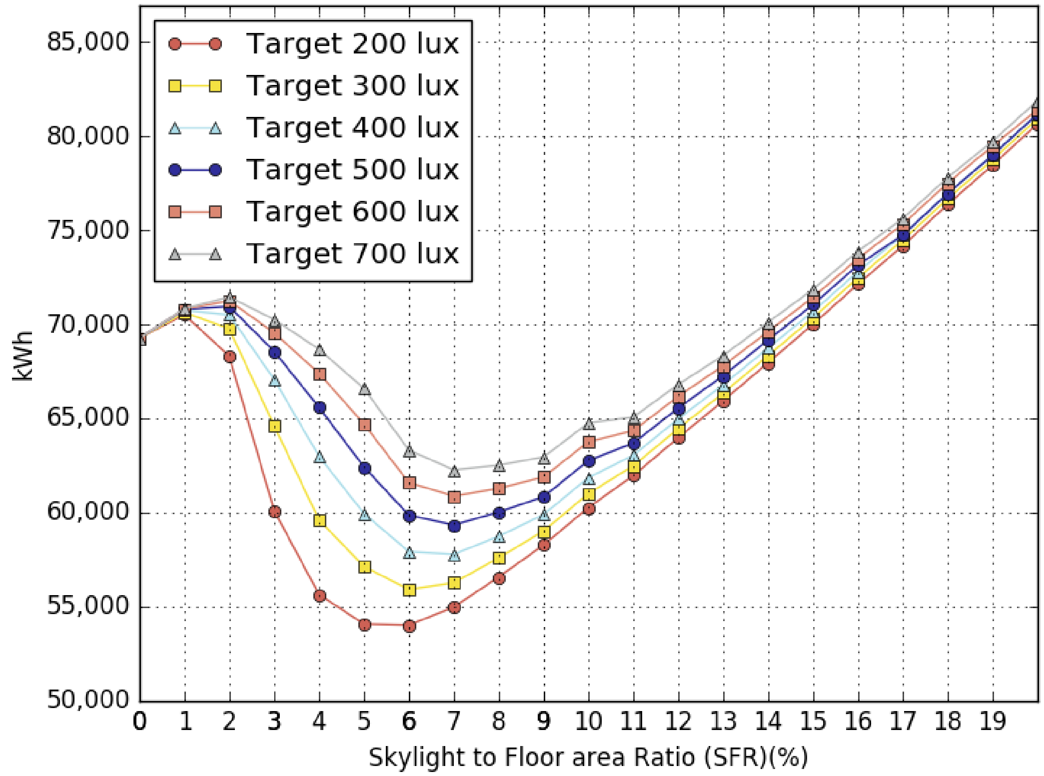

Figure 4.13: SFR Range of 0-20% and Corresponding Total Energy Consumption in the San Francisco Climate with Target Illuminance Range of 200-700 lux

this case is equivalent to 536.3 sqft of skylights. The additional 3% in SFR thus entails a considerable increase in the initial cost of buying and installing the units.

In addition, by increasing the lighting target level, not only does the optimal SFR becomes larger but also the total energy consumption for each SFR, even for the optimal ones, increases. As shown in Figure 4.13, the convex portion of each curve represents the optimal SFR with the minimum total energy consumption. As the target illuminance increases, the convex portions of the curves move toward the right and upwards. Moving toward the right

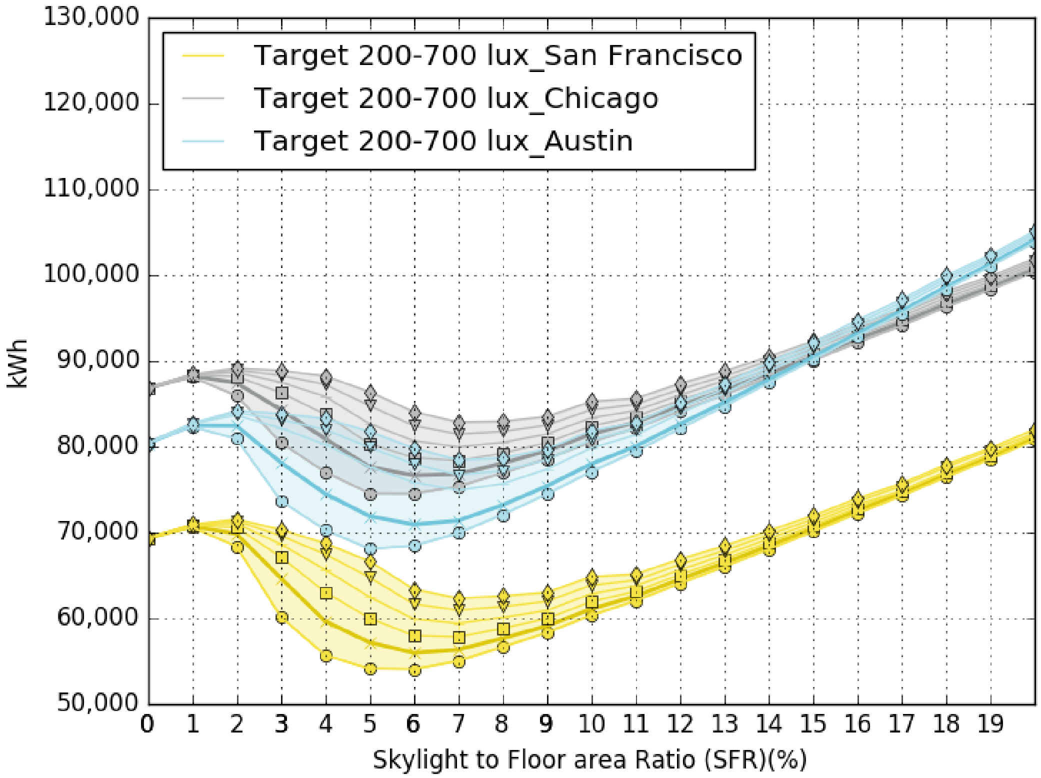

Figure 4.14: Showing the Influence Pattern of Target Illuminance Level on Energy Consumption is the Same in Different Climates of San Francisco, Austin and Chicago

means, a higher SFR is required to meet a higher target illuminance. As shown in this figure, for each SFR total energy consumption is rising with the increasing target level. For instance, the 6% SFR secenario consumes less energy wih target illuminance of 200 lux than 700 lux. Although 6% SFR provides the same amount of daylight, the light it provides is only sufficient for a lower set of illuminance targets. In other words, because the daylight provided by 6% SFR is more adequate for the illuminance target of 200 lux than for 700 lux, a lighting sensor turns off more electrical lighting for the scenario with illuminance target of 200 lux than for that with 700 lux. Therefore, the electrical lighting load is boosted by a higher set of target illuminance for each SFR which subsequently increases total energy consumption.

Two further sensitivity analyses were performed for the other two climates, Austin and Chicago, where the impacts of lighting levels were studied. Similarly to the findings for San Francisco, in the Austin and Chicago climates the optimal energy efficient SFR shifts from 5 to 8% as the target illuminance is changed from 300 to 400 lux and 600 to 700 lux, as shown in Figure 4.14. While the total energy consumption is different in the three examined climates, the target illuminance has the same pattern of influence on total energy consumption for each climate (refer to Figure 4.14). Meanwhile, with the same target illuminance, the optimal energy efficient SFR is the same for each of the three different climates.

4.1.1.5 Comparison of the Optimal Energy Efficient SFR for Different Lighting Power Densities

The number of lights to be installed in a room is a significant factor in determining energy consumption of buildings. Lighting Power Density (LPD) is defined by the amount of power required to light a specific area. This number depends on different qualitative and quantitative design factors, including illuminance or luminance target to meet, light types and their efficiencies, luminous intensity, luminous efficacy, color rendering, and glare issues (Efficient-Lighting, 2009; Lighting, 1995). The ASHRAE standard provides a maximum power density (0.95 for offices) for different locations; however, because of the mentioned design factors, the final designed LPD can be different from the one proposed by ASHRAE. Therefore, here I studied a range of lighting power densities (1.2, 1, 0.8, 0.6, and 0.4) while fixing other factors, including target illuminance of 300 lux.

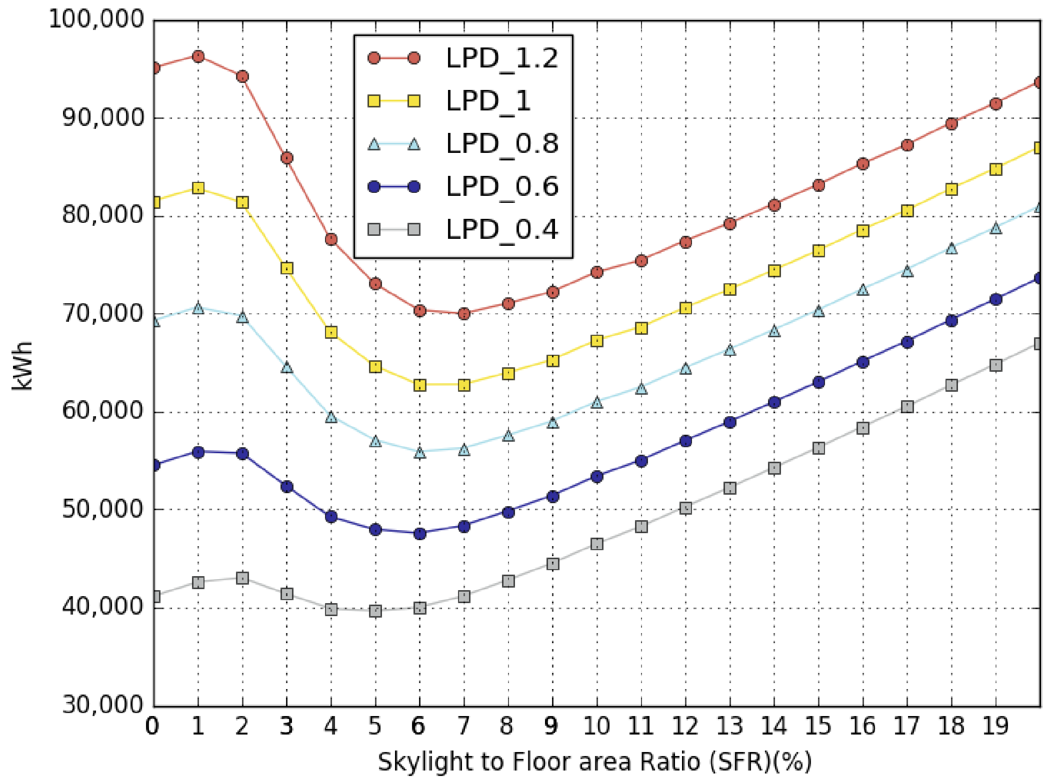

Figure 4.15: SFR Range of 0-20% and the Corresponding Total Energy Consumption in the San Francisco Climate with LPD Range of 0.4-1.2 watt/sqft

Not only do different LPDs change energy consumption but they also influence the role of daylight in deriving the optimal energy efficient SFR. Figure 4.15 illustrates the sensitivity analysis of LPDs on energy consumption and subsequently the optimal energy efficient SFR. As shown in Figure 4.15, the minimum point on the curve represents the lowest energy consumption and the optimal energy efficient SFR. The difference between the maximum point and the minimum point is more exaggerated in higher LPDs. In other words, the energy savings of the optimal SFRs over 0% SFR are enhanced for the scenarios with higher LPDs. The lower the LPD gets, the more flattened energy consumption curves become, which results in lower energy savings.

A lower required/designed LPD weakens the role of daylight on energy savings. Such a role is mainly defined by the share of lighting loads in total energy consumption. Daylight entering through skylights reduces the use of lights. If a space is required or designed to have a higher LPD, then lighting consumption is higher and represents a larger proportion of total energy consumption. Therefore, more skylights are needed to offset the lighting load in cases requiring higher LPDs. As shown in Figure 4.15, 0.4, watt/sqft, which is the lowest examined LPD gives 5% SFR as the optimal SFRs in the San Francisco climate. In addition, the energy consumption of the optimal SFR (5%) is marginally less than the baseline with 0% SFR. This implies that if a space is deprived of daylight and no skylights are installed, the energy consumption of this space almost equals the energy consumption of a space that has 4% SFR installed. In contrast, Figure 4.15 illustrates the optimal SFR of LPD 1.2 watt/sqft, which is 7%, reducing total energy consumption by 26% compared to the baseline with 0% SFR. Therefore, higher designed/required LPDs highlight the role of daylight and skylights in energy savings.

The optimal energy efficient SFR changes with different LPDs. Figure 4.15 shows that the optimal SFRs can be 5, 6 and 7% for different LPDs in the San Francisco climate. Thus, the optimal SFR is 5% for 0.4 watt/sqft LPD, 6% for 0.6 and 0.8 watt/sqft, and 7% for LPDs of 1 and 1.2 watt/sqft.

