Optimization of Daylighting and Energy Performance Using Parametric Design, Simulation Modeling, and Genetic Algorithms

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ABSTRACT

FANG, YUAN. Optimization of Daylighting and Energy Performance Using Parametric Design, Simulation Modeling, and Genetic Algorithms. (Under the direction of Dr. Soolyeon Cho).

With the increasing demand for sustainable design and green buildings, performance is becoming an important driving force behind design decisions. Currently, however, only limited design options have been explored, and there are limited performance evaluation methods available for designers in the early design stages. This research proposes a new building performance optimization process that can help designers evaluate both daylighting and energy performance, generate optimized design options, and understand the relationship between design variables and performance metrics.

The proposed method of performance optimization utilizes various tools and technologies including parametric design, building simulation modeling, and Genetic Algorithms. In this method, building design alternatives are extensively explored through parametric design. Daylighting and energy modeling and simulation are performed to evaluate building performance. Genetic Algorithms is used to identify design options with optimal energy and daylighting performance. A case study was conducted to test and verify the effectiveness of the optimization process. The geometry of the case study building was optimized through the test in three different climate conditions. Various results were analyzed and potential influence of design decisions in different environments were discussed.

BIOGRAPHY

Yuan Fang was born in 1988, in Harbin, China. She received her Bachelor's degree in Architecture from Harbin Institute of Technology and Master's degree in Architecture from Tianjin University. During her study, she was involved in number of architectural design and research projects.

She joined Ph.D. in Design program at North Carolina State University in 2013. She has conducted extensive research on building daylighting and energy performance optimization, green buildings design, renewable energy systems integration, and thermal comfort analysis.

She worked as a teaching assistant for Dr. Soolyeon Cho in Energy Modeling and Simulation Courses, and worked with faculty members and students in Building Energy Technology Lab (BETlab) on several research projects.

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CHAPTER 1: INTRODUCTION

1.1 Problem Statement

Because of the Energy Crisis and climate change, there are growing concerns for sustainability around the world. Buildings contribute to one of the largest energy consumption sectors of the total energy consumed (EIA, 2016). The interior environment of buildings is also closely related to the health and productivity of occupants (Edwards & Torcellini, 2002). Therefore, the development of green buildings or high performance buildings is becoming an intense research topic. It is important to minimize the energy consumption without sacrificing the comfortable and healthy indoor environment.

With continuous advancement of computational technology, there are numerous building performance simulation tools available for designers and engineers to evaluate various aspects of building performance. Building performance simulation has been applied to different stages of building design and construction (Augenbroe, 2002).

The early design stage is where most building design decisions are made, and where there is the greatest potential to achieve high performance building designs (Miles, Sisk, & Moore, 2001). However, design alternatives and how are they are related to building performance are not thoroughly explored in the early design stage. Currently, performance simulation and sustainable design technologies still not well adopted as expected.

Therefore, to achieve high performance buildings, it is important to optimize the design process that can fully explore design possibilities in the early design stage, and push design decisions towards optimal building performance.

1.2 Research Purpose

The primary goal of the research is to develop a building daylighting and energy performance optimization method in the early design stage for designers to make design decisions towards optimal performance. This optimization method is required to have following features.

First, it can expedite the generation of multiple design alternatives, so that the potential of building design can be extensively explored.

Second, the daylighting and energy performance of each design alternative can be obtained simultaneously.

Third, optimal design options can be found from the large number of design options, and the optimal solution should be reliable.

How this process can be integrated into early architectural design stage, and how the optimization results would influence the design decisions are discussed. This research also aims to test the applicability of this optimization process through case studies under different climate conditions. Finalized design options with enhanced daylighting and energy performance are proposed, and the relationship between building design variables and performance metrics is analyzed.

CHAPTER 2: LITERATURE REVIEW

The literature review consists of two main sections. The first section is the review various technologies supporting the building performance optimization process: parametric design, daylighting and energy performance simulation, and genetic algorithms. The second part is the review of precedent building performance optimization studies and their limitations.

2.1 Parametric Design

In architectural design practice and research, parametric design approach is becoming popular. Parametric design in architecture refers to the modeling process of building geometry using parameters and functions. Parametric design adopts similar programming technologies in computer science. It has the flexibility of programming, but its graphical user interface and visual codes make it more user friendly than traditional programming languages.

The advantage of parametric design over traditional design method is its ability to quickly generate design alternatives (Gerber, 2009). Parametric design maintains dynamic links between parameters and geometry defined by the parameters. The modification of parametric values lead to simultaneous updates of the building geometry. Once a parametric building model is developed, design alternatives can be rapidly generated through the manipulation of parameters. Figure 2.1 presents one simple example of parametric design. It shows the development of the box geometry involving three functions and three parameters. The three parameters control the width, depth, and height of the box. Different box geometries can be generated following the change of parameters. Parametric design is widely used in the exploration of patterns and forms. For example, Hemmati and Alavi's (2016) research presented different building envelope patterns generated though the data manipulation of one parametric model.

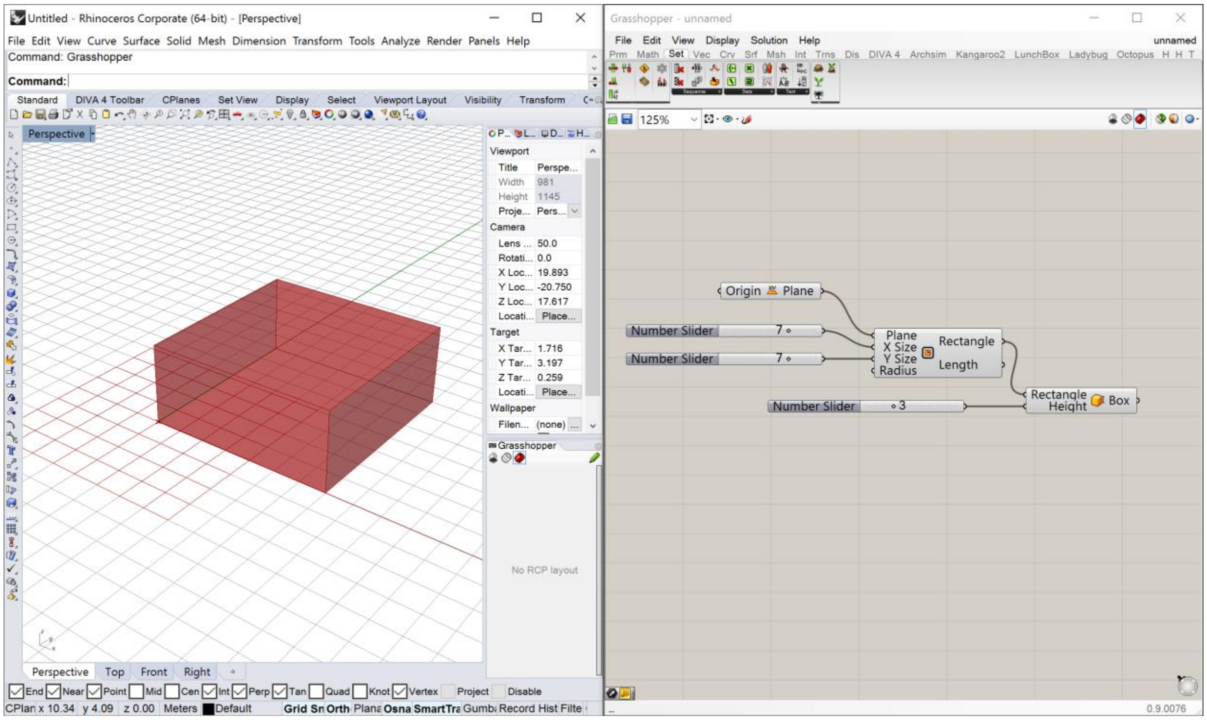


Figure 2.1 Parametric Design

By combining parametric design and building performance evaluation tools, it is able to create design options based on the design performance criteria, such as structural performance, lighting performance, energy performance. Rolvink, van de Straat, and Coenders (2010) explored building structural system using parametric approaches, and demonstrated how parametric design facilitate the generation of design alternatives. Labib (2015) used parametric design method to explore the geometry of light shelves and ceilings, and evaluated designs by their daylighting performance.

Furthermore, the exploration of design alternatives can be automated once the parametric model is developed (Kilian, 2006). Just as computer programming, a certain task can be accomplished automatically once a sequence of instructions are defined by the corresponding code. The automation of the design exploration can significantly save time and provides the opportunity for optimization.

The disadvantage of parametric design is that the modeling of the initial parametric model takes longer time than conventional methods. But as the number of design alternatives grows, parametric modeling method will quickly show advantage. Another disadvantage is that the design alternatives generated by a parametric model still follows the same design concept, and have lots of similarities. If the intent is to compare completely different design options, the parametric design method is not appropriate.

Eltaweel and Su (2017) reviewed that parametric design software was first developed in 2008, and the prevalent tools include Catia, 3D MAX, 3D Maya, Rivet, Grasshopper, Dynamo, Generative Components, Marionette, and Modelur. The most popular parametric design software is Grasshopper, which is a plugin for the NURBS (Non-Uniform Rational Basis Spline) modeling software Rhinoceros.

Grasshopper is an open software which can be enhanced by plugins. The plugins target various areas such as building geometry development, building structure, environmental analysis, mechanical engineering. Ladybug and Honeybee (Roudsari & Pak, 2016), Geco, Diva and Archsim are building performance analysis plugins. They create a link between parametric building model and building performance through energy modeling and simulation. Like normal energy modeling process, the required input data are usually climatic data, building geometry, materials, occupancy and several other schedules and HVAC description and operation. Their output usually includes energy consumption, thermal and visual comfort metrics, and daylight metrics.

2.1 Building and Daylighting

2.1.1 Benefits of Daylighting

Properly designed daylighting environment can significantly enhance the health and productivity of occupants, and improve the energy efficiency of buildings.

Edwards and Torcellini (2002) reviewed the effects of natural light on building occupants, and summarized that daylighting was found to be associated with higher productivity, lower absenteeism, improved mood, reduced fatigue, and reduced eyestrain. Solar radiation on the skin is essential for human body to produce vitamin D (Holick, 2004). Vitamin D is essential for the general health and well-being of people, and vitamin D deficiency has been proven to increase the risks of many common cancers, diabetes, autoimmune disease, and sclerosis (Holick, 2004). Full-spectrum light from the sun is the best type of light for human eyes' function, whereas most artificial light are concentrated in certain portion of the spectrum, and may lead to improper functioning of the eye (Edwards & Torcellini, 2002). Many other functions, including nervous system, circadian rhythms, and endocrine system are also influenced by different wavelengths of light (Edwards & Torcellini, 2002).

Researchers also found various benefits of daylight in different building types. In hospitals and assisted-living communities, daylight can improve the physiological and psychological states of both patients and staff (Edwards & Torcellini, 2002). Proper lighting environment can ease pain, reduce depression of patients, decrease length of stay in hospitals, and lessen agitation among dementia patients (Joseph, 2006). Walch et al. (2005) found that patients staying on the bright side of the hospital took 22% less painkilling medication per hour. Choi, Beltran, and Kim (2012) found a significant relationship between indoor daylight environments and a patient's average length of stay (ALOS) in a hospital, and the ALOS of patients in rooms located in the southeast area was 16% - 41% shorter than that in the northwest area.