The climates of Austin and Chicago were then analyzed to study the sensitivity of LPD on energy consumption in different climates. Figure 4.16 shows that the optimal energy efficient SFR shifts from 0 or 5 to 6% and 6% to 7% in cases that the LPD is increased from 0.4 to 0.6 and 0.8 or 1

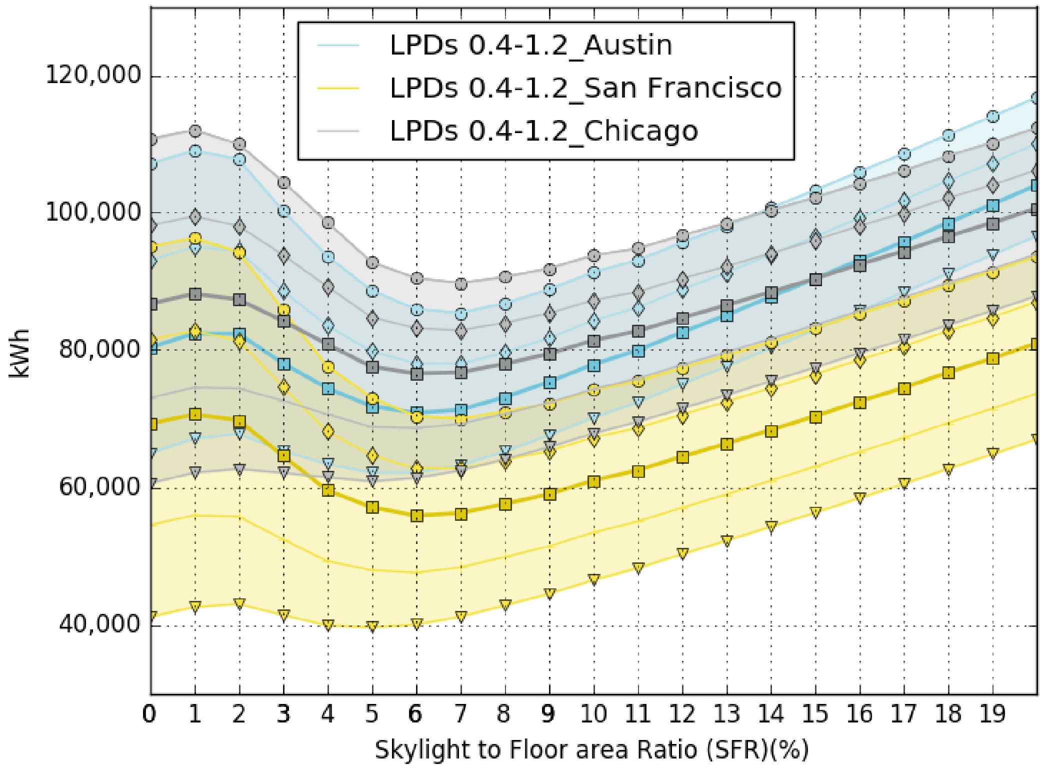

Figure 4.16: SFR Range of 0-20% and the Corresponding Total Energy Consumption in the San Francisco, Austin and Chicago Climates with LPD Range of 0.4-1.2 watt/sqft

to 1 or 1.2 watt/sqft. As would be expected, the three examined locations show different total energy consumption ranges due to their different climates which has been filled with different colored regions. In addition, the increase in LPD shows the same pattern of influence on total energy consumption for each of the different climates (as shown in Figure 4.16). Higher LPDs increase the optimal SFR while moving the energy consumption curve to the right; moreover, higher LPDs increase total energy consumption while shifting the whole curve upward; and more importantly it produces a deeper convex portion, which represents an increase in the amount of the energy saved by using the optimal SFR.

4.1.2 Multi-Objective Optimization using a Weighting System Including Qualitative and Quantitative Factors of Daylight

To aggregate all the qualitative and quantitative daylight factors for a multi-objective optimization requires an inclusive unified metric. In this study, percentage is the common metric which can be used to represent and aggregate the three factors of daylight, glare and energy. For the daylight factor, I defined an average daylight measure, MD, to calculate the percentage of occupied hours in which the space, on average, receives enough daylight. For the glare factor I determined DGPi to compute the percentage of occupied hours meeting the requirement of “imperceptible” glare. Finally, for the energy factor, RES was used which is the percentage of energy saving for each SFR against 100% SFR (the worst case scenario). See Section 3.5.1.1 where all the metrics of RES, DGPi and MD have been explained. Two approaches, Parametric Analysis and the Gradient Descent method, were applied to carry out a holistic unconstrained optimization using the aggregated metric.

4.1.2.1 Parametric Analysis Method Using Aggregated Metric

Here, I present results of a Parametric Analysis performed to obtain a multi-objective optimization for the different climates of San Francisco, Austin and Chicago. The target lighting level was considered as 300 lux, while LPD was held constant at 0.8 watt/sqft for all iterations.

The results of the unconstrained optimization show that each design factor has different optimal SFR. Figure 4.17 illustrates the result of the Parametric Analysis in the San Francisco climate, considering the three metrics of

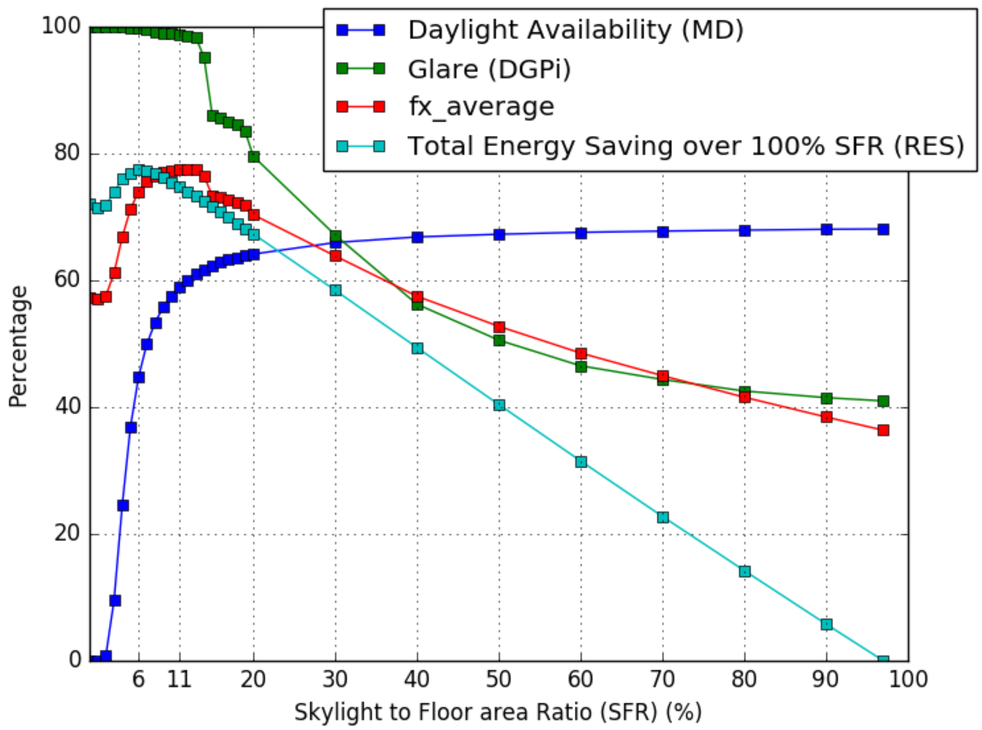

Figure 4.17: Parametric Analysis of DGPi, Mean Daylight illuminance (MD), Total Source Energy Saving over 100% SFR and Average Performance ($f(x)_{avg}$) of Daylight and Energy in San Francisco Climate

DGPi, MD and RES for the three factors of glare, daylight and energy, respectively, in addition to the aggregated percentage metric. Since DGPi represents the percentage of occupied hours for which the sensor receives "imperceptible" glare, a larger DGPi percentage implies a better daylight performance in regard to glare issues. Therefore, the graph shows that the larger DGPi occurs at the lower SFR, resulting in 0% SFR as the optimal value with the best glare performance.

The dark blue line shows that MD are ascending by increasing SFR, implying that more skylights provide better daylight availability in a year.

However, the MD curve behaves as a logarithmic curve reaching its best daylight performance at 100% SFR with 68% MD. While the curve shows steep slope for SFRs smaller than 11%, its rate of change starts to become less for SFRs bigger than 11%. This verifies that, at a certain SFR the daylight reaches its potential and by adding more skylights the daylight availability do not significantly improve.

One of the important conclusion from comparing different design factors is that the optimal SFR regarding a particular criterion does not guarantee optimal performance regarding other criteria. For instance, the light blue line shows that the maximum energy saving occurs at 6% SFR, where RES, DGPi and MD are 72%, 99.6% and 41.8%, 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 shows an acceptable glare performance, its glare performance is not better than SFRs smaller than 6%. Figure 4.17 presents 0%, 100% and 6% as the optimal solutions regarding glare, daylight and energy factors, respectively. Therefore, each objective function or design criterion results in different optimal solutions.

While increasing skylight area significantly improves daylight performance at lower SFRs, glare performance slowly worsens. Daylight always conflicts with glare performance criteria, while daylight and glare only conflict with energy performance within a certain SFR range. For instance, at SFRs smaller than 6%, daylight and energy savings are improved by adding skylights, while glare performance worsens. Beyond 6% SFR, daylight still improves by adding skylights, while energy and glare performance worsens. The harmonization and conflict between the three design criteria calls for trade-offs to find the optimal inclusive solution. After discussing the results of Parametric Analysis for the three factors of daylight, glare and energy, I present the result of the aggregated metric used to find the inclusive optimal solution.

$$f(x)_{avg} = \frac{\alpha MD + \beta DGPi + \gamma EnergySaving}{\alpha + \beta + \gamma} \tag{4.2}$$

α, β, and γ are 1.

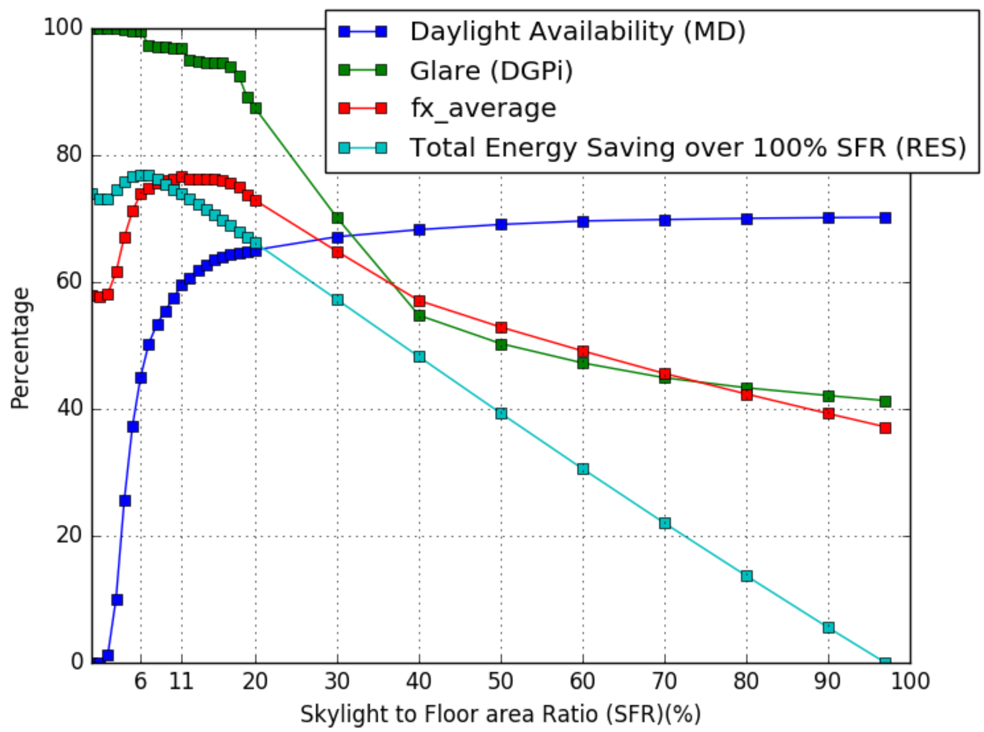

Figure 4.18: Parametric Analysis of DGPi, Mean Daylight Illuminance (MD), Total Source Energy Saving over 100% SFR and Average Performance ($f(x)_{avg}$) of Daylight and Energy in Austin Climate

A percentage, as an aggregated metric, unifies all three metrics calculated by Eq. 4.2. The red line in Figure 4.17 represents the average performance ($f(x)_{avg}$) of daylight, glare and energy factors. As shown in Figure

4.17, in San Francisco the inclusive optimal solution for both daylight and energy performance is 11%, which is in the upper bound of the energy efficient SFR range (3-13%). In addition, although 11% SFR is the maximum point on the $f(x)_{avg}$ curve, SFRs close to 11% approximately show the same performance. With a tolerance of 0.5% for the average performance, $f(x)_{avg}$, the SFR range of 10-13% includes optimal solutions considering both daylight and energy performances in San Francisco.