The benefits of daylight in office environments include reduced absenteeism, increased productivity, financial savings (Edwards & Torcellini, 2002). People prefer to work in daylight to artificial light and they prefer to be close to windows (Joseph, 2006). Leather, Pyrgas, Beale, and Lawrence (1998) found the area of sunlight penetration is significant positively related to job satisfaction, and negatively related to intention to quit. A successful example of daylighting in commercial office is Lockheed's Building 157 in Sunnyvale, California, which has 15-foot-high window walls, sloped ceilings, and a central atrium to bring daylight deep into the building (Romm & Browning, 1994). Absenteeism dropped 15 percent and productivity rose 15 percent, which helped Lockheed win a $1.5 billion defense contract (Romm & Browning, 1994).

The benefits of daylighting in school environments include improved health, student attendance and academic performance (Edwards & Torcellini, 2002). Nicklas and Bailey

(1997) compared the scores of students from schools using daylighting to schools using artificial light, and found students from daylit schools have higher scores in reading and math tests.

Another important benefit of daylighting is energy savings. Alrubaih et al. (2013) reviewed that artificial lighting systems consume about 25%-40% of the total energy consumption of buildings, and daylighting as an alternative to artificial lighting is considered to be one of the simplest method to improve energy efficiency. Daylight by itself does not lead to energy savings. Cost and energy savings are achieved through lighting control strategies and photo sensors, when artificial lighting can be dimmed or switch off when daylight is sufficient (Wong, 2017). Lockheed's Building 157 saved about 75 percent on its lighting bill, and the its energy costs was about half of a typical building constructed at that time (Romm & Browning, 1994). Opdal and Brekke (1995) compared the energy savings result from calculation and measurements and found 40% of lighting energy savings from calculation and 30% of lighting energy savings from measurements. Lee and Selkowitz (2006) performed a 9-month field study in the mockup of a commercial building in New York, and found 20–23% and 52–59% energy savings in two areas of the space through automated roller shades and daylighting controls.

In addition to the potential to reduce lighting energy, daylighting can also lower the building's cooling load by reducing the heat released by the lighting fixtures. However, excessive glazing area may contribute to great heat loss and heat gain, and increase the heating and cooling energy consumption of the building. Therefore, daylighting system need to be properly designed, so that the advantages of reduced lighting and cooling energy can overcome the disadvantages of increased heat loss and heat gain.

2.1.2 Daylighting Performance Metrics

Various performance metrics were defined by researchers to evaluate the quantity of natural light on task surfaces in the interior space. The most used metrics are discussed below.

Illuminance

Illuminance measures the amount of light on a surface per unit area, and its unit is lux. Illuminance is the most commonly used metric to evaluate the brightness of the indoor environment. Recommended levels of illuminance are defined by the Illuminating Engineering Society (IES) according to the space type, the type of visual tasks, the age of occupants, etc. Table 2.1 shows some examples of the recommended illuminance values for different building types and seeing tasks (DiLaura, Houser, Mistrick, & Steffy, 2011).

Daylight factor (DF)

Daylight factor (DF) measures the ratio of the indoor illuminance to the outdoor illuminance under overcast sky conditions. DF is easy to measure and calculate, and its concept is intuitive. Thus it is the most frequently used metric to evaluate the daylight condition of a building. However, DF is a static daylight metric, which means it does not change with the building location or orientation, and many daylighting design problems cannot be detected by DF (Reinhart, Mardaljevic, & Rogers, 2006).

Table 2.1 Building types and recommended illuminance values

Building types	**Area and seeing task**	**Recommended Illuminance values (lux)**
Residences	General lighting	50-100
	Noncritical kitchen duties	200-500
Office	Lobbies	100-200
	Reading	200-500 or 500-1000 or 1000-2000 depending on the reading material types
Restaurants	Kitchen	500-1000
	Dining	50-100
Stores	Merchandising areas	500-1000
	Feature displays	1000-2000
	Stockroom	200-500
Hospitals	Patients' rooms	50-100
	Emergency rooms	500-1000
	Operating rooms	1000-2000

Daylight autonomy (DA)

Daylight autonomy (DA) is the ratio of the number of hours in the year when the illuminance provided by daylighting is above the minimum illuminance requirement, to the total number of hours occupied in a year (Reinhart & Walkenhorst, 2001). DA is a dynamic daylighting metric. Dynamic daylight metrics are based on time series of illuminances, which are based on annual solar radiation data for the building site (Reinhart, Mardaljevic, & Rogers, 2006). The primary advantage of dynamic daylight performance metrics over static metrics is that they consider the quantity and features of daily variations of daylight together with irregular meteorological events (Reinhart, Mardaljevic, & Rogers, 2006).

Useful daylight illuminance (UDI)

Useful daylight illuminance (UDI) is the ratio of the number of hours in the year when illuminance provided by daylighting is within a useful range, to the total number of occupied hours in a year (Nabil & Mardaljevic, 2005). UDI aims to determine the daylighting level that is neither too dark nor too bright (Reinhart, Mardaljevic, & Rogers, 2006). UDI is usually presented by three metrics: UDI <100 lux, UDI 100-200 lux, and UDI >2000 lux. The illuminance range that considered useful is between 100 lux to 2000 lux. Illuminance below 100 lux in considered as too dark, and illuminance above 2000 lux is considered too bright.

Continuous Daylight Autonomy (cDA)

Continuous Daylight Autonomy (cDA) is similar as DA, but it provides partial credit to the times when the illuminance is below minimum requirement (Rogers, 2006). For example, the minimum illuminance requirement of a space is 300 lux, and at a certain time step the illuminance is 150 lux. DA would give it 0 credit, while cDA would give it 0.5 credit.

Spatial Daylight Autonomy (sDA)

Spatial Daylight Autonomy (sDA) is the percentage of area that meets the minimum daylight illuminance for a specified percentage of hours in a year (Heschong et al., 2012). It considers both the spatial and temporal characteristics of daylighting performance.

Annual Sunlight Exposure (ASE)

Annual Sunlight Exposure (ASE) is the percentage of area that exceeds specified illuminance for more than a specified percentage of hours in a year (Heschong et al., 2012). sDA and ASE are usually used together to evaluate the daylighting condition of the space.

2.1.3 Daylighting Simulation

Wong (2017) reviewed various methods to evaluate daylighting performance of buildings, including scale models with simulator, mathematical models, full scale models for field measurement, and computer simulation software. This review evaluated the strengths and weaknesses of each method, and found that computer simulation method is the most commonly used in the building design stage because of its capability of involving design variants and its accurate results.

Wong (2017) also provided an extensive review of computer simulation tools for daylighting performance, and the most frequently used programs are Radiance, Adeline, Ecotect, DOE, Daysim, and EnergyPlus. There are two most utilized illumination algorithms in daylighting simulation programs: ray-tracing (view-dependent algorithm) and radiosity (scene-dependent algorithm), which can be respectively represented by Radiance and Relux (Yu & Su, 2015).

Radiance is backward ray-tracing program, and it is considered as the most popular daylight modeling and simulation tool (Yu & Su, 2015). Radiance was widely used in daylighting related research topics, and it was extensively validated by researchers (Ochoa et al., 2011).

One major drawback of Radiance is the lack of user interface, so it is usually incorporated as a lighting simulation engine within other tools, such as Daysim (Ochoa et al., 2011).

2.2 Building and Energy

2.2.1 Energy Performance Metrics

Since the energy crisis in the 1970s, there are growing concerns for energy conservation and the use of renewable energy resources. Energy production is related to air pollution and global climate, which can directly lead to the prevalence of certain disease (Brown, Henze, & Milford, 2017).

Buildings, industries and transportation systems are the three major sectors in energy consumption. Energy consumed in the buildings accounts for about 20% of the total energy consumed worldwide (EIA, 2016). In the U.S., buildings sector accounts for about 41% of total energy consumption in 2010, which is 44% more than the transportation sector and 36% more than the industrial sector (D&R International, 2012).

Energy consumption in buildings has increased dramatically worldwide over the past few decades, and it is expected to keep growing. According to EIA (2016), energy consumption in buildings is expected to increase by an average of 1.5% per year from 2012 to 2040. Cao, Dai, and Liu (2016) reviewed that the main reasons for the energy consumption increase are the growth of population, the increased time people spent indoors, the demand for more building functions and higher indoor environmental quality, and global climate change.

To evaluate the energy performance of buildings, it is necessary to compare the calculated or measured building performance metrics to some reference values, which may represent the energy-related characteristics of the building components or the energy consumption of building systems (Borgstein, Lamberts, & Hensen, 2016). It is increasingly common to evaluate building performance based on normalized whole-building energy consumption metrics, such as Energy Use Intensity (EUI) (Borgstein, Lamberts, & Hensen, 2016).

EUI is the energy per square foot per year, and it is calculated by dividing the total yearly energy consumption of the building by its total gross floor area (EPA, 2016c). Table 2.2 summarizes U.S. national median EUI values for some typical building types (EPA, 2016b). These values can be used to compare a property's energy use to the national median. Source energy reflects the total amount of raw fuel required to operate the building, while site energy is the amount of heat and electricity consumed by a building which is usually shown in utility bills (EPA, 2016a).

Generally, lower EUI indicates better energy performance of a building. Building energy use can be influenced by numerous internal and external factors such as weather, plug loads, and occupant schedules, and certain building types always have higher EUI than others (EPA, 2016c). In the listed examples in Table 2.2, restaurants and hospitals have the largest EUI, whereas residence halls and dormitories have the least EUI.

Table 2.2 U.S. National Median EUI by Building Type

Primary Function	**Source EUI (kBtu/ft2)**	**Site EUI (kBtu/ft2)**
Restaurant	432	223.8
Hospital	389.8	196.9
College/University	262.6	130.7
Mall	235.6	93.7
Hotel	162.1	73.4
Office	148.1	67.3
K-12 School	141.4	58.2
Laboratory	123.1	78.8
Residence Hall/Dormitory	114.9	73.9

2.2.2 Energy Simulation

Building energy modeling and simulation is the process of predicting a building's energy performance prior to the building construction. It analyzes the energy consumption of a building at the design stage and it can speed up the design process, increase efficiency, enable the exploration of multiple design variants, and finally lead to more optimal designs (Augenbroe, 2002).

Before the prevalence of building simulation technologies, architects and engineers relied heavily on manual calculations and often use 'rule-of-thumb' methods and extrapolations in making design decisions, and this approach usually resulted in buildings with poor energy performance due to oversized plant and system capacities (Hong, Chou, & Bong, 2000).

With the development of computers, there is a rapid proliferation of building performance simulation tools in the past few decades. Those tools are becoming more easily for designers to use because of the improved user interface, reduced calculation time, easy data transfer between programs, and intuitive result display. The most popular energy modeling tools include DOE-2, EnergyPlus, Energy 10, TRNSYS, HAP, IES-VE, and TRACE 700. These tools focus on various aspects of building performance, including building energy efficiency and consumption, thermal comfort, ventilation and indoor air quality, lighting environment, and acoustic environment (Wang & Zhai, 2016).

The EnergyPlus is one of the most popular building performance simulation programs. It is an advanced whole-building energy simulation engine, and it can be used to model both energy consumption and water use in buildings. The EnergyPlus simulation result is highly accurate, and it was validated by different researchers (Mateus, Pinto, & da Graca, 2014; Anđelković, Mujan, & Dakić, 2016). EnergyPlus is funded by the U.S. Department of Energy, and it is a free, open-source, and cross-platform software.

2.4 Building Performance Optimization

2.4.1 Optimization

One common approach that designers seek the best design solution is “design of experiment” and comparison, where different design variables are combined to establish multiple design alternatives, and the optimal design is found through the comparison of their performances. This process is intuitive and flexible, so it is widely used in practice and research problems.

For example, Mahmoud and Elghazi (2016) used an experimental method to the evaluation of kinetic facades system performance, and found optimal design solutions with best daylight performance. Ho, Chiang, Chou, Chang, and Lee (2008) explored the performance of 4 types of shading designs with different height and width combination for a classroom design, and found the optimal design with maximum uniform illumination distribution. However, only limited design options can be explored in this method.

Optimization is the process or methodology of making a design or decision as functional or effective as possible (Merriam Webster Online, 2017). Mathematically, optimization is the process of finding the minimum or maximum value of a function by choosing the best value of variables. Optimization provides the possibility to explore a large number of design solutions efficiently, but the transfer of a building design problem into the mathematical domain is not an easy task. With the development of parametric design, building performance simulation and optimization technologies in recent years, optimization of building performance has become possible. The applications of mathematical optimization started since the 1980s and 1990s, but most studies in building performance optimization with building energy simulation and an algorithmic optimization engine were published in the late 2000s (Nguyen, Reiter, & Rigo, 2014).

Building performance optimization is usually considered as a process automated by a building simulation program and an optimization engine, which consists of optimization algorithms (Nguyen, Reiter, & Rigo, 2014).

Optimization process usually requires two types of inputs: variables and objective functions. In building performance optimization, variables are the values controlling the geometry or properties of the design, and objective functions are the building performance metrics usually calculated by simulation tools (Machairas, Tsangrassoulis, & Axarli, 2014). Typical design variables explored in optimization studies are the orientation of a building, the shape of a building, construction dimensions, construction materials, window to wall ratio, lighting equipment, and HVAC system sizes. Optimization methods were applied to a wide variety of building design problems such as energy, cost, orientation, façade design, thermal comfort, daylighting, massing, structure, and life cycle analysis (Machairas, Tsangrassoulis, & Axarli, 2014).

2.4.2 Multi-Objective Optimization

In building design problems, designers often need to deal with multiple conflicting objectives, such as maximum thermal comfort versus minimum energy consumption, or maximum equipment capacity versus minimum cost. There are two common methods to solve this problem. The first method is weighted sum model, where different weight is applied to various objectives, and the weighted objectives are summed up to a single cost function. Then the problem is transformed to a single objective problem. Weighted sum approach is easy to apply, but the result heavily depends on the weigh allocated to each objective, which require professional knowledge and experience.

The second method is Pareto optimization, which is to find the trade-off front, or Pareto front between each objective. Pareto front is defined based on the concept of dominance (Evins, 2013). For example, a two-objective minimization problem is illustrated in Figure 2.4. The two objectives are a and b. The solutions shown in red squares are non-dominated since there are no solutions with better performance in both objectives. They are called non-dominated solutions and make up the Pareto front. All the green dots are dominated solutions, since there are solutions that are better in both objectives. Genetic algorithms show strong advantages in solving multi-objective problems.

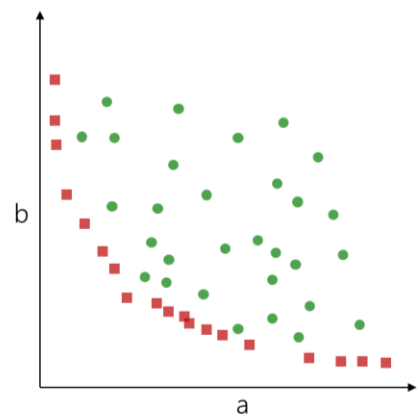


Figure 2.2 Pareto front (red dots) and dominated solutions (green dots)

2.4.3 Genetic Algorithms

It is important to choose the proper optimization algorithm for different optimization problems. Numerous types of optimization algorithms have been developed in recent years. Nguyen, Reiter, and Rigo (2014) reviewed the different optimization algorithms, and classified them as local or global methods, deterministic or stochastic methods, heuristic or meta-heuristic methods, derivative-based or derivative-free methods, bio-inspired or non-bioinspired methods, trajectory or population-based methods, single-objective or multi-objective algorithms, etc. The strength and weakness, and typical algorithms of each family were also thoroughly reviewed. Similar reviews were also conducted by Evins (2013), and Machairas, Tsangrassoulis, and Axarli (2014).

From the review of previous studies, it can be concluded that the stochastic population-based algorithms, such as Genetic algorithms, Particle swarm optimization, and Hybrid algorithms, were the most frequently used in building performance optimization (Nguyen, Reiter, & Rigo, 2014).

Genetic algorithm is the most popular optimization algorithm in building performance studies. Genetic algorithm was first proposed by Holland (1975) in the 1970s as a heuristic search method. It is based on the natural selection process in biological evolution (Galletly, 1998). It recurrently modifies a population of solutions using principles that can be observed in nature, such as selection, crossover, and mutation. Genetic algorithm randomly selects solutions of good performance from the current population and uses them as parents to produce the next generation, and the population "evolves" toward an optimal solution (MathWorks, 2016). It is suitable for building performance optimization for the following few reason: it can handle both continuous and discrete variables; it allows parallel simulations on multi-processor computers; it is suited to solve multi-objective problems; it is robust in handing discontinuity, multi-modal, and constrained problems; it is robust to high simulation failure rates (Nguyen, Reiter, & Rigo, 2014).

The tools that were used in building performance optimization studies can be separated into three categories: custom programmed algorithms, optimization packages, and special optimization tools for building design (Machairas, Tsangrassoulis, & Axarli, 2014). Custom programmed algorithms are the most flexible, but advanced programming skills are required. Examples of optimization tools for building design include MultiOpt (Chantrelle, Lahmidi, Keilholz, El Mankibi, & Michel, 2011), GENE_ARCH (Caldas, 2008), ParaGen (Turrin, von Buelow, & Stouffs, 2011). These tools are developed by third party developers, but they are not widely used and their performance is not widely tested and validated.

Currently, the optimization packages are becoming popular because they do not require advanced programming skills, have enough flexibility, and users can work in familiar software environment. Genetic algorithm based optimization packages are available in the Grasshopper parametric modeling environment. Galapagos is one example which is able to conduct single objective optimization. Labib (2015) used Galapagos to study the interaction between light shelves and complex ceiling forms for optimized daylighting performance. Ercan and Elias-Ozkan (2015) also used Galapagos to optimize the design of shading devices for daylighting performance. Octopus is also a plugin for Grasshopper, which is based on genetic algorithm and can produce trade-off solutions for multi-objective optimization problems. Zhang, Zhang, & Wang (2016) performed a multi-objective optimization of a community center building using Grasshopper and Octopus.

2.5 Review of Building Performance Optimization Studies

The number of building performance optimization papers has increased significantly in recent years. Evins (2013) summarized that 38% of the reviewed work focused on the optimization of building envelop; 21% focused on building form; 17% focused on HVAC systems; 16%

focused on renewable energy generation, and the others focused on control strategies and lighting systems. 53% of the studies addressed single objective optimization; 8% of the studies used weighted sum approach in multi-objective optimization, and 39% applied Pareto multi-objective optimization (Evins, 2013). Genetic Algorithm was the most common optimization method, which was used in more than half of the works, and the other popular methods are direct search, simulated annealing, particle swarm (Evins, 2013). The most common optimization objective was energy consumption, which was found in 60% of the studies, and the other common objectives are cost, comfort, daylight performance, CO_2 emission, etc (Evins, 2013).

In this review, precedent building performance optimization studies are categorized according to their major area of optimization: building systems, building envelope, and building geometry.

2.5.1 Optimization of Building Systems

HVAC system

The Heating, Ventilation and Air Conditioning (HVAC) systems are essential to maintain comfortable interior thermal environment, and they have significant influence on the building energy performance. The optimization objectives usually include building energy, life cycle cost, and thermal comfort. Typical variables considered are equipment number and size, water and air temperature set points, etc.

Wright, Loosemore, and Farmani (2002) investigated a multi-objective genetic algorithm optimization method to identify the optimum pay-off between energy cost and occupant thermal discomfort. The 11 design variables were all related to HVAC system, such as supply air temperature, supply air flow rate, coil width, coil height, number of rows, number of circuits, and maximum flow rate. Feasible solutions were found within a few generations.

Kusiak and Xu (2012) performed a multi-objective optimization of HVAC system to achieve minimum energy consumption while maintaining acceptable indoor room temperature. The optimization model was based on particle swarm optimization algorithm. 21 parameters were selected as the candidates for the optimization model, and these parameters include supply air temperature, fan speed, room temperature, room humidity. The optimized model was applied on the actual HVAC system, and it demonstrated 29.99% decrease in energy consumption.

Renewable energy system

While sustainable design strategies can reduce the energy demand of buildings, renewable energy system can generate energy for building's demand, and achieve low or zero carbon buildings. Renewable energy systems explored in building performance optimization studies include combined heat and power systems, solar technologies, and ground energy and storage systems (Evins, 2013). Since the equipment for renewable energy generation require large capital and operating cost, studies usually try to find trade-offs between system efficiency and cost.

Kayo and Ooka (2009) used multi-objective genetic algorithm to optimize a distributed energy system. The objectives are the minimization of energy consumption and cost, and design variables are different levels of cool heat supply, hot heat supply, hot water supply, and electricity supply. This method was applied to a hospital building in Tokyo, and optimal design options were found.

Fan and Xia (2017) presented a weighted sum multi-objective optimization for building envelop retrofitting. Rooftop solar panel system was also taken into consideration. The optimization objective is to maximize energy savings and economic benefits. Design variables are solar panel types, and window, wall, roof materials. The result showed that, the optimal retrofitting plan would yield promising energy savings with acceptable economic benefits in a 24-year period.

2.5.2 Optimization of Building Envelope

Building envelop is the physical separator between the interior and exterior environment, which has great influence on the building performance. Building envelop optimization studies mostly concerned the selection of construction types and building materials, and some studies considered basic shape variables like window to wall ratio and orientation. The most investigated optimization objectives were energy performance, thermal comfort, and environmental impacts. The studies that explored more complex building shape variables are discussed in the next section.

Schwartz, Raslan, and Mumovic (2016) proposed a multi-objective optimization process for a residential complex refurbishment. The optimization objectives are minimum life cycle carbon footprint and life cycle cost over 60 years. The variables are the wall insulation materials, thermal bridge insulation, and window to wall ratios. The study successfully found the optimal design solutions. The results also indicate that the optimization of annual energy consumption, which is more commonly considered, might result in higher life cycle CO_2 emissions.

Ascione, Bianco, De Masi, Mauro, & Vanoli (2015) adopted a multi-objective approach to optimize the energy performance and thermal comfort, and the methodology was applied to a residential building in two different Mediterranean climates. The problem was solved using Genetic Algorithm in MATLAB and energy simulation engine EnergyPlus. Design variables were related to the thermo-physical performance of the building envelop, such as the thermal transmittance, the thermal capacity, thickness of materials, and the radiative properties of external coatings. This methodology was considered effective, and different optimization results were found for the different climates.