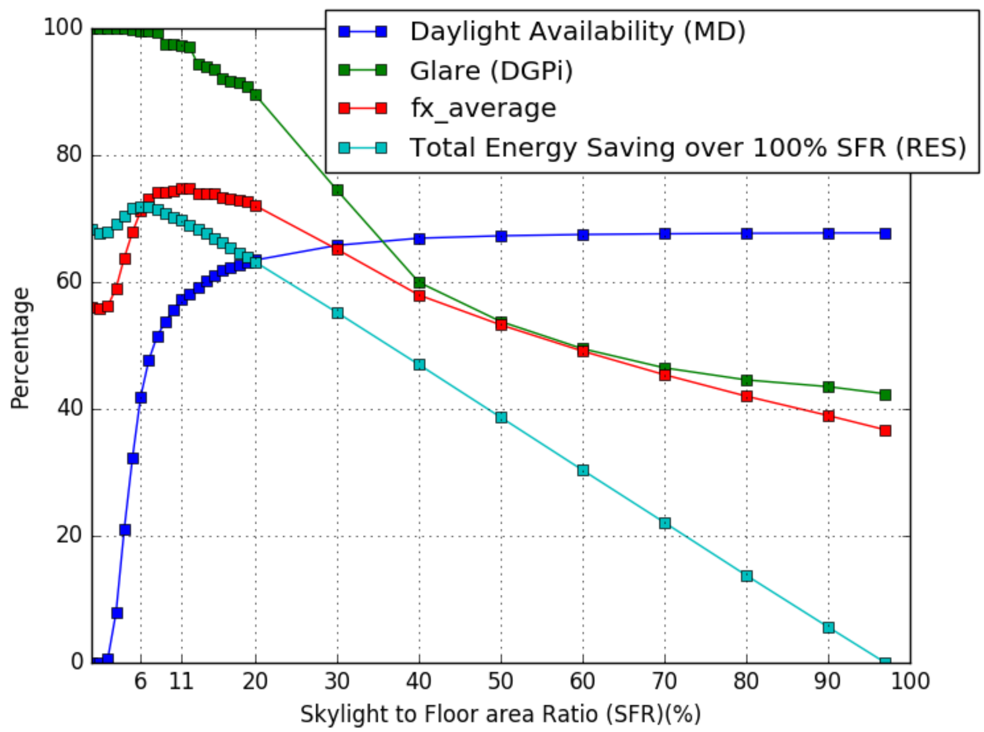

Figure 4.19: Parametric Analysis of DGPi, Mean Daylight Illuminance (MD), Total Source Energy Saving over 100% SFR and Average Performance $f(x)_{avg}$ of Daylight and Energy in Chicago Climate

In this Parametric Analysis I considered the multipliers (α, β, and γ) as 1 in order to keep an equal weight for all the factors, energy, daylight and glare.

The multipliers impose a weighting technique which can influence the optimal result. If α and β are considered 0 and $\gamma = 1$, the red line of $f(x)_{avg}$ would trace the blue line of RES, which eventually would show 6% as the optimal scenario. In addition, the red line in Figure 4.17 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.

The Parametric Analysis for unconstrained multi-objective optimization was then repeated for the Austin and Chicago climates. Not only is the inclusive optimal solution for both daylight and energy performance in the San Francisco climates 11% SFR, but this SFR also shows the best performance in the Chicago and Austin climates. Although the unconstrained optimization approach shows that the optimal "solution" regarding energy efficiency and holistic performance is 6% and 11%, respectively for different climates, the range of optimal "solutions" differ in various climates. In San Francisco the tolerance of 0.5% indicates the SFR range of 10-13% performs the best considering both qualitative and quantitative daylight factors while the energy efficient SFR range is 3-14% (Figure 4.17). With the same tolerance, the SFR range of inclusive optimization for Chicago is shown to be 10-12%, while its range of energy efficient solutions is 3-13% (Figure 4.19). In Austin, however, the inclusive optimal solutions are in the range of 10-14%, while the range of energy efficient scenarios is 3-11% (Figure 4.18).

For the tolerance of 0.5%, the analyses for Chicago and San Francisco show that the inclusive optimal "solutions" fall into the upper bounds of energy efficient ranges. However, in Austin the inclusive optimal SFRs not only share but also exceed the upper bound of the energy efficient range. This implies that the tolerance of 0.5% results in solutions that show acceptable daylight performance without saving energy. Therefore, for the Austin climate, it is not appropriate to adopt a tolerance of 0.5% for finding an SFR range of the inclusive holistic solutions.

4.1.2.2 Gradient Descent Optimization Method Using Aggregated Metric

Here, I present the results of the Gradient Descent optimization method to optimize the SFR by considering all the qualitative and quantitative factors of daylight, glare and energy. The intent was to investigate the feasibility of applying GD for optimizing the average performance. The target lighting level was considered 300 lux while LPD was held constant at 0.8 watt/sqft for all iterations. The GD method was applied to perform an unconstrained multi-objective optimization for the San Francisco climate.

The results of the GD method and PA have been shown in Figures 4.20 and 4.17. The GD method results in 10.94% while the PA method presents 11% as the inclusive optimal SFR. Although the GD method and PA reasonably agreed on the inclusive optimal SFRs, both methods required different numbers of iterations to achieve the optimal solution. Considering SFR resolution of 0.01%, for a Parametric Analysis 10,000 iterations would have been necessary. However, I reduced the iterations to 30 in order to find the optimal solusion. In section 3.5.1.4, it has been explained how to reasonably lower the number of iterations in Parametric Analysis. As shown in Figure 4.20, the GD method required 5 iterations to find the optimal solusion with higher SFR resolution of 0.01%. Therefor, not only the GD method was used for minimizing energy

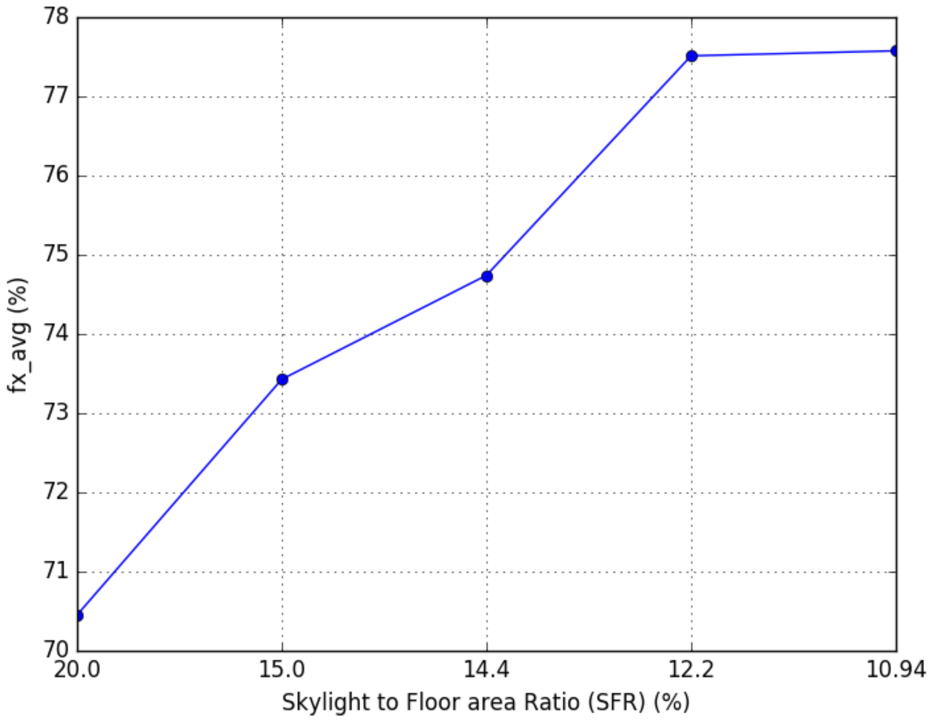

Figure 4.20: Gradient Descent Method to Find the Inclusive Optimal SFR by Maximizing Average Performance

consumption but also it was applied for optimizing the holistic performance of skylights.

4.1.3 Discussion of Aggregated Metric and Unconstrained Optimization

For the unconstrained optimization I used the aggregated metrics to compile the proposed energy, daylight and glare metrics, including RES, MD, and GDPi, and RES. I also applied a weighting technique to contextualize design decisions by assigning different multipliers to various metrics. This method transfered a complex multi-objective optimization to a simpler single-optimization question. Although 0 and 1 can be assigned to the multipliers to include or exclude design metrics, multipliers can be any number between 0 and 1. The relative ratios of the multipliers magnify or degrade the role of one metric over the others. For instance, as there is no active occupant in a storage space, the quality of daylight does not matter. However, energy efficiency is still an acceptable design criterion for a storage space. Therefore, 0 can be assigned to the multipliers of glare and daylight factors to erase them from the equation and 1 should be assigned to the energy factor to drive the optimization equation. For school and office spaces, all the metrics should be bigger than 0 because daylight, glare and energy factors should all play their roles in design. However, which factor should be a bigger player in school and office is an interesting future topic which was not studied in this body of research.

The other challenge with a unified metric in unconstrained optimization is that the aggregated percentage unit looses its intuitive interpretation. For instance, 11% SFR with average performance of 75% is the inclusive optimal solution in the San Francisco climate. It is wrong to interpret this as DGPi, MD, and RES of 75% for glare, daylight and energy metrics, respectively even if the multipliers are defined as 1 for all the metrics. The study shows that in the case of San Francisco, the inclusive optimal SFR with average performance of 75% is the outcome of DGPi of 98%, MD of 58% and RES of 70%. If different multipliers are considered in the equation, then it is even more challenging to make sense of the aggregated metric and multipliers. For instance, if the ratio of the glare multiplier to daylight multiplier is two, one may ask a question: what exactly does it mean to say that the glare factor is twice as important as the daylight factor? Such questions raised in this approach are mainly due to the fact that the proposed aggregated method is at the early stage of development. The questions can be answered by conducting case studies to tune the multipliers for different spaces and earn a sense toward the aggregated metric. This opens a new research topic for future studies.

It is probable that the aggregated metric in the unconstrained optimization approach does not result in inclusive optimal solutions. The risk associated with this approach is that the optimal solution is the average performance of three metrics, and it does not necessarily guarantee that the metrics meet thresholds. This is because this approach does not impose any constraints on the optimization process to make the solutions remain within the boundary of a feasible region. This dissertation examined this approach for different climates and the optimal "solution" proposed by this approach was inclusive, meaning it was energy efficient and it showed appropriate daylight performance. However, when a tolerance of 0.5% was assigned to approximate a range of optimal "solutions" with close average performances, the solutions proposed by this approach for Austin were not energy efficient, although they showed acceptable daylight performance. The same tolerance was applied to the climates of San Francisco and Chicago, which resulted in optimal and inclusive "solutions".

If the current proposed approach is used to situate a range of optimal "solutions", a researcher needs to verify all the final "solutions" by checking MD, DGPi and RES to assure that these metrics show acceptable performance. In future studies, to lower the possibility of such an error, the tolerance threshold needs to be calibrated based on case studies in different climates. The other solution is to represent the units in a mathematical equation which imposes a large cost to SFRs that lie close to the threshold, thereby creating a "barrier" to excluding the feasible and inclusive SFRs.

4.2 Constrained Optimization

This study has applied a constrained optimization approach by searching for energy efficient SFRs, that meet minimum thresholds for daylight and glare performances. As explained in sections 3.5.2.2 and 3.5.2.1, while energy consumption as a quantitative factor was measured in kWh, for daylight and glare factors I implemented two sets of combined metrics (UDI and sDA, as well as MD and mDGP). The minimum thresholds for UDI, sDA, MD and mDGP are 100%, 100%, 50%, and 35%, respectively. The following paragraphs discuss the results of the constrained optimization.

4.2.1 Multi-objective Optimization Using Metrics of UDI, sDA and kWh

For the metric set of kWh, UDI and sDA, Figure 4.21 illustrates the Parametric Analysis of the constrained optimization in the San Francisco climate. As shown in this figure, the SFR range of 4-10% meets 100% sDA while only 9% and 10% SFRs achieve 100% UDI. In this climate, energy efficiency is achieved for SFR in the range of 3-14%. The intersection of different ranges for various metrics of glare, daylight and energy saving represents the inclusive and holistic solutions. As the 9-10% range of SFR is the intersection of 4-10%, 9-10% and 3-14%, the optimal solutions in San Francisco are 9% and 10% SFR. If the objective function is to find the maximum energy efficiency while achieving the defined daylight quality, then, the cohesive and inclusive optimal SFR in the San Francisco climate is 9%. This is because for SFRs above 6%, energy efficiency is increased by lowering SFRs.