Azari, Garshasbi, Amini, Rashed-Ali, and Mohammadi (2016) utilized a multi-objective optimization method to optimized energy consumption and life cycle impacts on the environment. Design variables include insulation materials, window types, window frame materials, wall thermal resistance, and window-to-wall ratios. The energy simulation tool was eQuest 3.65 and environmental impact estimation tool was Athena IE. A hybrid artificial neural network and genetic algorithm was used as the optimization method.

Some studies included the daylighting performance as optimization objectives.

Lartigue, Lasternas, and Loftness (2013) provided a methodology for optimizing the building envelope with respect to minimum heating load, minimum cooling load and maximum daylight. The variables to optimize are the window to wall ratio and the window type. Energy performance simulation software was TRNSYS, daylighting simulation software was Daysim, and optimization tool was GenOpt. Trade-off solutions between different objectives were found using Pareto approach.

Carlucci, Cattarin, Causone, and Pagliano (2015) presented a multi-objective optimization of a net zero-energy house in southern Italy to minimize thermal and visual discomfort. The four objectives are minimum thermal discomfort during winter and summer and minimum visual discomfort due to glare and inappropriate daylight level. EnergyPlus was the daylighting and energy simulation engine, and GenOpt was the optimization engine. Design variables include wall, roof, floor materials, glazing materials, control strategies for shading devices, and opening of windows.

2.5.3 Optimization of Building Geometry

One of the most important design decisions made in early design stage is the building form, shape, or geometry. It does not only determine the aesthetics and functions of a building, but also greatly influences a building's energy and daylighting performance. The main design variables of concern are window design, shading design, roof design, façade design, building shape design, etc.

Tuhus-Dubrow and Krarti (2010) developed a simulation–optimization tool to optimize building shape and building envelop features. This tool coupled a genetic algorithm to a building energy simulation engine, and aimed to find optimal building design for minimum energy consumption. Different building shapes, including rectangle, L, T, cross, U, H, and trapezoid were investigated. Building envelope features, including wall and roof constructions, foundation types, insulation levels, and window types and sizes were also considered. The optimization results indicated that rectangular and trapezoidal shaped buildings generally have lowest life-cycle cost.

Lin and Gerber (2014) developed an Evolutionary energy performance feedback for design (EEPFD) methodology using parametric design and multi-objective optimization. A prototype tool, H.D.S. Beagle, was also developed to facilitate the development of the methodology. H.D.S. was a plug-in for Autodesk Revit, which integrates Autodesk Green Building Studio and Microsoft Excel. Optimization objectives were spatial programing compliance, energy performance, and financial performance. Complex building geometries with multiple design variables were explored in the research.

Futrell et al. (2015) used a bi-objective optimization method to investigate building design for minimum energy demand and maximum daylight. Design variables were ceiling height, window transmittance, window width, shade length, and light shelf length. A classroom design in Charlotte, NC was optimized for north, south, east, and west orientations. For each orientation, trade-offs between thermal and daylighting performance were found using Pareto front. Results showed that for the south, east, and west orientations, energy and daylighting performance are not in strong conflict. A stronger conflict was found for the north orientation.

Caruso and Kämpf (2015) optimized the three-dimensional form of buildings for minimum energy consumption due to solar irradiation. A cumulative sky model approach was used for the computation of solar irradiation on the building envelope, and an evolutionary algorithm was used to find the optimal building form. Various families of building forms were investigated, and optimal shapes were found.

Ercan and Elias-Ozkan (2015) presented a methodology to explore shading device design alternatives for optimal daylight performance in an office building in a hot and humid climate. Parametric design tool Grasshopper was used to generate design alternatives for shading devices with four design variables. The optimization objective was minimum solar irradiation and the variance between the analysis nodes. Weighted sum approach was used to solve this multi-objective optimization problem.

Zhang et al. (2016) provided an approach to optimize the shape of free-form building based on solar radiation and space efficiency. Rhinoceros and Grasshopper was used to develop the parametric free-form building model. A multi-objective genetic algorithm was used to find trade-offs between the three objectives: maximum solar radiation gain, maximum space efficiency, and minimum shape coefficient. Compared to a cube-shaped reference building, the optimized free-form shape building achieved 30–53% higher solar radiation, 15-20% lower shape coefficient, and less than 5% of space efficiency.

2.6 Summary of Literature Review

The findings from the literature review are summarized below:

First, design decisions made in the early design stage have significant impacts on the building's daylighting and energy performance. Great performance improvement was found after implementing building performance optimization. However, there are not enough tools and methodologies for designer to easily evaluate and optimize their design in early design stage.

Second, daylighting is an essential part of interior environment for occupants' health and comfort. It is also an effective sustainable strategy to improve buildings' energy performance. Even though there are a growing number of studies on the optimization of building performance, daylighting performance were usually not one of the optimization objectives to be considered.

Third, precedent building performance optimization studies usually employed fixed building geometry, and the variables to be optimized were physical properties of material or settings of building systems. The studies that evaluated alteration in building shapes were restricted to simplified performance objectives, such as solar radiation. There is a lack of studies that combined both variance in building geometry and sophisticated energy modeling and simulation process.

Fourth, parametric design is found to be a powerful approach in generating design alternatives, and the combination of Rhino and Grasshopper was the most used parametric design tools. Ladybug and Honeybee are energy and daylighting modeling plugins for Grasshopper, and the developed energy and daylighting models are simulated in EnergyPlus and Daysim, which are two of the most reliable simulation engines in the industry. Galapagos and Octopus are genetic algorithm based optimization engines in Grasshopper. Genetic algorithms were the most popular optimization algorithms in building performance optimization, and were proved to be reliable in both single-objective and multi-objective problems.

This research aims to establish a building performance optimization process considering both daylighting and energy performance. It could integrate both building geometry alternation and detailed energy and daylighting simulation. This optimization process is executed in Rhino and Grasshopper platform with various environmental analysis and optimization plugins.

CHAPTER 3: CONCEPTUAL FRAMEWORK AND RESEARCH OBJECTIVES

3.1 Conceptual Framework

The proposed building performance optimization process is integrated in schematic design phase, which is an important early architectural design phase (Figure 3.1). After understanding the project goals and requirements, architects develop preliminary building design concept, including study drawings illustrating the spatial relationships, scale, and form of the design. The building performance optimization process aims to provide designers with optimized design options without compromising original building design concept. If the proposed design options are meet the performance target and other design requirements, the design will be continued into the next design stages. If it is not satisfactory, initial design concept could be modified and this optimization process could be repeated multiple times, until a desirable design is obtained.

The four main components inside the framework are parametric building design, energy and daylight modeling, simulation and building performance metric, and optimization. The goal is to seamlessly connect the four components, and automate the building design generation, performance simulations and optimization process.

Parametric design is a method to define building geometry with design parameters and functions. Design alternatives are generated with the change of design parameters. The tools for parametric modeling are Rhino and Grasshopper.

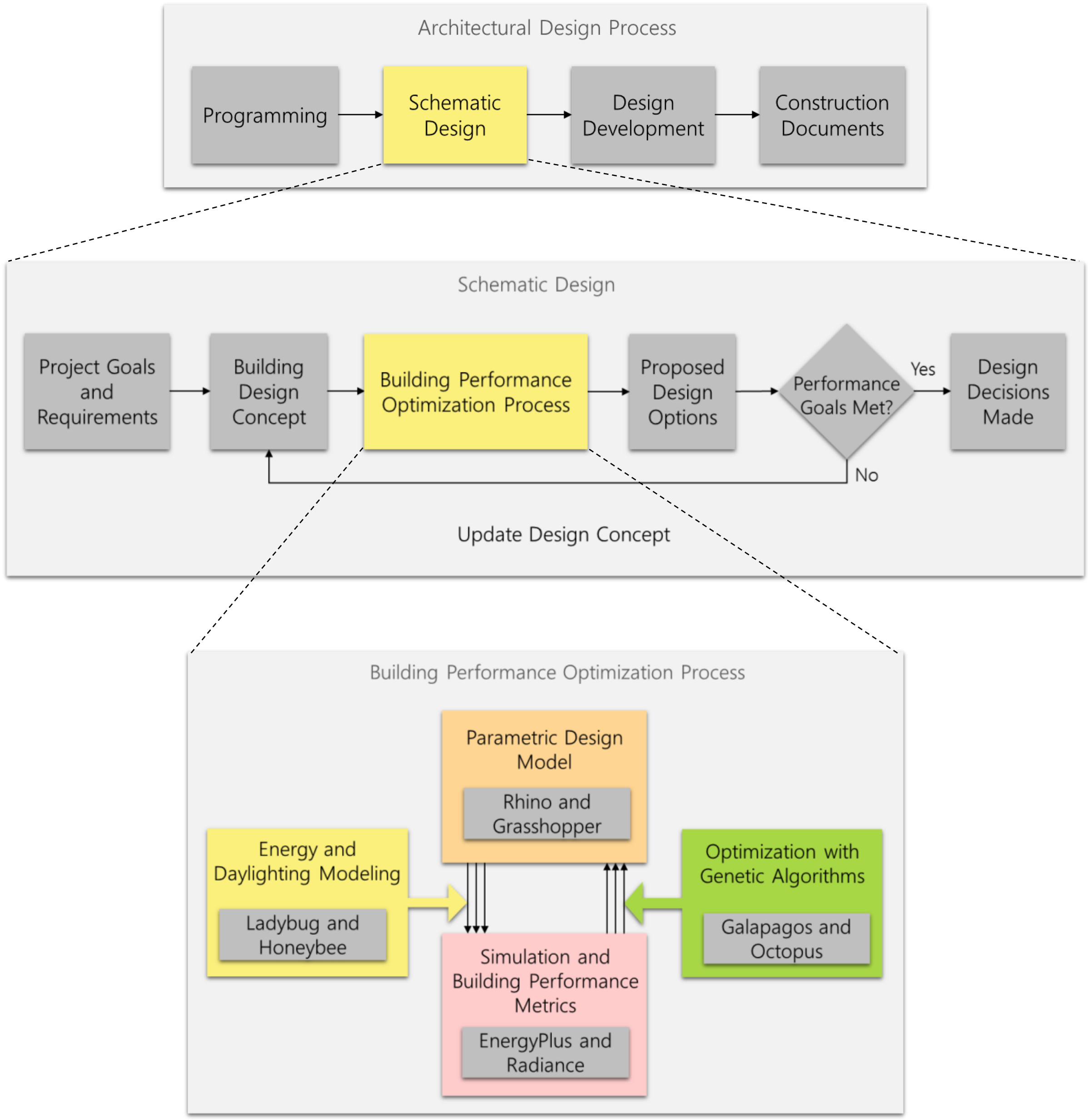


Figure 3.1 Building Performance Optimization in Architectural Design Process

In energy and daylight modeling process, detailed building information is assigned to the parametric model, such as geometry adjacency information, construction types and materials, loads, occupancy and operational schedules. The energy modeling tools are Ladybug and

Honeybee. Ladybug provides the main functions of energy and daylighting modeling, while Honeybee is used for the manipulation and visualization of weather data and simulation data. Ladybug will generate an idf file for energy simulation in EnergyPlus and a rad file for daylight simulation in Radiance. After simulation, Ladybug imports simulation result file back to grasshopper, and read the energy and daylight performance metrics.

The optimization process needs two type of input: variables and fitness function. In building performance optimization, variables are the building design variables in grasshopper that can control the building geometry. The fitness function is the energy or daylight performance metrics calculated by the simulation engine. For single objective optimization, the fitness function is the minimum or maximum value of the performance metric, such as minimum energy load or maximum UID. Then genetic algorithm is used to examine the relationship between design parameters and performance metrics, and generate new design options towards better performance. For multi-objective optimization, multi-objective genetic algorithm is used to find the Pareto front, which is the trade-off solutions between different objectives. The optimization process is stopped at a user specified criterion, such as total simulation time.

Each component requires different tools, and the structure of the tools is shown in Figure 3.2. Rhino is a 3D NURBS modeling tool. Grasshopper is a plug-in for Rhino, and it provides parametric modeling platform that integrates the functions in Rhino and other add-on programs. Ladybug, Honeybee, Galapagos, Octopus, and TT toolbox are plug-ins for Grasshopper. Ladybug and Honeybee are energy and daylighting modeling tools. They are connected to energy and daylighting simulation engines EnergyPlus and Radiance. Galapagos and Octopus are optimization tools. Galapagos is for single objective optimization, and Octopus is for multi-objective optimization. TT toolbox is used to record each simulation data, and export the data to an Excel document.

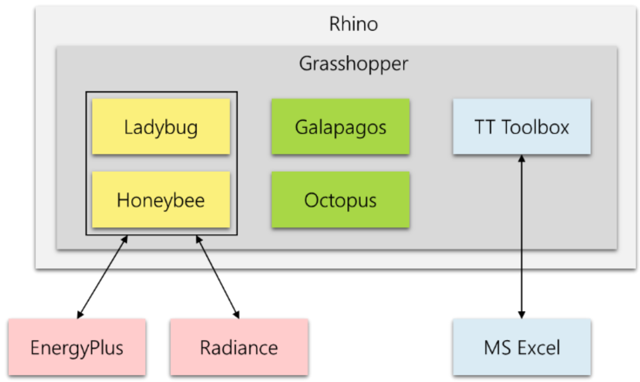


Figure 3.2 Structure of Optimization Tools

3.2 Research Goals and Objectives

The goal of the research is to develop and verify an optimization process for high performance buildings design. This process can help designers identify designs with optimized daylighting and energy results, and understand how design parameters influence building performances. To achieve the goal, objectives are specified as follows:

1. Define a case study model, building design variables, and optimization objectives.

2. Develop the optimization framework with a parametric design model, energy and daylighting modeling components and optimization engines.

3. Use this framework to optimize daylighting and energy performance of the case study building respectively, and optimize both daylighting and energy performance using multi-objective optimization techniques.

4. Analyze the data from the optimization process, and examine the relationship between design variables and performance metrics. Compare the three optimization results, and propose best design solutions. Compare the optimization results of the same design in different climate zones.

5. Summarize the research findings. Identify the limitations in the optimization process, and propose future studies.

CHAPTER 4: METHODOLOGY

4.1 Research Framework

4.1.1 Overview

The overall research strategy and process is shown in Figure 4.1. There are four main steps. The first step is to identify design parameters and build a parametric design model. The second step is the development of daylight and energy model for three optimization cases. The three cases represent the same building geometry in different climate zones in United States: hot, mixed, and cold climate. The purpose is to compare how the optimization results are different, and how the relationship between design variables and performance are different in the three climate zones.

The third step is nine optimization processes - a daylighting optimization process, an energy optimization process, and a multi-objective optimization process considering both daylighting and energy for each climate zone. The reason to separate three optimization processes is to fully explore building design potential under different objectives, and compare the performance difference.

The fourth step is the analysis and evaluation of simulation data and optimized design after the optimization processes are accomplished for each climate. The optimal designs are compared visually, and the settings of each optimized design are compared. The building performance improvement, and the variables with the most influence on the building performance are also analyzed.

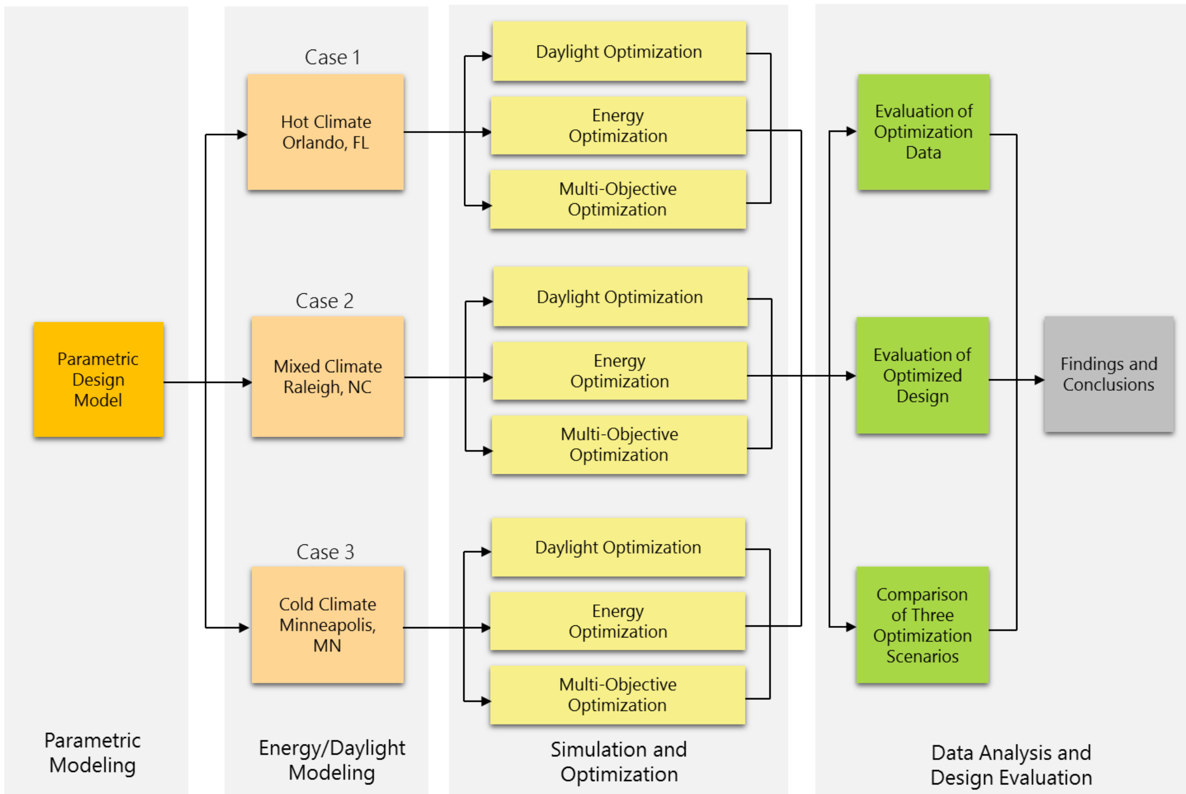


Figure 4.1 Research Diagram

4.1.2 Integrated Daylighting and Energy Simulation

To achieve energy savings from daylighting, it is necessary to install lighting control system in the building. Lighting controls can adjust the level of electric light to complement the illumination provided by daylight, or turn off the light when daylight illuminance is adequate. In building performance simulation, the process is similar. Figure 4.2 illustrates the integrated daylighting and energy simulation process for daylight energy savings. A daylighting simulation is required first to calculate the illuminance at the lighting sensor positions for every hour in a year, and electrical light would be turned off or dimmed according to the daylight illuminance. Then a year-long lighting schedule will be generated. The schedule will be input into energy model to incorporate the electrical lighting, heating or cooling energy requirement differences due to daylighting. Ladybug and Honeybee have the functions of exporting and importing lighting schedules, which makes each daylighting and energy simulation sequence automated.

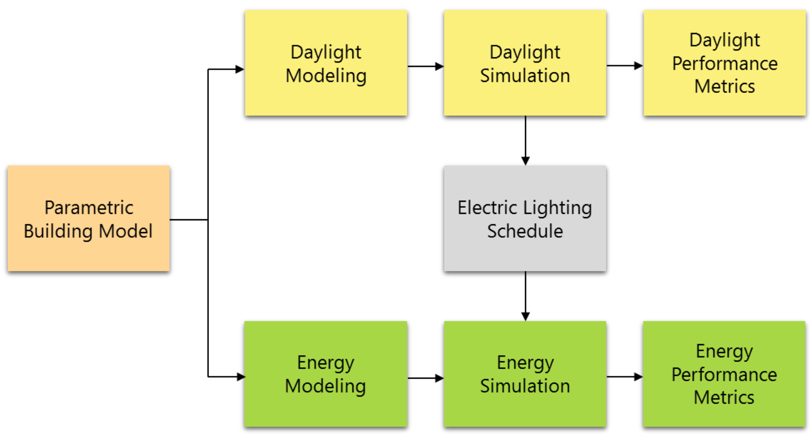


Figure 4.2 Integrated Daylight and Energy Simulation

Figure 4.3 shows the workflow of this process in grasshopper. Group A is the components for developing the building geometry. The geometry is connected to components in Group B for energy and daylighting modeling. The daylight model is connected to components in Group C for daylighting simulation. Group D connects both the energy model from Group B and the daylighting simulation output from Group C for energy simulation. Group E is the components for optimization. Group F is the components for data output.

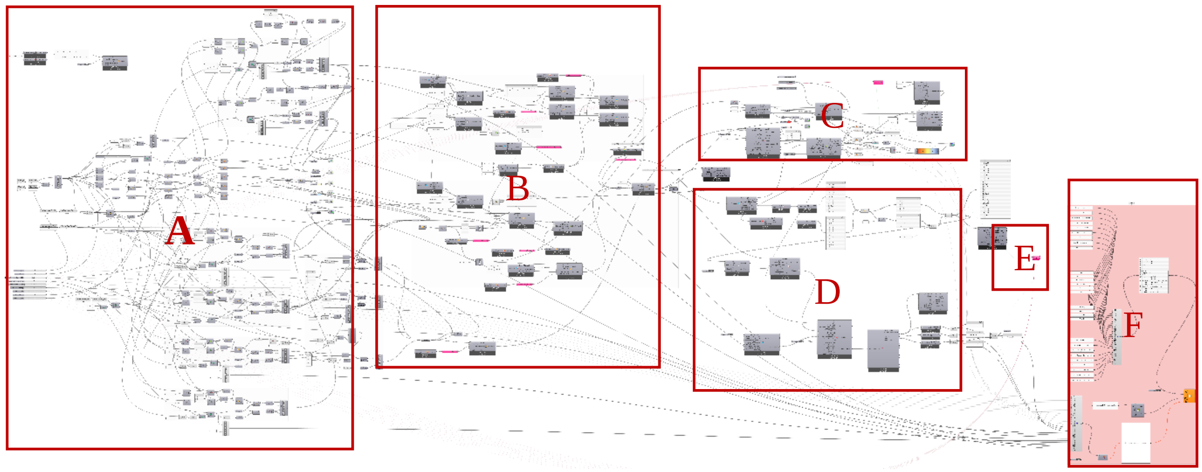


Figure 4.3 Optimization Process in Grasshopper

4.1.3 Daylighting Optimization

Figure 4.4 presents the detailed daylighting optimization process. The process begins in Grasshopper with parametric design variables and building geometry. Ladybug and Honeybee provides the functions of daylight and energy modeling. In the daylighting modeling process, the parametric building geometry is connected to Radiance materials component, with the setting of material transparency, reflectance, etc. Then the building materials are connected to daylighting simulation component, with the input of weather files, daylighting sensor placement, and other simulation settings. A rad file is generated and daylighting simulation is executed in Radiance. After simulation, Ladybug imports simulation result file back to grasshopper, reads the daylight performance metrics, and generates an annual lighting schedule.