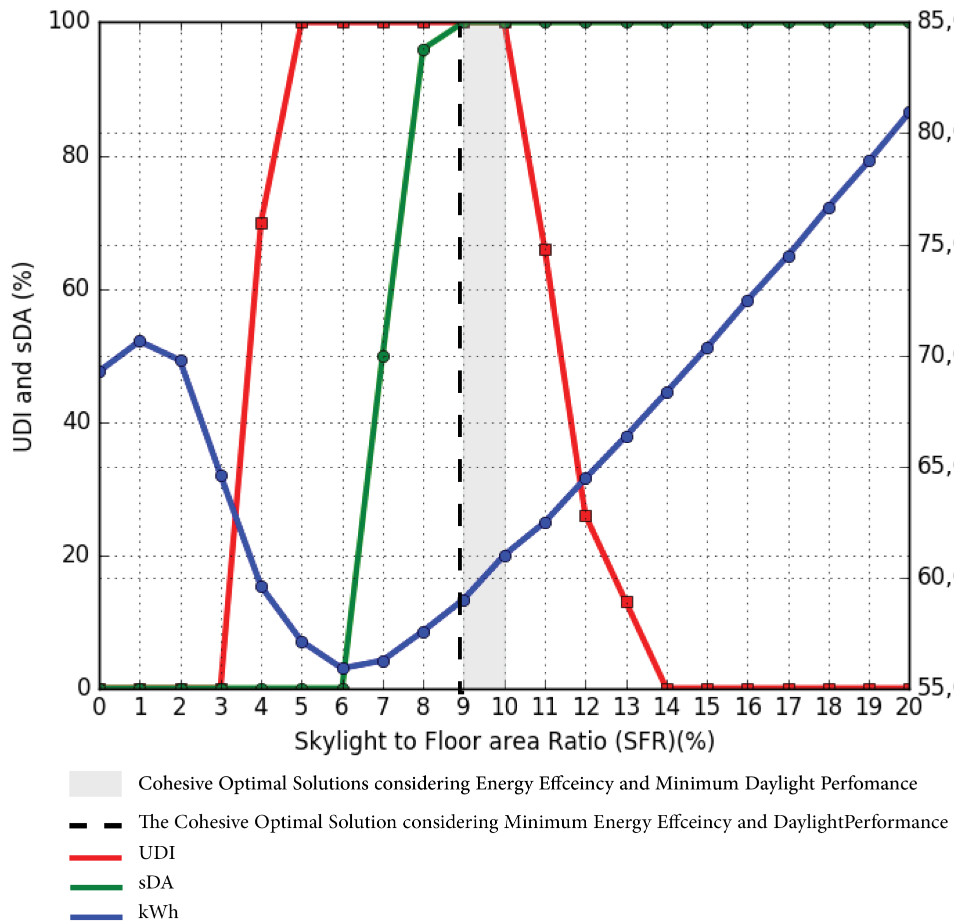

Figure 4.21: Constrained Optimization to Find Energy Efficient Scenarios with Conditions of sDA and UDI> 100% in San Francisco

The same metric set of kWh, UDI and sDA was repeated for the Austin and Chicago climates to perform constrained optimization. The Parametric Analysis for the Austin climate shows that any SFR bigger than 8% meets sDA of 100% while UDI of 100% only occurs at an SFR range of 5-11% (Figure 4.22). In addition to daylight performance, all the SFRs meeting the UDI target are energy efficient compared to the base model with 0% SFR, because SFRs in the range of 3-11% are considered energy efficient in the Austin climate. If the design criteria are based on energy efficiency and minimum daylight performance, then the SFR range of 8-10% can be defined as the cohesive optimal "solutions", because all SFRs in this range achieve energy efficiency and provide acceptable daylight quality. However, if the objective function is set to maximize energy efficiency while reaching at least the minimum daylight quality, then 8% is the cohesive optimal "solution".

Figure 4.23 shows that a range of 4-9% SFR provides UDI of 100% in the Chicago climate, while any SFR greater than 9% has sDA performance of 100%. Considering that energy efficiency only occurs in the range of 3-13% SFR in Chicago, 9% is the only energy efficient SFR that meets the defined daylight thresholds for sDA and UDI. In other words, according to the constrained optimization with such conditions, 9% SFR is the cohesive and inclusive optimal solution in Chicago.

4.2.1.1 Discussion of Multi-Objective Optimization Using UDI, sDA and kWh

Different SFR ranges meet the performance targets for the three design factors, including energy, UDI and sDA. However, the inclusive and holistic solutions lie in those portions of these ranges that intersect. The energy efficient scenarios are a range of SFRs that consume less energy than the baseline (0%). The constrained optimization has shown that not all energy efficient scenarios result in acceptable daylight performance. For instance, while all SFRs between 3% and 14% are energy efficient in the San Francisco climate, through sDA analysis I found that SFRs of 3-8% do not meet the desired

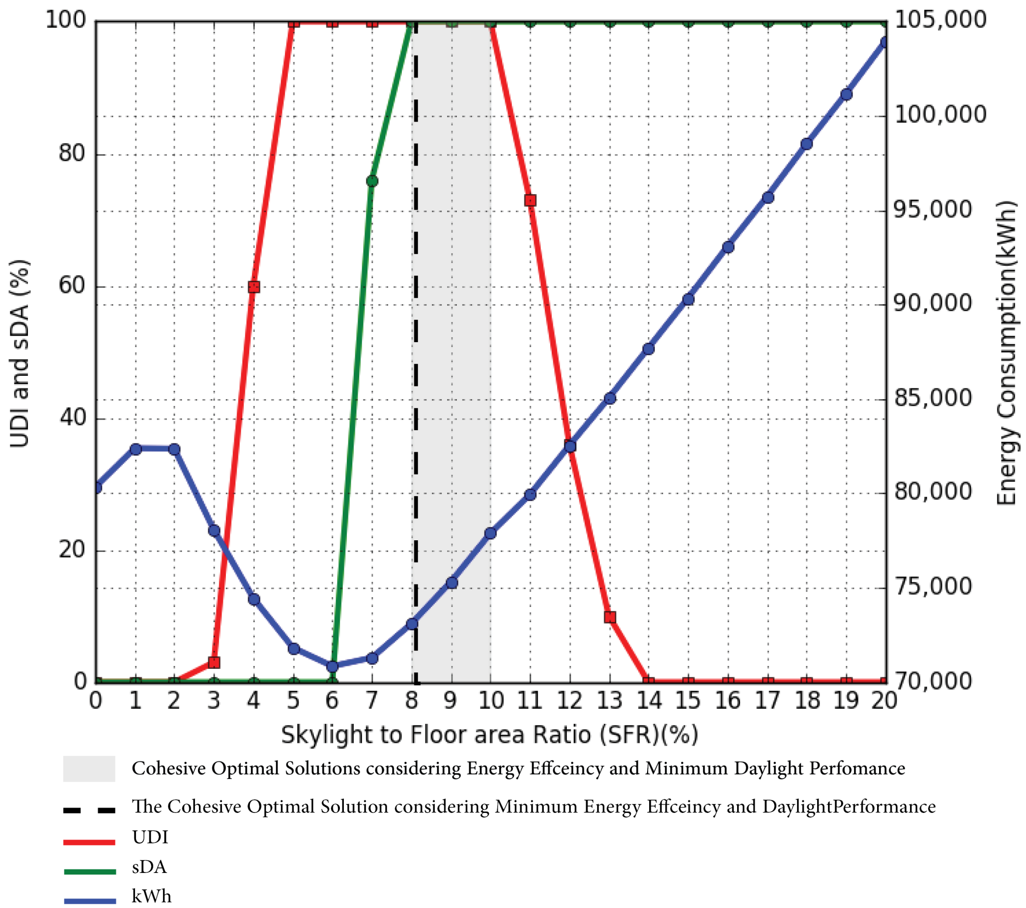

Figure 4.22: Constrained Optimization to Find Energy Efficient Scenarios with Conditions of sDA and UDI> 100% in Austin

daylight performance. Interestingly, a 6% SFR, which is the optimal SFR in regard to energy, does not meet the defined daylight target (sDA of 100%). In addition, in this climate SFRs between 11% and 14% are energy efficient and provide adequate daylight; however, UDI analysis shows that they receive too much daylight, which increases the glare probability. The three different metrics, sDA, UDI and kWh, provide different insights regarding the SFR ranges that achieve daylight performance and energy efficiency.

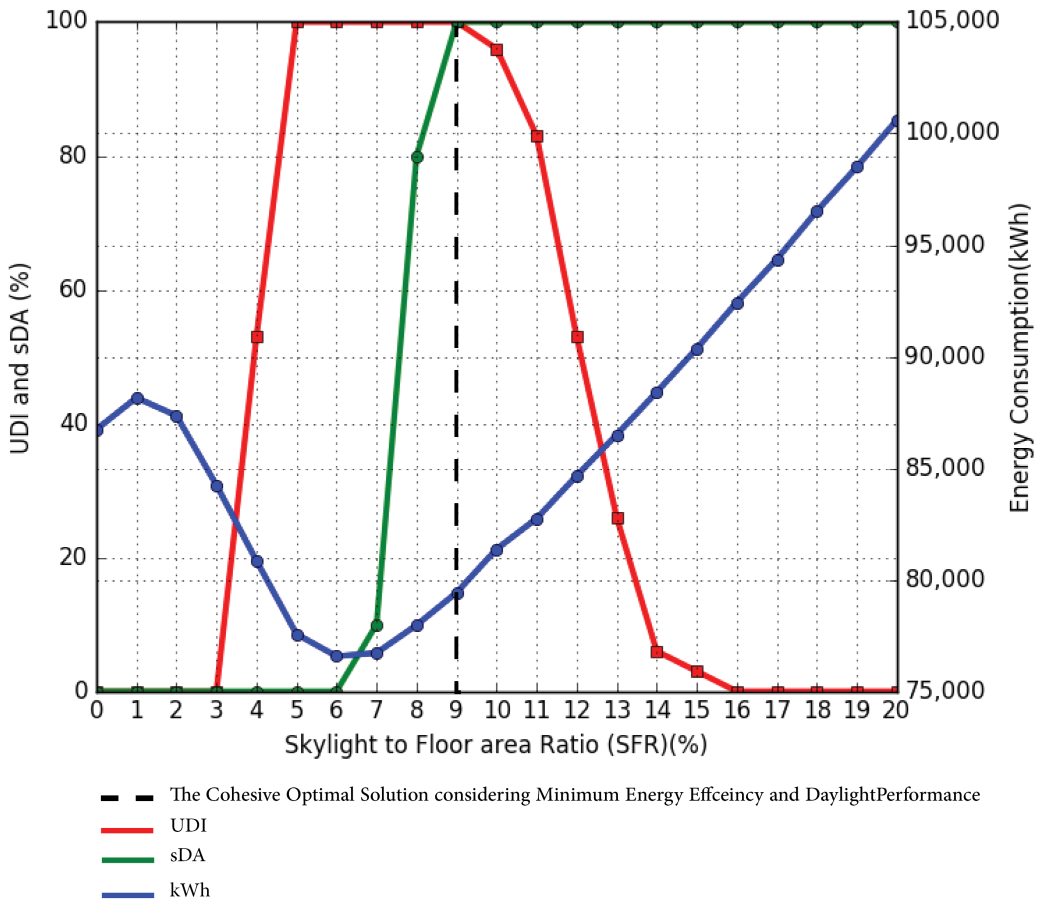

Figure 4.23: Constrained Optimization to Find Energy Efficient Scenarios with Conditions of sDA and UDI> 100% in Chicago

Among the different metrics used in this section, sDA proved to be the most significant player. While the cohesive optimal solution for the Chicago and San Francisco climates is 9%, for the Austin climate it has been shown that 8% SFR is the most energy efficient scenario that meets the defined daylight performance target (UDI and sDA of 100%). Although the constrained optimization study shows that the inclusive optimal solutions differ in various climates, in all climates the inclusive optimal SFR falls into the lower bound of the SFR range that meets the sDA of 100%. If the minimum threshold of sDA was defined as 50% instead of 100%, the cohesive optimal solutions would have been 7%, 6.5% and 7.5% for the San Francisco, Austin and Chicago climates, respectively (refer to Figures 4.22, 4.23 and 4.21). Again, these optimal solutions are the smallest SFRs among the SFR ranges that meet the sDA threshold of 50%. Therefore, sDA is the most significant criterion in this constrained optimization.

The reason behind the significance of sDA in searching for the optimal solution lies in the definitions of the metrics. sDA is the percentage of floor area that provides 300 lux for at least 50% of the occupied hours. UDI has the same definition while imposing lower and upper limits to the illuminance threshold, in order to provide minimum daylight and avoid excessive daylight and glare issues. As the lighting target level of sDA is 300 lux, this target level is situated within the useful illuminance range of UDI (100-2000 lux). Therefore, the smallest SFR achieving the defined sDA provides the useful illuminance range and meets UDI of 100%. Since sDA has no upper limit threshold for illuminance, the higher SFR still provides sDA of 100%, while failing to reach UDI of 100%. This is because the larger SFR provides excessive daylight and increases the probability of glare issues. Therefore, as shown in the study, the cohesive optimal solution occurs in the lower bound rather than the upper bound of the SFR range that meets the sDA target.

The lower bound of the SFR range not only meets sDA of 100% and holds a lower probability of glare issues, but also saves energy. Electrical lighting reduction accounts for a large portion of energy savings in models with skylights. All the SFRs meeting sDA of 100% provide sufficient daylight availability, among which the smallest one consumes less energy, because it provides enough daylight to decrease electrical lighting loads and it has a lower conduction loss rate compared with other, higher SFRs. Therefore, the lower bound of sDA is the cutting edge to define the cohesive optimal solution that offers a holistic performance which includes both qualitative and quantitative aspects of daylight.