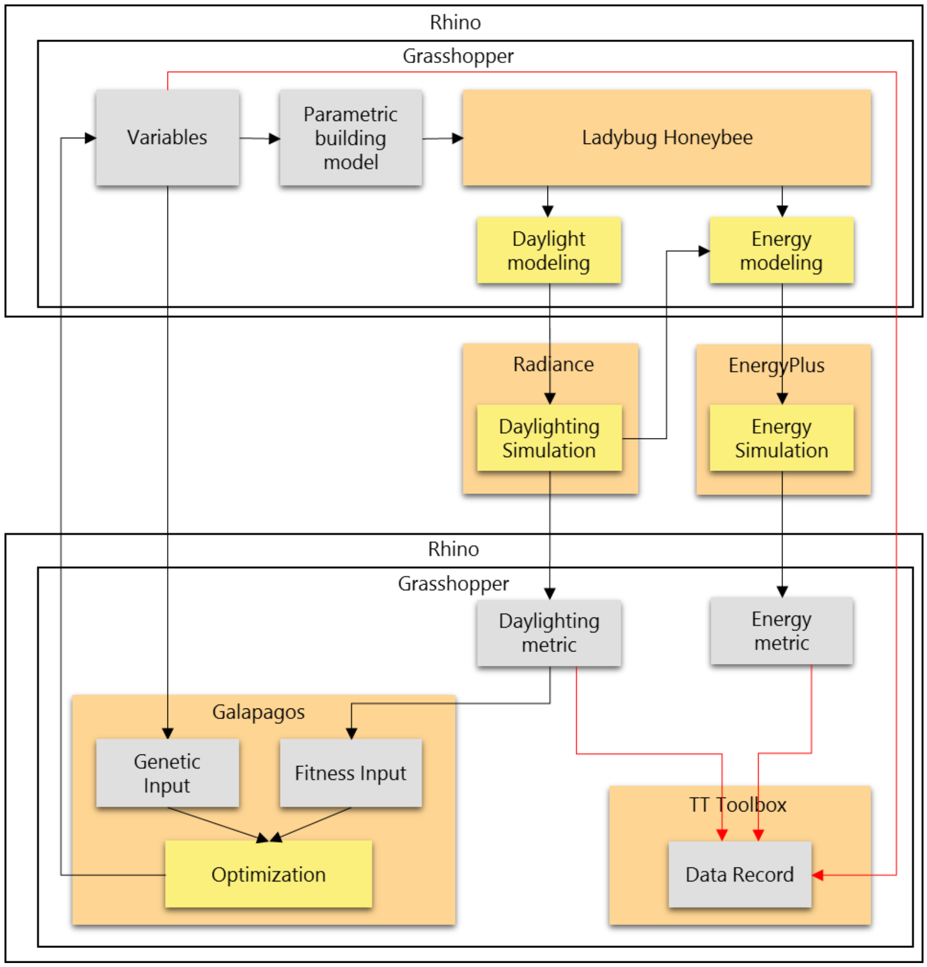


Figure 4.4 Daylighting Optimization Process and Tools

In the energy modeling process, parametric building geometry is connected to EnergyPlus materials, and connected to a Honeybee thermal zone component. Honeybee automates the process of intersecting the masses, and finding adjacent surfaces. Honeybee assigns construction set, schedules and internal loads for each space based on the building type and climate zone. The lighting schedule generated by daylighting simulation is also added to the energy model. An idf file is generated and energy simulation is executed in EnergyPlus.

Ladybug brings the energy simulation result back to grasshopper, and reads the energy performance metrics.

The optimization process uses Galapagos to search for optimal building configurations for the maximum UDI, which is the percentage of hours in a year that the illuminance is between 100 and 200 lux. The design variables are connected to the Genetic input of Galapagos, and the UDI output are connected to the Fitness input. The population size of each generation is 100 with an initial boost of twice the population for the first generation. The design variables, daylighting metrics, and energy metrics of each simulation are automatically exported to an Excel file using TT Toolbox.

4.1.4 Energy Optimization

Figure 4.5 presents the detailed energy optimization process. The overall procedure is the same as daylighting optimization. The difference is only in the optimization objective, which is the minimum energy required for the building. Therefore, the fitness input for optimization is the total energy load for heating, cooling, and lighting. The design variables, daylighting metrics, and energy metrics are exported to another Excel file using TT toolbox.

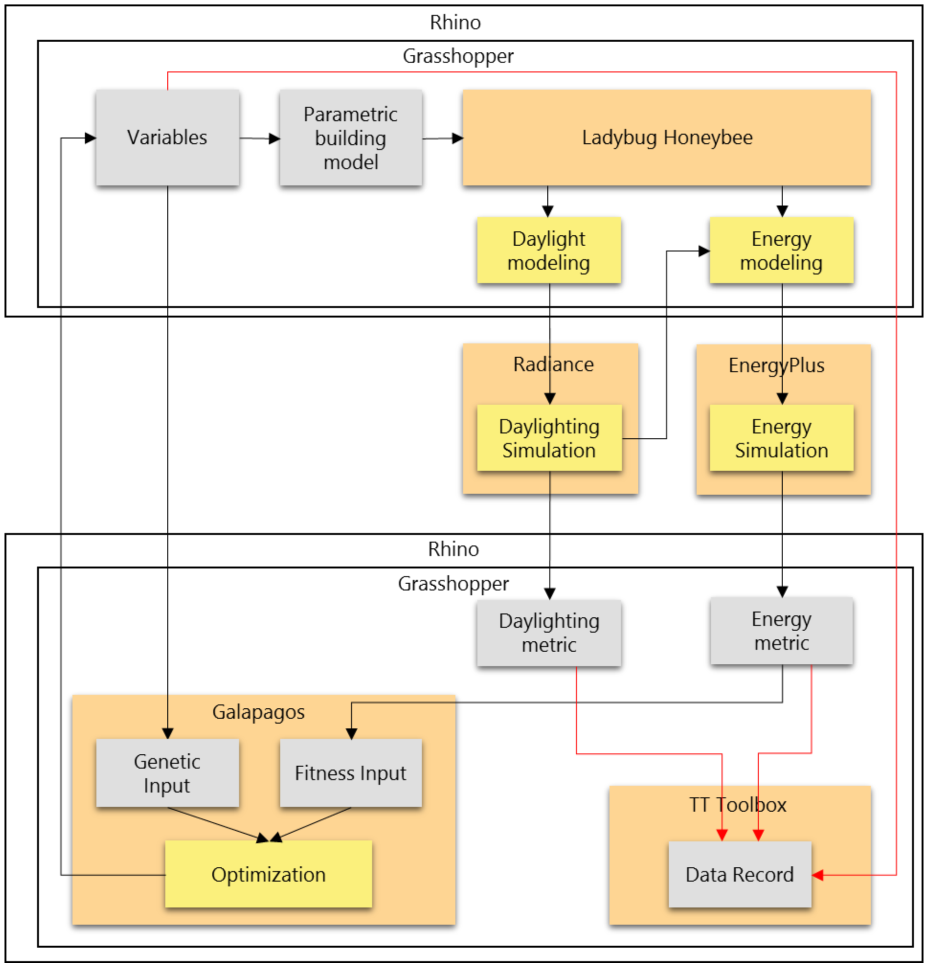


Figure 4.5 Energy Optimization Process and Tools

4.1.5 Multi-Objective Optimization

Multi-objective optimization is also similar as the previous two processes. The only difference is that it uses a different optimization engine, that can evaluate multiple objectives at the same time. Octopus, a multi-objective optimization plug-in for Grasshopper, is used to perform the optimization.

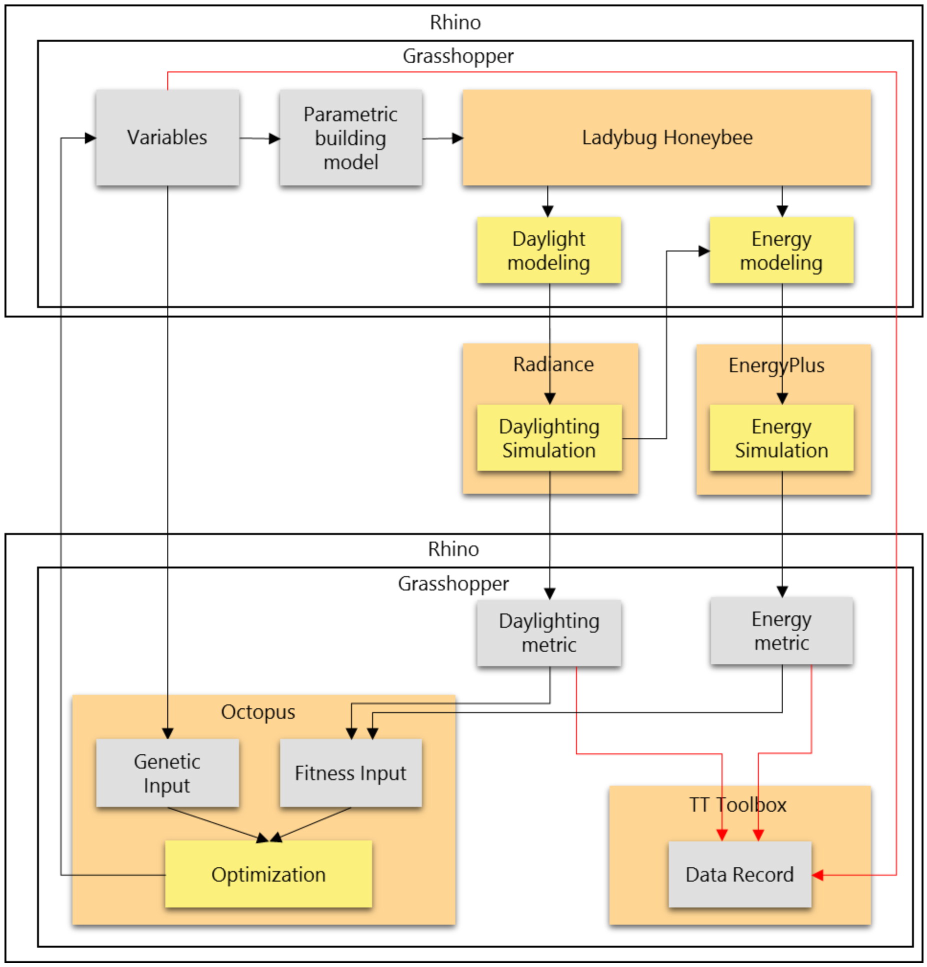


Figure 4.6 Multi-Objective Optimization Process and Tools

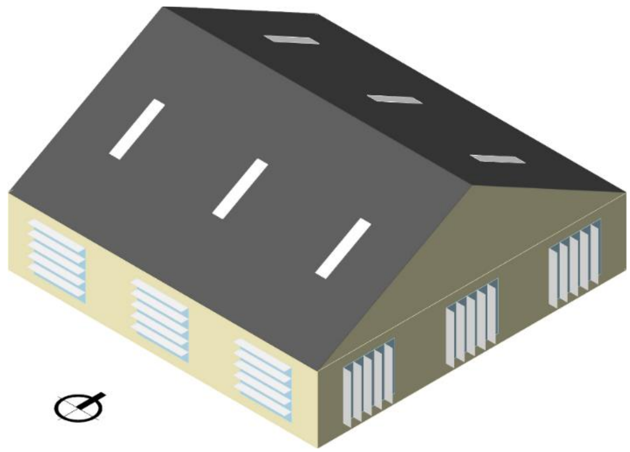
The two objectives are maximum average UID, and minimum total cooling, heating, and lighting load. The target is to find design with balanced performance between daylighting and energy. Octopus by default find the minimum value of each objectives, so the objective to be maximized (average UDI) should be multiplied by -1. Pareto frontiers with trade-off between each performance metric are found after the optimization process.

4.2 Research Design

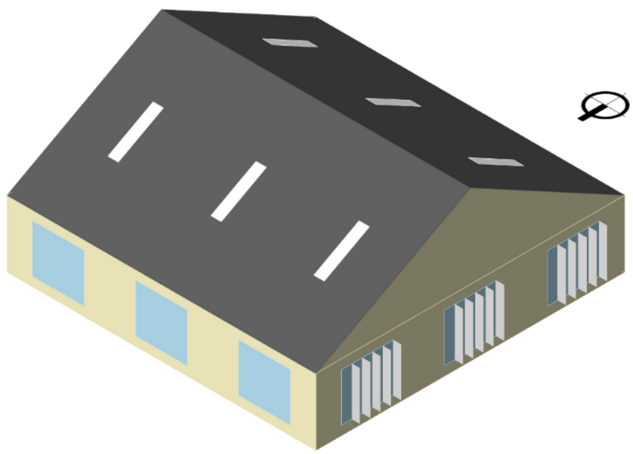
4.2.1 Case Study Model

A simple building geometry is chosen as the case study model, as shown in Figure 4.7. This building is a 3600 square feet office building with a pitched roof. Building shape, sizes of windows, shadings, and skylights on different parts of the building are explored for optimal daylighting and energy performance. There are three windows on each facade of the building, and three skylights on the north and south side of the roof. There are horizontal shadings on the south windows, vertical shadings on east and west windows, and no shading on the north windows. To simplify the problem, placement of the doors and the interior partition are not considered in the optimization process.

The model is developed with OpenStudio open office construction set, loads, schedules, and thermostat settings for the simulation. There are about 36 daylighting sensors evenly spaced on the height of 2.5 feet (0.76 meter) above the floor. As the shape of the building changes, the number and placement of the sensors might be different as shown in Figure 4.8.

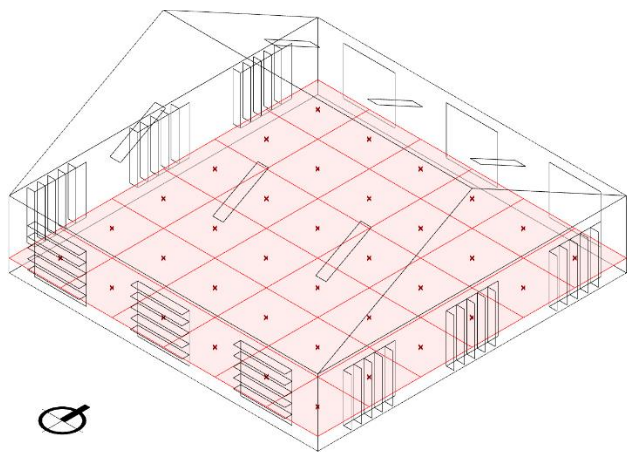


(1) Southeast view

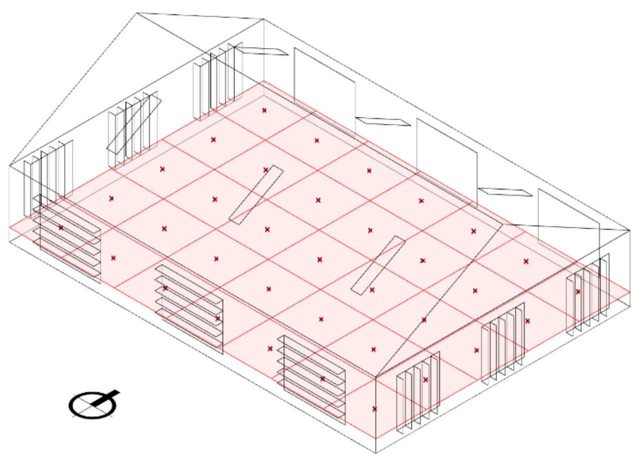


(2) Northwest view

Figure 4.7 Case Study Model



(1) 36 sensors



(2) 35 sensors

Figure 4.8 Placement of Sensors

4.2.2 Optimization in Three Different Climate Conditions

Climate is one of most important factors that determines buildings' energy consumption because of the direct relationship between outdoor temperature and building cooling and heating load. Daylighting performance is greatly influenced by the latitude of the building location.

Figure 4.9 presents the 18 climate zones in the US. Three representative cities are chosen as the locations for the three optimization cases (Table 4.1). Orlando represents climate zone 2A, which is hot climate. Raleigh represents climate zone 4A, which is mixed climate. Minneapolis represents climate zone 6A, which is cold climates. These three cities present three typical climate conditions in the US, and they show great difference in both temperature and latitude. The models are built with DOE commercial reference buildings template from OpenStudio. The construction set and climate files for the three models are listed in Table 4.1.

The main purpose to compare optimization results between climate zones is to see how the same building design would change with the climate features to achieve optimal performance. Another purpose is to compare if the relationship between design variables and performance metrics are different in different climates. The output to be compared are the geometry of the optimized design under three climate conditions, the performance improvement of optimized design on the baseline design, the relationship between design variables and design performance, and the relationship between different performance metrics.

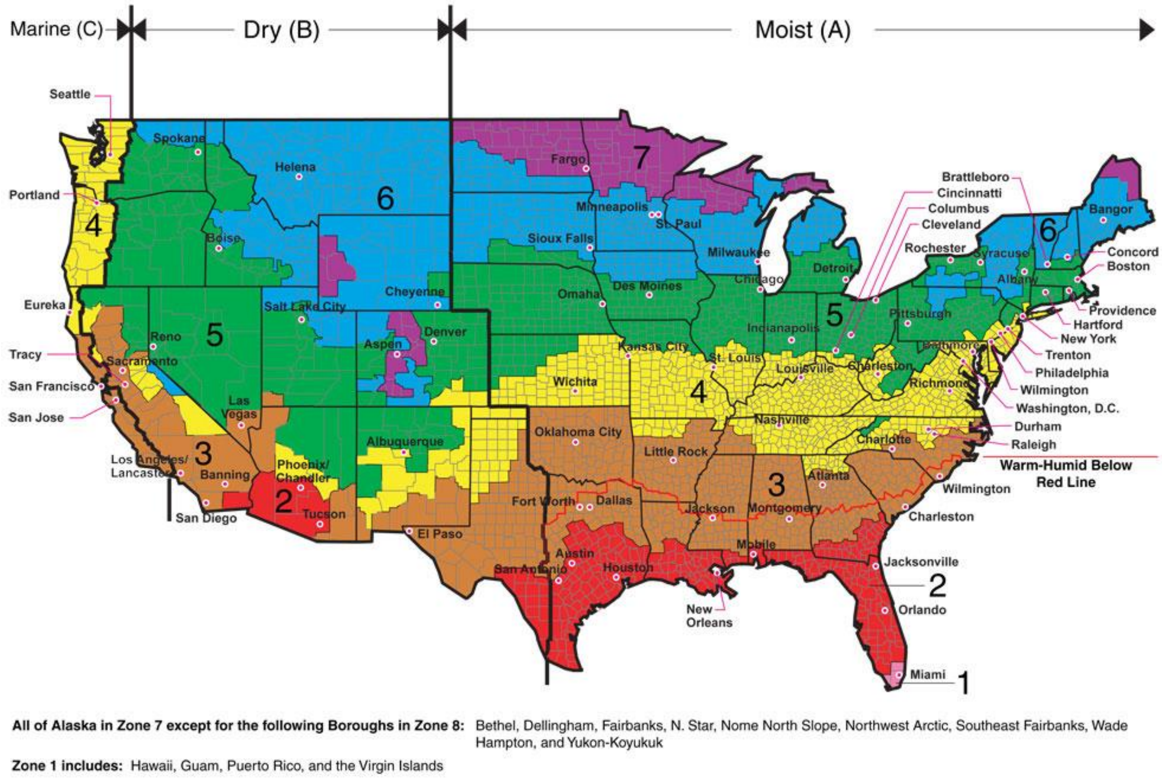


Figure 4.9 US Climate Zones (IAQSource, 2016)

Table 4.1 Representative Cities

Climate Zone	City	Construction Set	Weather File
2A	Orlando, Florida	DOE Ref 2004 – CZ1-2 - Office	USA_FL_Orlando.Intl.AP.722050_TMY3
4A	Raleigh, North Carolina	DOE Ref 2004 - CZ4 - Office	USA_NC_Raleigh-Durham.Intl.AP.723060_TMY3
6A	Minneapolis, Minnesota	DOE Ref 2004 - CZ6 - Office	USA_MN_Minneapolis-St.Paul.Intl.AP.726580_TMY3

4.2.3 Building Parameters

Some building parameters are fixed throughout the optimization process. The building is fixed at 3600 square feet. The height of the building (from ground to the edge of the pitched roof) is 13 feet. The windows on the four facades is fixed at the height of 9 feet. The length of skylight is 10 feet. The height of the windows and the centerline of the windows are also fixed.

There are three sets of building construction materials for the models in three different climates zones, which are OpenStudio DOE Ref 2004 Office Climate Zone 1-2, Climate Zone 4, and Climate Zone 6. The details of each material are listed in Table 4.2, 4.3 and 4.4. To avoid excessive heat gain or heat loss from the skylight, an insulated translucent material is used as its glazing material. The material has a U-Value of 0.45, and it is the same for the three climate zones.

Radiance materials for daylighting simulation are the same for the three climate zones. The reflectance of the ceiling, floor, interior, exterior walls, and louver are respectively 0.8, 0.2, 0.5, 0.5, and 0.8. The window is a transparent material with visible transmittance of 0.65. Skylight is a translucent material with transmittance of 0.24. Details of Radiance materials are listed in Table 4.5.