4.2.2 Multi-Objective Optimization Using Metrics of MD, mDGP and kWh

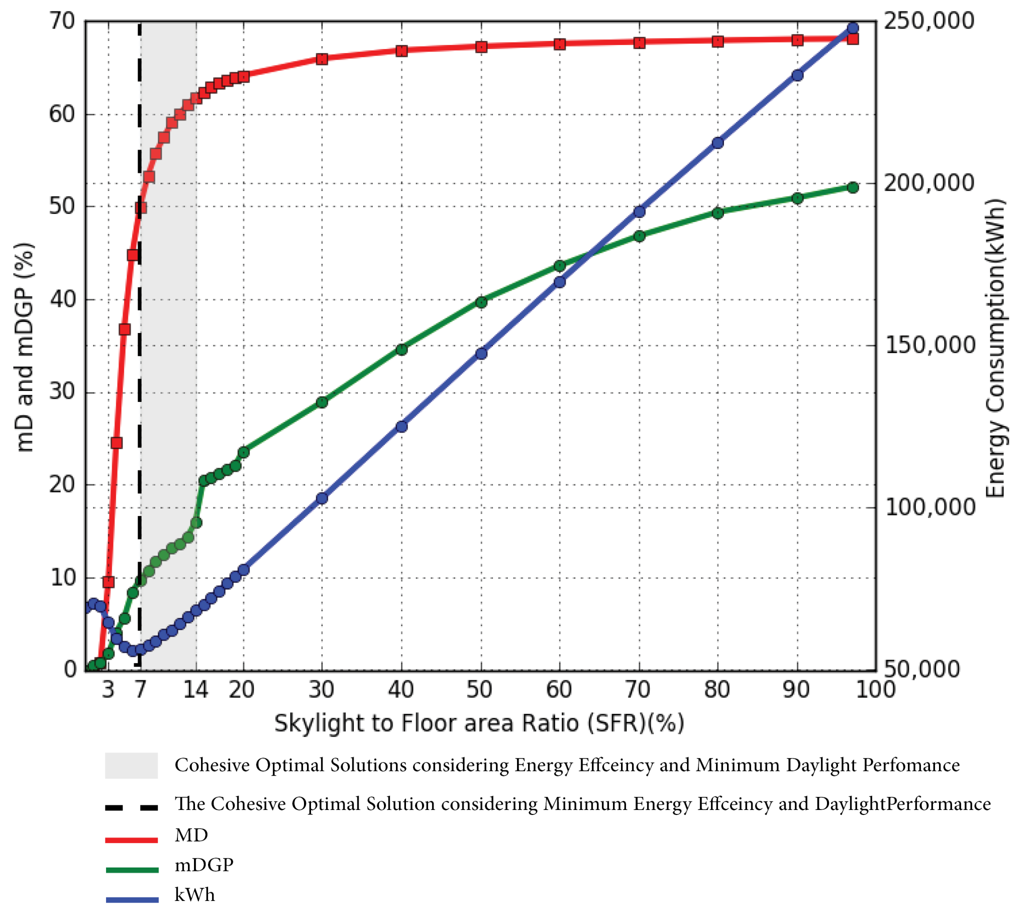

Figure 4.24: Constrained Optimization Using Metrics of MD, mDGP and kWh in San Francisco

This section presents the results for the constrained optimization which holds conditions including meeting the minimum of 50% MD and maximum of 35% mDGP, as well as saving energy over the baseline (0% SFR). Figure 4.24 shows mDGP, MD and kWh for the SFR range of $0-100\%$ in the San Francisco climate. As shown in this figure, on the one hand, all SFRs of below 40% meet the mDGP target by demonstrating mDGP of "imperceptible glare" (35%). On the other hand, all SFRs greater than 7% show MD of 50%. In addition, the energy efficient SFR in the San Francisco climate is 3-14%. All the ranges meeting different conditions for various metrics intersect at 7-14% SFR. This optimal range represents the inclusive solutions that consume less energy compared to 0% SFR and achieve the targets for daylight performance. Within this range, the optimal solution is 7% SFR, that maintains the minimum energy consumption while providing sufficient daylight with minimal glare issues.

This constrained optimization with metrics of MD, mDGP and kWh was then repeated for the climates of Austin and Chicago. Figure 4.25 shows the constrained optimization using MD, mDGP and kWh for the Austin climate. In this climate while the range of energy efficient scenarios is 3-11%, MD and mDGP targets are met by SFRs greater than 7% and smaller than 40%, respectively. Therefore, the inclusive solutions that save energy and meet the daylight performance targets are 7-11% SFR. If the optimal solution is defined as the SFR with the greatest energy saving that also provides the expected daylight performance, then, the inclusive optimal solution in the Austin climate is 7% SFR.

Figure 4.26 shows the constrained optimization for the Chicago climate, in which the thresholds of mDGP and MD are met for SFRs of less than 50%

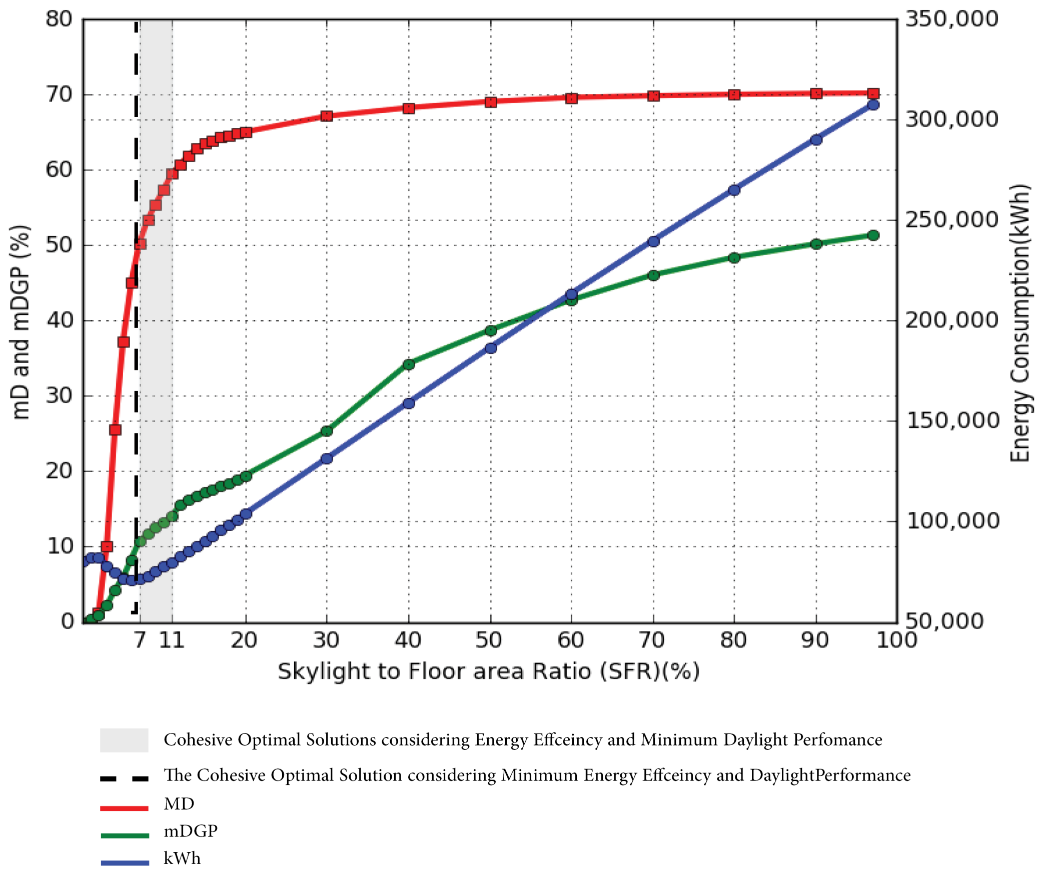

Figure 4.25: Constrained Optimization Using Metrics of MD, mDGP and kWh in Austin

and greater than 8%, respectively. Considering that energy efficiency occurs within the SFR range of 3-13%, all the energy and daylight conditions are met by the SFR range of 8-13%. In this range the most energy efficient scenario that maintains the expected daylight performance is 8% SFR for the Chicago climate.

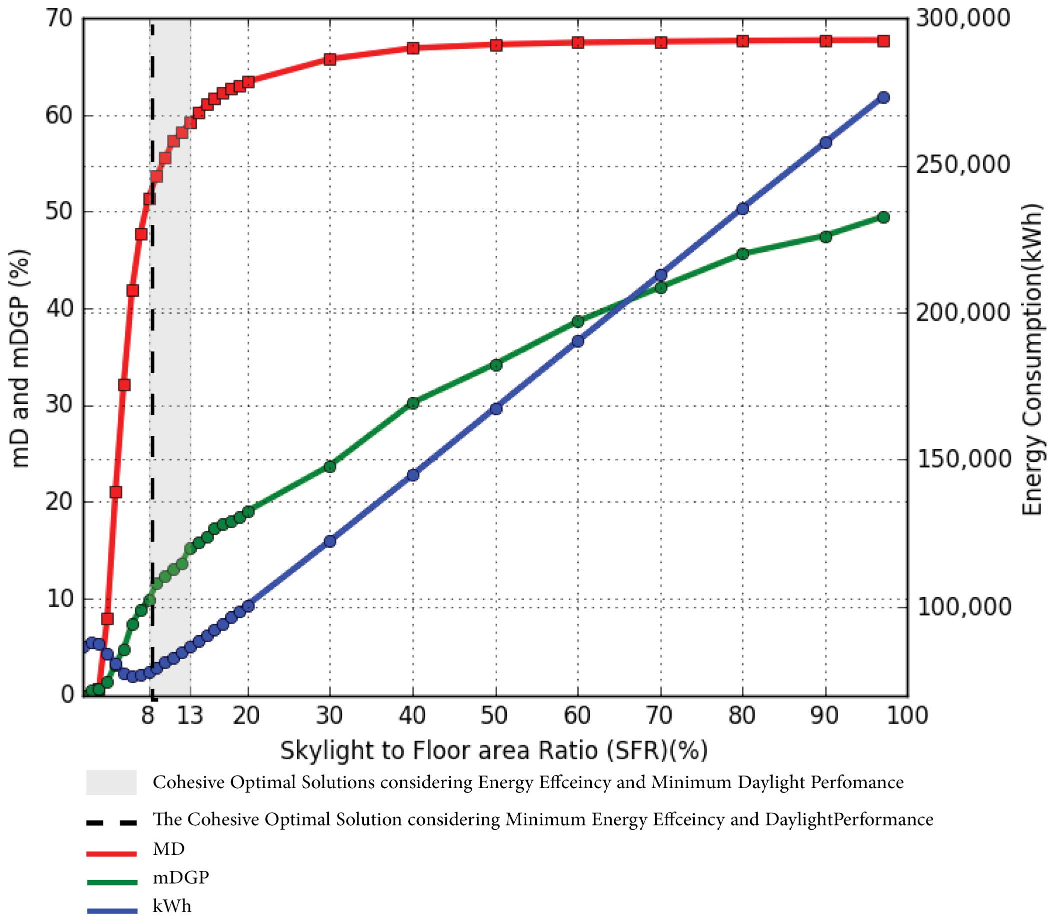

Figure 4.26: Constrained Optimization Using Metrics of MD, mDGP and kWh in Chicago

4.2.2.1 Discussion of Multi-Objective Optimization Using MD, mDGP and kWh

In this section I constrained the optimization by setting conditions for the metrics of MD and mDGP. This approach was applied for the different climates of San Francisco, Austin and Chicago. The results show that different SFR ranges meet each condition of daylight, glare and energy objectives; however, the inclusive solution that meets the targets for both daylight and energy performance is the intersection of these ranges. In each of the different climates, the upper bound of the energy efficient range confines the upper bound of the optimal solution range. This is because MD has no upper limit and the maximum SFR meeting the mDGP target is significantly greater than the upper bound of the energy efficient range. Therefore, the maximum SFR saving energy is the intersection of all the ranges for various metrics and sets the upper bound of the optimal "solutions".

Of the inclusive optimal solutions the lower bound is always the minimum SFR that meets daylight target (MD of 50%). This is because the lower bound of the SFR range meeting the MD target is greater than the smallest SFRs meeting mDGP target, which is 0%, and energy efficiency, which is 6%. Considering the intersection of all these ranges, the minimum SFR meeting the MD target sets the lower bound of the optimal solution range. In addition, the minimum SFR meeting the MD target consumes the least energy. Therefore, the lower bound of the SFR range meeting the MD limit is the optimal solution, if the objective of optimization is to find a solution with the greatest energy saving that maintains acceptable daylight performance.

The inclusive optimal solution found by this approach differs from the optimal energy efficient solution. While a 6% SFR consumes the least energy in the SFR range of 0-100% for different climates, the inclusive solutions in San Francisco, Austin and Chicago are 7%, 7% and 8% SFR, respectively. Among the SFRs meeting the MD target, the energy and glare factors direct the optimization by lowering the SFRs. As energy and MD play roles in defining the upper and lower limits of the optimal solution, glare is not a significant factor to determine the optimal solutions.

As different climates show distinct upper limits for the SFR range that meets mDGP of 35%, the upper limits are significantly higher for the glare factor than for the energy factor. In Austin and San Francisco, the upper limit for glare was shown to be 40% SFR, while in Chicago it was even higher, at 50%. This is because Chicago has the coldest climate and the cloudiest sky. In addition, due to Chicago's latitude, the sun is positioned more due south than in the other climates. Thus, it is less probable to locate the shiny sun through skylights in Chicago than in the other examined climates. This explains why the maximum SFR, which meets the glare limits (35% mDGP), is higher in Chicago than in the other locations. Whether investigating the climates of San Francisco and Austin or Chicago, the upper limits of the SFR meeting the mDGP target are still high. mDGP is the average daylight glare probability for the occupied hours. As the glare limit was set to detect "imperceptible glare", the threshold was defined to be very sensitive to glare incidents; therefore, its bar is the lowest among the possible DGP thresholds. However, even with such a low threshold, the maximum SFR to meet the mDGP target is higher for glare than for the energy factor. While energy effectively determines the upper limit of the inclusive optimal solutions, the optimization process becomes insensitive to the glare factor.

Among the metrics of MD, mDGP and kWh, MD as a daylight availability factor is the most deterministic player, because it defines "the optimal solution". The MD metric is the average of occupied hours that meets the illuminance target across different daylight sensors. Therefore, it is an indicator that shows the average performance of daylight. If the MD limit is not defined as a low number, it can guarantee the presence of daylight across the space and over time, eventually assuring saving electrical lighting loads. The minimum SFR meeting the MD target also saves energy, because it lowers the amount of electrical lighting while not significantly increasing HVAC loads. In other words, although all SFRs that meet MD of 50% assure reduction of electrical lighting loads, only the smallest of these have the lowest conduction loss rate, minimum HVAC loads and maximum energy performance. In addition, glare issues always conduct the optimization process to a lower SFR. As a result, the constrained optimization examined in this section is driven by finding the minimum SFR that meets the MD threshold.

Sections 4.1 to 4.2.1.1 showed that constrained and unconstrained optimization with various metrics result in various optimal solutions. The inclusive optimal SFRs depend on the applied metrics and targets, conditional statements, multipliers and optimization approaches. In the final section, I discuss the results of a Parametric Analysis for the monetary gains obtained based on daylight and energy performance.

4.3 Optimization Based on Monetary Metric

Another holistic view toward toplighting optimization is to consider the cost benefits from both enhanced daylight performance and energy savings. In this approach, while considering sDA and UDI of 100% to define daylight performance targets, the energy consumption of each SFR was compared to the 0% SFR baseline. The total cost benefits were estimated after converting the energy consumption to its dollar cost saving and including the monetary gains of increased productivity rate at 1%. Figures 4.27, 4.28, and 4.29 compare scenarios in the SFR range of 0-20% in terms of their energy cost savings and the total monetary benefits. As shown in this figure, significant peaks occur for 9-10%, 8-10% and 9% SFRs for the climates of San Francisco, Austin, and Chicago, respectively. These peaks are defined as the inclusive optimal solutions considering both daylight and energy performance for these climates (see section 4.2.1 for more information). As depicted in Figures 4.27, 4.28, and 4.29 the energy saving is negligible if it is compared with the total cost savings, including energy efficiency and increased productivity rate. The maximum energy saving occurs in the San Francisco climate which is \$555 per annum while the productivity boosted by toplighting comfort adds \$9,000 per annum to the cost benefits. The energy savings for the Chicago and Austin climate has been estimated at around \$300 per annum. Thus, the productivity gain is 160-300% more than energy cost savings in all these climates. Therefore, if the quality of daylight performance is converted to its quantitative metric of increased productivity, it outshines the energy cost savings.

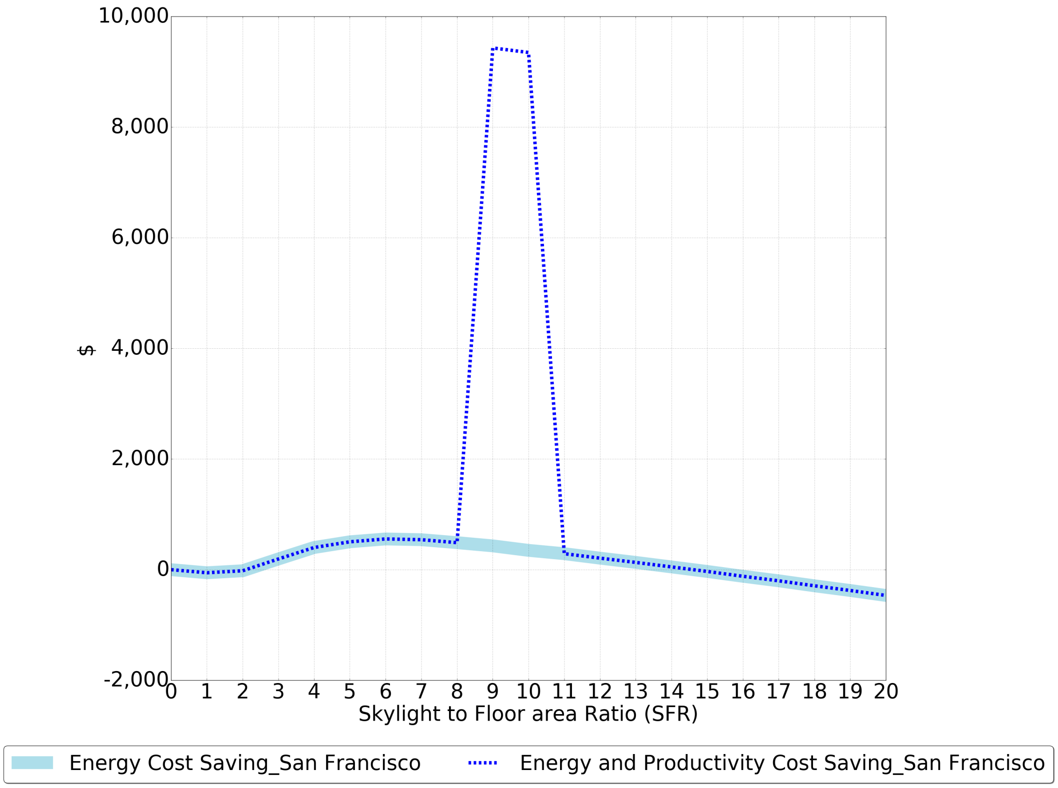

Figure 4.27: Monetary Benefits from Energy Savings and Increased Toplighting Comfort for the San Francisco Climate

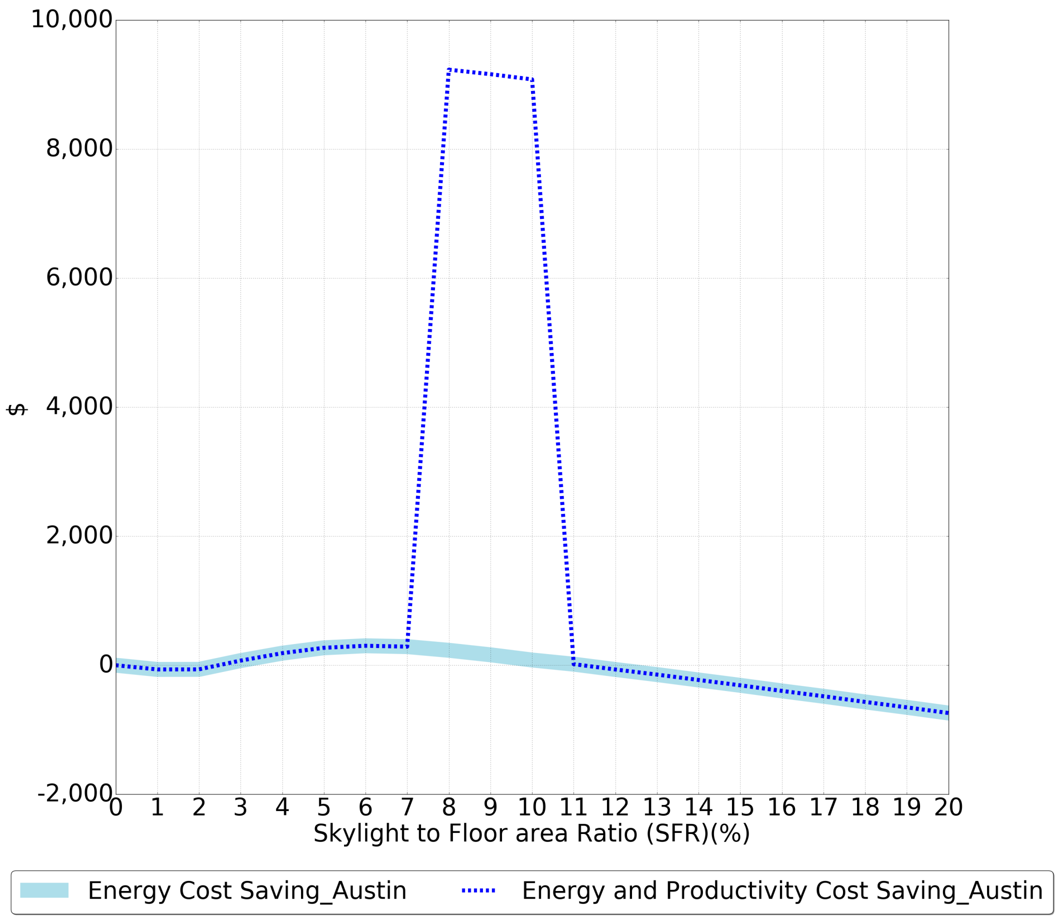

Figure 4.28: Monetary Benefits from Energy Savings and Increased Toplighting Comfort for the Austin Climate

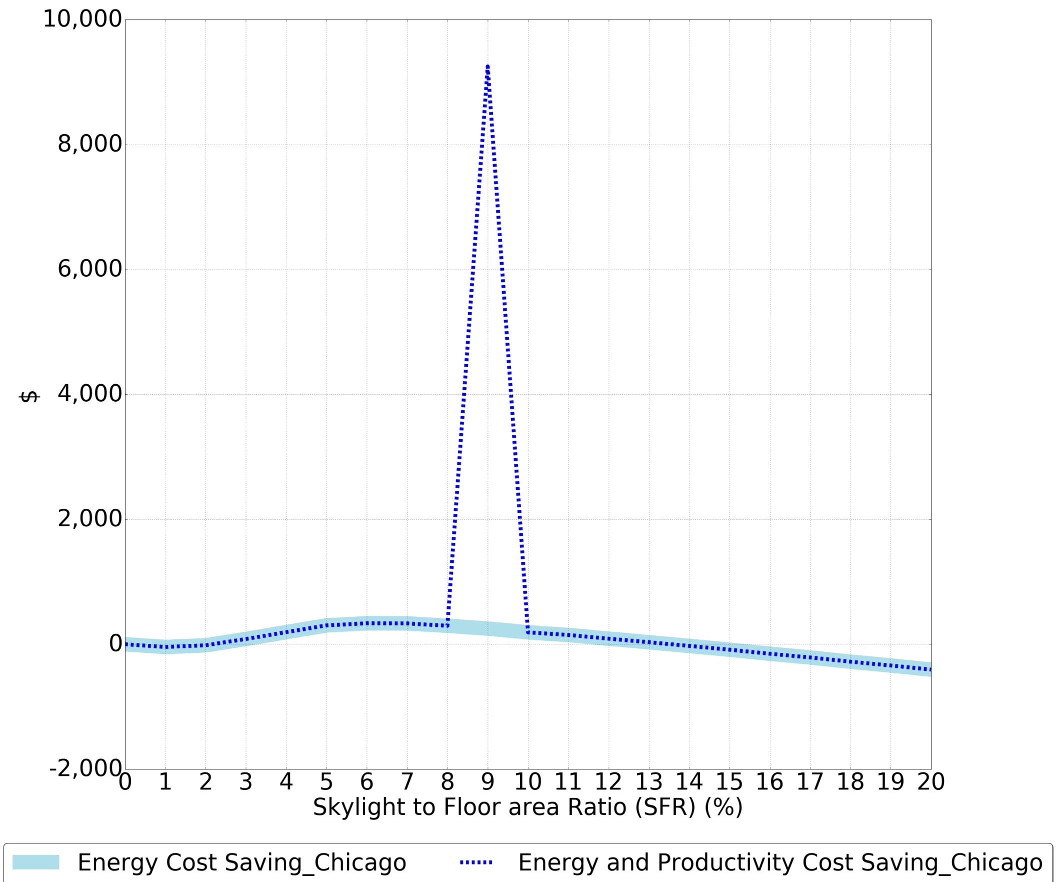

Figure 4.29: Monetary Benefits from Energy Savings and Increased Toplighting Comfort for the Chicago Climate

Chapter 5

Conclusion

This dissertation has engaged different design criteria to find an energy-efficient skylight size that provides a daylit productive environment. Energy consumption became the quantitative factor, while daylight availability and glare were defined as qualitative factors of skylight design. In this study an algorithmic platform was developed that integrated both qualitative and quantitative aspects of daylight as driving forces in the multi-objective optimization process. Different optimization approaches were plugged into the platform to find the most robust and inclusive skylight sizes. As pointed out earlier, the major contribution of this study has been its proposed approaches rather than the optimal skylight sizes resulting from these approaches.

This chapter provides a concise review of the studied skylight optimization and a wider perspective of multi-objective optimization toward sustainability. First the main points and findings of the previous four chapters are summarized. Then, the limitations and advantages of the different metrics which were used in the study are discussed. I also propose future avenues for developing further daylight aggregated metrics. After discussing metrics, I assess the strengths and limitations of the multi-objective optimization approaches to achieve sustainable and contextualized solutions. Finally, I draw conclusions regarding the overall significance and contribution of this research, and I suggest future opportunities for research.

5.1 Summary of Previous Chapters

In Chapter 1 I introduced the definitions of daylight and its advantages, including total energy saving and improvements in morale and mood. I also described the possible disadvantages of daylight, which include substantially increased HVAC loads, glare issues and visual discomfort. An intricate dynamic exists between daylight and energy. Whether or not the total source energy is increased by adding skylights depends on the trade-off between the increased direct solar gain and conduction loss rate, as well as the decreased lighting loads and electrical internal heat gain. To study these complex energy impacts of daylight, integration between daylight and energy simulation tools was required. The energy flux is measurable, and thus, this dissertation considered the energy impacts of skylights in design decisions as a quantitative aspect of daylight.

In addition to the energy impacts of daylight, natural light has qualitative aspects, since it affects human beings physiologically and psychologically. Although daylight exposure through the design of buildings cannot guarantee our physical and mental health, many studies suggested that poor daylight design can have detrimental effects (Edwards and Torcellini, 2002). The human body needs exposure to direct sunlight in order to produce Vitamin D, which regulates the body's melatonin production and circadian rhythms (Tregenza and Wilson, 2011). In investigating the synergic impacts of daylight on the physiology and psychology of a human body, case studies have pointed out the significance of daylight in increasing productivity rate (Romm and Browning, 1994); however, productivity is not achieved if the space suffers from flooded daylight and glare issues. Since it is challenging to actually measure physiological and psychological impacts of daylight and the resultant increased productivity, these effects and side-effects were referred to as qualitative aspects of daylight. Therefore, daylight design has a qualitative aspect relating to human health and productivity, which cannot be achieved if daylight design does not provide an even distribution of horizontal daylight and does not avoid glare issues.

This study attributed qualitative and quantitative aspects of daylight to three factors: energy, daylight availability and glare, which have played significant roles in skylight design. While research about the quantitative and qualitative aspects of daylight has moved along in parallel, they are rarely considered in a cohesive and inclusive platform to evaluate proper toplighting strategies. Therefore, this dissertation devised an algorithmic platform to provide effective SFR for single-storey buildings in different climates. To achieve this aim, the platform considers contexts by engaging both qualitative and quantitative aspects of daylighting, including energy efficiency, glare and daylight availability.

This dissertation pursued the following main objectives:

- Propose a road map to integrate daylight and energy engines in order to find solutions with optimal energy performance.
- Develop a methodological framework which can be repeated by others to practice a cohesive skylight design by including qualitative and quantitative aspects of daylight.
- Examine or develop metric(s) for qualitative aspects of daylight or its holistic performance, including both daylight and energy factors.
- Set up different optimization approaches to find the best effective skylight design and contextualize design solutions.

- Find out the impacts of climatic conditions on an optimal design solution.

Chapter 2 discussed the relation of robust skylight design to the theory of the three pillars of sustainability: environment, economy and society. This study showed energy savings for specific ranges of SFRs which could eventually reduce CO_2 emissions. Robust skylight and toplight design is able to substantially impact the environment, especially considering the 67% market share of one-storey buildings in American commercial buildings. In addition, this review examined financial gains through decreased utility bills and increased productivity rate. Such monetary gains situated the question of skylight design in the economic sphere of sustainability. Moreover, this dissertation proposed robust skylight designs while it took into consideration quality of daylight as it provided horizontal daylight and avoided discomfort glare. Such design intends to improve the quality of life for the dwellers/employees. The study presented here concerned about the betterment of human life, which related skylight design and quality of daylight to the society term of sustainable design.

In addition to the simpler theory of three pillars, the applied approaches in this dissertation were consolidated by the new theory of sustainability which includes different voices and context contingency. The dissertation involved a priori groups and engaged their interests in order to collectively find optimal solutions. The results of this dissertation verified the new concept of regenerative sustainability because this study confirmed that there was not a "right" solution that was cohesive and inclusive. In fact, it was shown that there existed "ranges" of robust solutions depending on different applied optimization approaches, metrics, thresholds and design factor multipliers. The thresholds and design factor multipliers were basically defined by the context of the project at hand. I induced that the regenerative sustainability matches the mathematical theory of Pareto optimization, where conflicting objectives (interests) exist and result in solutions that show reasonable trade-offs among different objectives (interests). Therefore, this dissertation was supported by the paradigm of regenerative sustainability and the results of this dissertation validated the concept of such theory.

In addition to reviewing the relevant theories of sustainability, Chapter 2 presented the literature regarding to qualitative aspects of daylight. I summarized case studies that showed improved productivity rates. These studies showed that lighting and daylighting improvements boost productivity and even sales; however, the increased productivity is associated to a very wide range ($2-40\%$), due to its context dependency. In other words, each project shows a specific increase in productivity, sales or absenteeism, and it is challenging to find any regularity that can be applied for future projects. Nevertheless, most of the case studies have concluded that the increased productivity rate exceeds other savings, including energy efficiency. For instance, Pennsylvania Power & Light installed new lighting system and implemented daylighting strategies which improved the productivity by 13% (Romm and Browning, 1994). In this project the payback period from energy savings was estimated at four years; however, the savings from boosted productivity shrunk the payback years to only 69 days. The report concluded that a total yearly energy cost of a company can be offset by even the smallest increased in productivity (1%) (Romm and Browning, 1994).

After discussing the role of productivity on return on investment for the owners, I reviewed the metrics for the qualitative aspects of daylight, including daylight availability and glare. For years, daylight availability has been measured by a horizontal illuminance metric; however, DF, as one of the historical metrics, does not take into account different climates, sky conditions, complex geometries of interiors, surrounding objects and orientation of windows (Tregenza and Wilson, 2011). Currently dynamic metrics, which involve annualized and climate-based daylight simulations, have been gathering momentum in building design and research. Among these state-of-the-art metrics, sDA is the most popular one. sDA refers to the percentage of floor area that receives sufficient daylight (minimum cap) for at least 50% of the annual occupied hours (Reinhart, 2011).

In regard to glare issues and extensive daylight, current practices apply either horizontal illuminance or luminance projection on the field of view. UDI is one of the horizontal metrics used to avoid glare issues. UDI of 50% for 100-2,000 is a percentage of floor area that meets an illuminance range of 100 and 2,000 lux for at least 50% of occupied hours (Nabil and Mardaljevic, 2006). UDI assumes a useful daylight illuminance between 100 and 2,000 lux. It suggests that horizontal light above 2,000 lux increases glare probability. However, disagreement exists among researchers regarding to the upper limit of UDI (2,000, 2,500, 5,000 or 8,000) (Wymelenberg and Inanici, 2011; Mardaljevic et al., 2009; Olbina and Beliveau, 2009). In contrast to UDI, Van Den Wymelenberg and Inanici argued that vertical illuminance (Ev) at the monitor is a better metric for glare and visual comfort than horizontal illuminance-based metrics.

Apart from illuminance-based metrics, glare can also be estimated based on luminance observed in the view of the occupants. DGP is the most commonly-used metric in the building industry and research. If the direct sun is present, DGP predicts glare incidence better than DGI. However, DGP still does not show an acceptable performance if the sun is seen in the celestial sky and is in the occupant's angel of view (Wymelenberg and Inanici, 2011). Another recent metric has been proposed by Suk, which suggests that the luminance-base metric regarding glare is a function of the luminance ratio between the task and the glare source, as well as the absolute luminance of the glare source (Suk, 2014). Currently the glare metrics are being developed and examined through case studies, questionnaires, and HDR photography. Although there is not a solid glare metric that is verified, I included the glare issues in the proposed multi-objective optimization platform in order to minimize the probability of the glare incidence. Moreover, my intension for inclusion of glare was to remind designers and researchers that glare is a daylight factor which should play a role in design decisions. I examined DGP as a luminance-based metric and UDI as a horizontal illuminance-based metric, which are currently the most used metrics in the industry.

In addition to qualitative impacts of daylight, a separate body of research has investigated energy consumption by adding daylighting strategies, either sidelights (windows) or toplights (skyights). Such investigation has only become possible after the development of integrative tools, coupling daylight and energy engines. The peer-reviewed papers in this area conclude that daylighting strategies can reduce lighting loads in a range of $20-77\%$. Most studies have associated the daylighting strategies with significant reductions in lighting loads that can offset probable increased HVAC loads (Bodart and Herde, 2002; Superlink, 1993; P. Ihm, 2009; Li and Wong, 2007; Yangi et al., 2010; Reinhart and Wienold, 2011; Li et al., 2008). Even though the tradeoff between lighting and HVAC loads depends on many different parameters, including HVAC systems, climates, constructions, fenestration sizes, it is the fenestration configuration that significantly impacts the balance between lighting and HVAC loads.

To what extent apertures can be extended and still save total energy consumption prompts the question of optimization. There have been recent attempts to optimize window sizes based on energy consumption. GAs and Parametric Analysis are the most practiced methods in optimization but have disadvantages. Parametric Analysis is an exhaustive search but is significantly time consuming. In addition, GA is a non-deterministic method which means 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). Considering the shortcomings of GA and PA, I proposed Gradient Descent method for optimization and I verified the results of this method by exhaustive search via PA. PA also was used to carry out sensitivity analyses for LPD, SFR, lighting level, and climate.

In Chapter 3, Methods and Methodology I laid out the adopted methodology and methods to incorporate different interests and contextualize design solutions. As I was adopting a constructivist ontological position, which molded my paradigm of how to tackle the design question at hand, I intended to create a context by considering all the interests of different groups (in terms of daylight, glare, and energy). However, I implemented post-positivist methods to propose contextualized solutions for this multi-faceted design problem. A literature review was applied to investigate evidence of the increased productivity rate, while I used simulation tools, including Radiance and EnergyPlus, to predict the energy and daylight performances. I used Radiance through its host, Ladybug and Honeybee. All the simulation tools were accessed through Grasshopper. I developed the integrative and optimization algorithm (IA) by scripting the Python component in Grasshopper. The use of Python facilitated switching between thermal and daylight engines, managed both the qualitative and quantitative data, stored them, processed them for optimization, and automated the entire process.

Three different approaches were implemented to find skylight sizes that provide effective daylight by decreasing energy consumption, increasing available daylight, and avoiding glare incidence which ultimately helps to boost workers' morale and productivity. I examined unconstrained optimization, which did not entail any limitation on different design parameters other than maximizing the total performance with the aggregated unit. The aggregated unit was an average performance of daylight, glare and energy factors. Each of these factors has its own multiplier to scale its weight in the average performance equation. This approach utilized percentage as the unit to unify the design factors, including glare, daylight and energy, represented by metrics of DGPi, MD and RES, respectively. In this approach, different optimization methods including Parametric Analysis and Gradient Descent methods were applied.

The results of the GD and PA methods agreed with each other and verified that the optimal energy efficient SFR is 6% for all the studied climates. However, the GD method found the optimal skylight size with lower iterations and with higher resolution of SFR. The computational time is valued in daylighting design because Radiance simulation is related to a computationally expensive process. Therefore, adding to the number of iterations would significantly increase computational time, which makes researchers and designers reluctant to study the optimal solution. Although the GD method is faster and finds SFR with higher resolution, tuning the algorithm requires knowledge about the fundamental concept of the algorithm. The challenge associated with the GD method was to carry out initial iterations in order to set γ.

The optimization of skylight sizes in regard to energy saving is influenced by many parameters, including the HVAC system, construction, LPD, and the target lighting level. The unconstrained optimization approach in this study was extended to carry out sensitivity analysis for LPDs in range of 0.4-1.2 watt/sqft and lighting target levels between 200-700 lux. The results show that the total energy consumption is increased with higher LPDs and lighting target levels. In addition, the optimal SFR shifts from a smaller ratio, 0 or 5%, to a bigger one, 7 or 8%, by increasing LPDs and light levels. It is also found out that if the advanced lighting system reaches 0.4 watt/sqft, installation of skylights can not guarantee saving energy in all climates. In this case, the electricity to produce the light is so low that savings on such a low electrical lighting load may not offset the increased HVAC loads.

After performing the unconstrained optimization approach with GD to optimize energy efficiency, I utilized PA to perform multi-objective optimization. To consider both daylight and energy performances, I aggregated the metrics of RES, DGPi and MD into an average performance. If all the metrics have the same significance factor, 11% is the inclusive and holistic optimal solution for all the climates. If a range of optimal solutions is of interest, a tolerance threshold should be defined to approximate solutions with close average performances. Taking this method, the optimal ranges of inclusive solutions fall into the upper bound of energy efficient ranges.

The second approach was constrained optimization, which defined a set of daylight performance targets as searching for SFRs that saved energy or showed the maximum energy savings. This approach utilized Parametric

Analysis and examined whether different daylight metrics would change the final skylight design solution. Two sets of combined metrics were applied. For both sets, kWh represented the total source energy consumption and two sets of metrics were applied in order to obtain required daylight and glare performances: sDA and UDI of 100%, and MD and mDGP.

Through PA it was found that with the metric set of kWh, sDA and UDI, the inclusive optimal SFR is 9% in the Chicago and San Francisco climates, while the optimal SFR in Austin climate is 8%. These optimal solutions are the most energy efficient scenarios that meet the daylight targets.

In addition, the constrained optimization method has shown that it is likely that the optimal SFR range could be extended if the optimization search was defined based on saving energy rather than maximizing saved energy. The results show that in two climates the range of inclusive optimal solutions was extended, as both daylight and energy were held to minimum performance. The studies for Austin and San Francisco showed that the optimal solutions are in the ranges of 8-10% and 9-10% SFR, respectively. However, in Chicago the optimal solution range was not extended and kept to 9%. This shows that in Chicago inclusive optimal solutions were not affected by loosening the bar for the energy performance from maximum to minimum energy saving. Because Chicago is a cold and cloudy climate, 100% sDA and UDI are stringent daylight targets to achieve. This shows that the thresholds of metrics are climate-dependent; therefore, the targets need to be defined with care.

The second set of metrics for constrained optimization was established on energy efficiency measured by kWh and daylight performance estimated by MD greater than 50% and mDGP lower than 35%. This approach resulted in 7%, 8% and 7% SFRs as the inclusive optimal solutions for the climates of

Austin, Chicago and San Francisco, respectively. These optimal solutions are the most energy efficient scenarios that meet daylight performance targets. Where the bar for the energy factor was set to save energy rather than to maximize energy saving, the optimization reached a range of optimal solutions instead of a single optimal solution. The study showed that the constrained optimization with the metric set of MD and mDGP found the inclusive optimal SFR ranges to be 7-14% , 7-11% and 8-13% for the climates of San Francisco, Austin and Chicago, respectively.

As daylight quality can be measured by its increased productivity rate, in the third approach I combined the monetary savings from energy efficiency and productivity. The literature review showed there has previously been little consistency in reported increased productivity; hence, I applied 1% increased productivity in order to avoid exaggerating the savings through productivity. 1% increased productivity was estimated as a cost saving of $9,000 in this approach. The study showed that the minimum increased productivity rate significantly overshadowed even the largest energy cost saving, which was $555 per annum in San Francisco. This highlights the fact that the qualitative aspects of daylight, if considered and quantified, may swing design decisions because of the considerable monetary benefits associated with them.

This research has not only met all the main objectives mentioned at the beginning of this section, but has also provided the following contributions:

- Examined and verified the results of a new numeric optimization, Gradient Descent.

- Noticed a mismatch between daylight and energy assumptions in daylight and energy engines, which alerts researchers and designers to be cautious.

- Found out the important influence of illuminance target level on energy optimization.
- Highlighted the role of lighting power density in energy optimization.
- Included a discussion of the savings from productivity in comparison to energy cost saving.
- Developed a sense of the relative importance of different qualitative and quantitative factors: glare, daylight availability and energy.
- Shed light on the mechanism of objective functions as a driving force to define optimal solution(s).

This study has proposed and applied three different approaches to find a robust skylight design which includes all the qualitative and quantitative aspects of daylight. The three approaches not only had different logistics to find the holistic optimal solutions, but they also applied different metrics. In the section that follows, I explain the challenges confronted in this study, and how I resolved them. I also suggest future possible areas for further research.

5.2 Challenges with Metrics

This research addressed the challenge of finding metrics for holistic optimization, including energy and daylight performances. Total source energy and utility were utilized to study the energy impacts of skylights. Both source and utility were derived from site energy consumption. Energy consumption was a measurable metric, therefore, it was straightforward and clear what to use for this design factor, which was dollars and kWh. The challenge arose for qualitative aspects of daylight, encompassing boosted morale and human well-being. Measuring such qualities seems impossible unless through their side effects, including productivity, or the fundamental requirements for their presence or absence, including daylight availability and glare. As daylight satisfaction is a sensation, daylight metrics and their thresholds should be verified by on-site experiments. Currently researchers have been developing daylight metrics. Scholars continue to debate on what an appropriate daylight metric should be. However, this dissertation proposed and applied both new metrics and the most commonly-used metrics in the industry for assessing daylight performance.

In addition, the challenge of finding daylight metrics needs to be extended to the metric of holistic performance. To solve this problem, I applied either a unified unit, such as dollar and percentage, or held each metric to its original unit but confined it to an acceptable threshold.

5.2.1 The Roles of Applied Daylight Metrics in Optimization

Among the various daylight and glare metrics applied in this dissertation, some played strong roles in the optimization process while others did not show a critical contribution. The proposed metrics in this dissertation were MD, mDGP and DGPi. In addition, I applied the most common metrics in the industry comprising sDA and UDI. The metrics for horizontal daylight availability, sDA and MD, were also significant players to find the inclusive optimal solution. The Constrained Optimization approach showed that the smallest SFR reached the targets of sDA, and MD became the inclusive optimal "solution", with the most energy savings. Moreover, the constrained optimization approach shows that the upper bound of the inclusive optimal "solutions" was delineated by the largest SFR that was energy efficient compared to the scenario with 0% SFR. If UDI was used to prevent extensive glare issues, then UDI would determine the upper bound of the optimal solutions.

DGPi and mDGP, as glare metrics, did not interactively conduct the optimization process. Both metrics are originated from DGP, which is a luminance-based metric. This insensitivity toward the optimization raises the question of whether the current DGP and its DGP-originated metrics are qualified for the glare analysis of skylight design. Intuitively I maintain that luminance-based metrics should be better predictors of glare issues, because glare is the optimal noise in the field of view which the eye perceives. Glare is not the light that falls onto the horizontal desk, therefore, horizontal illuminance-based metrics cannot precisely locate the glare spots. However, scholars have argued that extensive horizontal illuminance increases the probability of glare issues in the field of view. Although, by their definitions, DGP-originated metrics should have played a cutting edge role in drawing the boundaries of optimal solutions, this dissertation showed that UDI as an illuminance-based metric had a stronger role in the optimization process. These flaws in DGP have also been reported in other studies (Wymelenberg and Inanici, 2011; Suk, 2014). As the field of daylight metrics, specifically glare metrics, is continuously changing, it is my hope that new luminance-based metrics and their simulation tools will be developed soon. The availability of such metrics and tools makes the accurate analysis of glare possible and will encourage researchers and designers to include glare issues in the optimization of the design process.

5.2.2 Limitations of Current Dynamic Metrics

As the most commonly used daylight metrics, UDI and sDA suffer from an embedded shortcoming in their definitions. Both metrics are pinned to meet the daylight targets for 50% occupied hours. Why is 50% the target? The literature does not point to extensive case studies to confirm that 50% occupied hours is the appropriate target. It was chosen by the scholars in the field, such as Reinhart, Nabil and Mardaljevic. In addition, another shortcoming of these metrics is that if the space meets the daylight targets for any percentage of hours below 50%, it will be disregarded by these metrics. In other words, they discount spaces that do not fully contribute to daylight availability for occupied hours lower than 50%. A solution is to assign partial credits to such spaces. However, on what basis these credits should be awarded is another challenge these metrics need to overcome in order to truly represent the daylight availability in the space. Future development of daylight metrics should include both spatial and temporal targets for both annual daylight availability and distribution of daylight.

5.2.3 What are Daylight Metrics Missing?

The other challenge with daylight metrics is the lack of a universal benchmark that could be accessed by researchers and designers. It is important to verify daylight results by comparing them to the results of existing case studies that have already been validated. The evaluation of qualitative aspects of daylight can be handled by experimenting with different daylight scenarios and distributing questionnaires asking dwellers if they are satisfied with the existing daylight. Then, the results need to be collected, sorted and made accessible to researchers and designers. For example, ASHRAE provides baselines for different climate zones which researchers utilize to experiment with new metrics, devices, simulation tools, or energy efficient scenarios. The proposed big data can be used to develop new glare or daylight metrics or for verifying design scenarios based on the current metrics.

5.2.4 Different Optimization Approaches: Their Potentials and Limitations

In this study, the unconstrained optimization utilized a weighting technique to contextualize design decisions by assigning different multipliers to various metrics. It was explained that the relative ratio of the multipliers can magnify or downplay the role of one of the metrics over the others. However, this dissertation examined two scenarios for the multipliers: single-objective and multi-objective scenarios. In the first scenario, the energy factor multiplier was set to zero and the daylight and glare factors were set to one. In the latter, I applied the weight of one to all metrics. I only experimented with very limited multipliers, although the multipliers can vary based on the function of the space and the context of the design. The intent was to provide a platform and to encourage the active groups in each project to tune these multipliers, probably through dialogue, discussion, on-site studies and experiments.

In addition to multipliers, the other challenge with this approach was to make sense of the aggregated unit. What range of the aggregated unit is appropriate? And how to back-trace from the aggregated unit to its compilers and justify the performance of each sub-metric? These questions cultivate a new research area for future studies.

As this dissertation utilized various approaches, the question is raised: which optimization approaches and methods are appropriate? If the daylight metrics were the same in constrained and unconstrained optimization approaches, the results would have been much closer. Therefore, with regard to the accuracy of the results, there is not a significant difference between constrained and unconstrained approaches used in this dissertation. What may make the unconstrained approach appealing to researchers is that it is simpler to apply, because it utilizes a unified metric without any constraints. However, one of the disadvantages of unconstrained optimization is to tune the multipliers and make sense of the aggregated metric.

In terms of Gradient Descent versus Parametric Analysis, each offers its own advantages and disadvantages. As mentioned, GD is faster and results in the optimal solution with higher resolution. However, implementation and initialization of GD is cumbersome and needs some level of expertise. GD is also better suited to messy and complex design questions than PA is. Although this study only considered single-variable optimization, design questions are always related to a handful of variables. In such cases, PA consumes extensive time and is a more expensive method than GD, because the number of iterations to carry out an exhaustive search by PA is a function of the variables. However, what makes PA unique is that this method helps in discovering the dynamics and (co)relations between variables and objective functions. For instance, PA in this study helps us to understand the impacts of raising lighting levels on energy, daylight and holistic performances, while such dynamics can not be understood by the use of GD.

The future study area is derived from the limitation of the unconstrained optimization. This approach with the applied metrics does not guarantee that the solution(s) will meet specific targets. Since the metrics in this approach do not have any constraints, an improper ratio of multipliers may skew the optimization toward a solution that is not holistic and inclusive. I have offered suggestions to avoid such a failure. First, the final results need to be evaluated as to whether or not they meet daylight and energy performance targets. Second, multipliers or the mathematical equation of average performance can be redefined in such a way to assure that all metrics and their aggregated unit fall into a feasible region, by assigning penalties to the ones that are unacceptable. These penalties should be assigned before aggregating the metrics, which creates a barrier for some solutions where optimization should not be converged[1]. In other words, the optimization is unconstrained for the aggregated metric but constraints are applied to daylight, energy or glare metrics (sub-metrics).

In addition, this dissertation practiced the Gradient Descent method for the unconstrained optimization approach. However, instead of the Gradient Descent method, Parametric Analyses were used in the constrained optimization. A future research opportunity is raised to apply the Gradient Descent method for the constrained optimization approach.[2] Generally future studies can pivot toward using the already theoretical optimization algorithms in order to solve complex design questions and propose contextualized solutions.

5.3 Towards Multi-Objective Optimization

Multi-objective optimization from the realm of mathematics was bridged to the constructivist paradigm and found multiple optimal solutions that are socially and locally constructed. Climate, as a local factor, was studied in this dissertation, in addition to the interests of different social groups, including

[1] Barrier Optimization Method
[2] lagrange method

the owner, environmentalists and occupants. Qualitative and quantitative aspects of daylight were brought in as objective functions. As the paradigm of constructivism supports context-dependency, I applied different optimization approaches and involved all the related interests and included their roles in the optimization process.

This dissertation showed that in a single-objective optimization, such as energy efficiency, the results may be different than in a multi-objective optimization that is inclusive and considers both energy and daylight performances. Whether or not the energy efficient optimal solution contains appropriate daylight performance depends on the applied daylight metrics and their targets to achieve. In this dissertation, the energy efficient optimal solution differs from the inclusive optimal solution suggested by the three approaches. For instance, 6% SFR is the energy efficient optimal solution in San Francisco climate while different optimization approaches resulted in various inclusive optimal solutions e.g. 11%, 9% and 7%. However, if the bar was set low for daylight metrics such as MD and sDA, the energy efficient optimal scenario might have reached the desired daylight performance.

I argue that "solutions" should be pursued in the optimization process rather than an absolute "solution". This study shows that a unique optimal "solution" calculated by single-objective optimization was different from an inclusive optimal "solution" proposed by multi-objective optimization. However, instead of focusing on a sole optimal "solution", an optimization method should offer a range of "solutions". Design challenge is a multi-faceted problem in which many factors may be left out, even in multi-objective optimization. Those factors may pivot the final optimal solution if considered in the optimization process. In this study, while the energy efficient optimal solution was different from the inclusive one, the range of energy efficient scenarios comprises the inclusive optimal solution(s). Therefore, optimization approaches should always generate a range of appropriate "solutions" for designers to choose from. This will help designers to accommodate other design parameters and adjust the final solution by holding a more holistic perspective. I conclude that this dissertation has bridged multi-objective optimization to design questions which sheds light on the application of current known mathematical methods to solve messy and complex questions of design.

5.4 Expanding the Variables of Multi-Objective Optimization

As this dissertation only applied single-variable, SFR, to multi-objective optimization, further studies can be developed by adding more variables. In addition to skylight sizes, other variables can be added to the multi-objective optimization to lead to more inclusive and holistic optimal solutions. The current optimization platform with its different approaches can be used for other variables including different shading devices, visible transmission, solar heat gain coefficients, constructions, toplighting strategies, building geometries, and neighborhood masses. Such variables can be studied and plugged into the developed platform with subtle changes and effort.

There are other variables that can be added to the platform but more efforts are needed to define new objective functions. The first example is windows; although windows can be added to the current platform, the current objective functions cannot provide inclusive and holistic solutions for windows. Glare, daylight availability and energy have been the driving forces in the current optimization platform to find a robust toplighting strategies. However, another implication of sidelights is that they provide views to the outside. Therefore, the objective functions of the current platform should be expanded to adopt view availability and view qualities in order to generate more robust window design. Natural ventilation and thermal comfort are other aspects that were left out in this study. If the goal is to optimize fenestration sizes and their positions on the building skin, the impact of natural ventilation on energy consumption and thermal comfort should be considered in the optimization process. This requires new objective functions to be developed based on the adaptive thermal comfort method proposed by ASHREA-55 or Universal Thermal Climate Index (UTCI). For accuracy of the result, ventilation engines performing Computation Fluid Dynamics (CFD) should be coupled with daylight and energy engines in order to provide solutions that promote visual and thermal comfort while saving energy.

In addition, the algorithm in this study was based on the total source energy consumption by balancing decreasing electrical lighting and increasing HVAC loads. Because increasing HVAC loads boosts initial costs, this can impact design decisions in regard to applying toplights. To what extent we can increase HVAC loads depends on whether or not such an increase is plausible and achievable for a project at hand. As a result, future optimization should also introduce new HVAC limitations in the algorithm.

Lastly, future studies can integrate life-cycle assessments into multi-objective optimization platforms. Life-cycle assessments, e.g. materials with operation cost assessments, effectively help finalize design decisions. Although adding more variables makes the optimization process lengthier and messier, multi-variable and multi-objective optimization in the mathematical realm can handle such a complexity.

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Vita

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