Table 4.2 Construction set: DOE Ref 2004 – CZ1-2 - Office

	Construction Name in OpenStudio Library	**U-Value (Btu/h·ft2·°F)**
Roof	ASHRAE 90.1-2004 ExtRoof IEAD ClimateZone 1-4	0.07
Exterior Wall	ASHRAE 90.1-2004 ExtWall Mass ClimateZone 1-2	0.65
Exterior Floor	ExtSlabCarpet 4in ClimateZone 1-8	0.99
Window	ASHRAE 90.1-2004 ExtWindow ClimateZone 1-2	1.03
Interior Floor	Interior Floor	0.26
Interior Wall	Interior Wall	0.45
Interior Ceiling	Interior Ceiling	0.26

Table 4.3 Construction set: DOE Ref 2004 - CZ4 - Office

	Construction Name in OpenStudio Library	**U-Value (Btu/h·ft2·°F)**
Roof	ASHRAE 90.1-2010 ExtRoof IEAD ClimateZone 1-4	0.07
Exterior Wall	ASHRAE 90.1-2010 ExtWall Mass ClimateZone 3-4	0.17
Exterior Floor	ExtSlabCarpet 4in ClimateZone 1-8	0.99
Window	ASHRAE 90.1-2010 ExtWindow ClimateZone 4-6	0.57
Interior Floor	Interior Floor	0.26
Interior Wall	Interior Wall	0.45
Interior Ceiling	Interior Ceiling	0.26

Table 4.4 Construction set: DOE Ref 2004 - CZ6 - Office

	Construction Name in OpenStudio Library	**U-Value (Btu/h·ft2·°F)**
Roof	ASHRAE 90.1-2004 ExtRoof IEAD ClimateZone 5-6	0.07
Exterior Wall	ASHRAE 90.1-2004 ExtWall Mass ClimateZone 6	0.11
Exterior Floor	ExtSlabCarpet 4in ClimateZone 1-8	0.99
Window	ASHRAE 90.1-2004 ExtWindow ClimateZone 4-6	0.57
Interior Floor	Interior Floor	0.26
Interior Wall	Interior Wall	0.45
Interior Ceiling	Interior Ceiling	0.26

Table 4.5 Material Information for Radiance

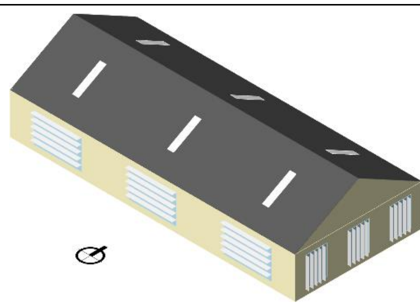
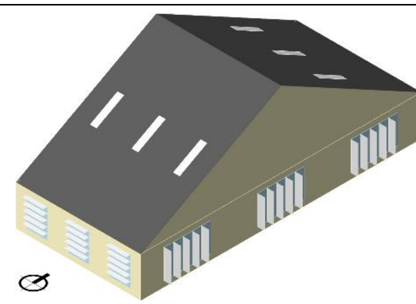
	Material Type	**Values**
Shading	Radiance opaque material	Reflectance: 0.8
Interior Wall	Radiance opaque material	Reflectance: 0.5
Interior Ceiling	Radiance opaque material	Reflectance: 0.8
Interior Floor	Radiance opaque material	Reflectance: 0.2
Window	Radiance glass material	Visible transmittance: 0.65
Skylight	Radiance translucent material	Transmittance: 0.24 Diffuse reflectance: 0.21 Specular reflectance: 0.08 Surface roughness: 0 Transmitted specularity: 0

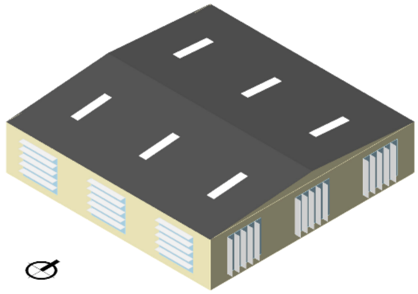
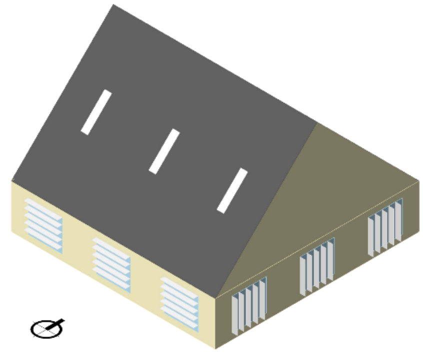
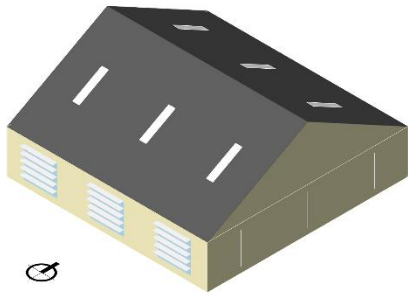
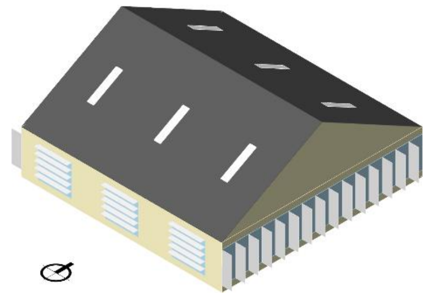
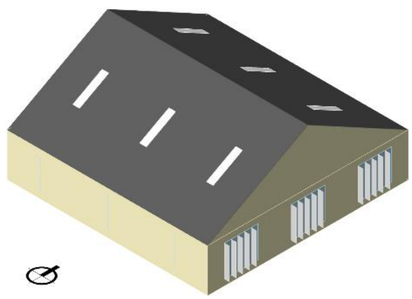
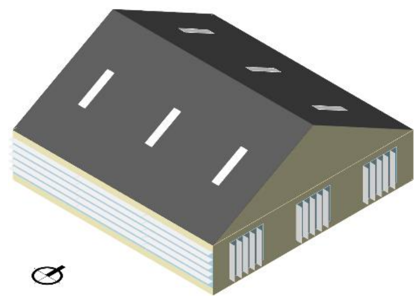
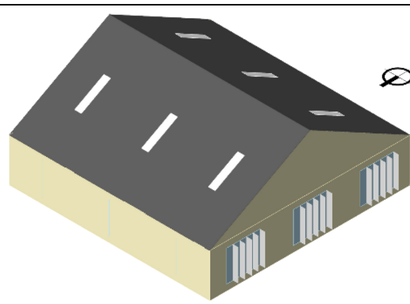
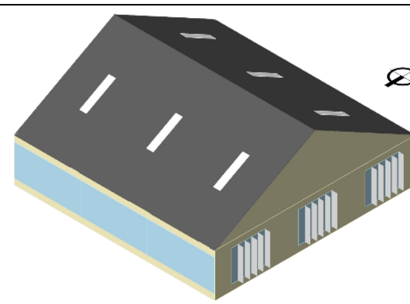
4.2.4 Independent Variables

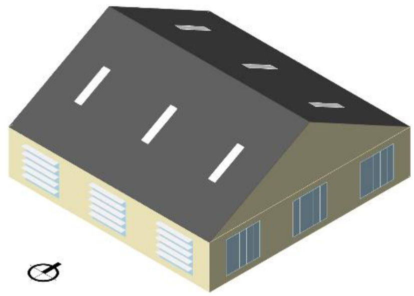
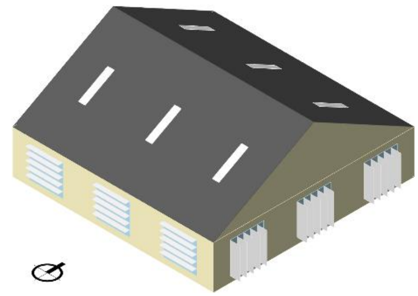
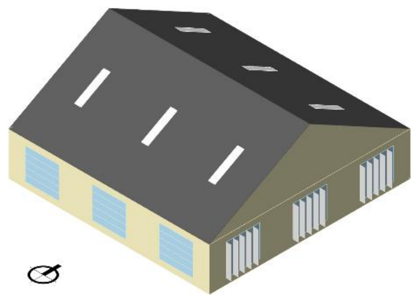
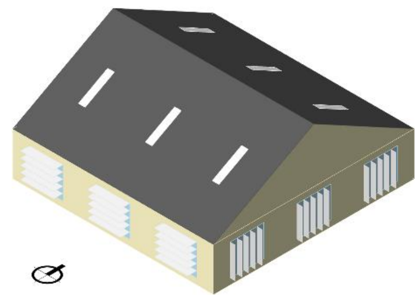
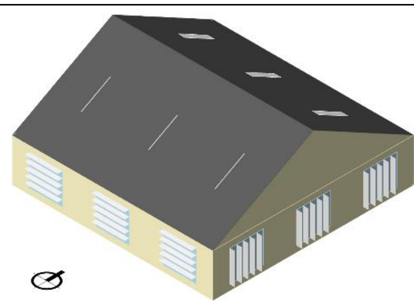
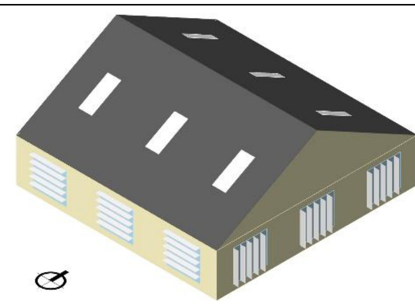
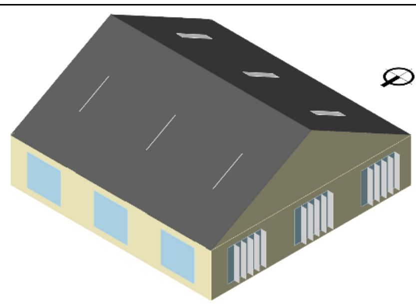
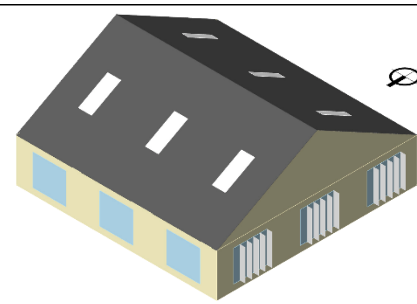
There are 9 independent design variables for the building geometry: room depth, roof height, width of the east and west windows, width of the south windows, width of the north window, length of the vertical shading on the east and west, length of the horizontal shading on the south, width of the south skylight, and width of the north skylight. Changing those variables results in the creation of multiple design options. Each variable is divided into 10 steps within their range, and represented by numbers from 0 to 1. There are 11^9 design possibilities in total.

The variables, their ranges, and building examples are listed in detail in Table 4.6. The building examples present the minimum and maximum value of the variable in each row, with all the other variables at the medium value. Windows with the width of zero, or windows that fill the whole wall would lead to energy simulation failure. Therefore, the minimum window width is set to 1 inch, and the maximum window width is when there is 1 inch space between windows and 1 inch space between the windows and the wall.

Table 4.6 Design Variables and Ranges

	Variable	Minimum	Maximum
1	Room Depth		
		40 ft.	90 ft.

2	Roof Height		
		When roof slope is 1/12	When roof slope is 12/12
3	East West Window Width		
		No windows	Full-wall windows
4	South Window Width		
		No windows	Full-wall windows
5	North Window Width		
		No windows	Full-wall windows

6	East West Fin Length		
		No shading	1.5 times of fin distance
7	South Overhang Length		
		No shading	1.5 times of overhang distance
8	South Skylight Width		
		No skylight	2 ft.
9	North Skylight Width		
		No skylight	2 ft.

4.2.5 Dependent Variables

The daylighting simulation output includes DF (Daylight Factor), DA (Daylight Autonomy), UDI (Useful Daylight Illuminance) <100 Lux, UDI 100-2000 Lux, UDI > 2000 Lux, sDA (spatial Daylight Autonomy), and cDA (continuous Daylight Autonomy). Daylighting optimization objective is maximum UDI. UDI is preferred over other daylighting metrics as is because it has both an upper and lower illuminance threshold, thus it can exclude conditions of too dark or too bright daylight.

The energy simulation output includes annual heating, cooling, equipment and lighting energy loads. Since the equipment load stay the same for all the design options, it is not considered in this research. Energy optimization objective is minimum total energy load. The total energy load is the sum of heating, cooling, and lighting loads. EUI (Energy Use Intensity) is also calculated by dividing the total energy load by the floor area of the building.

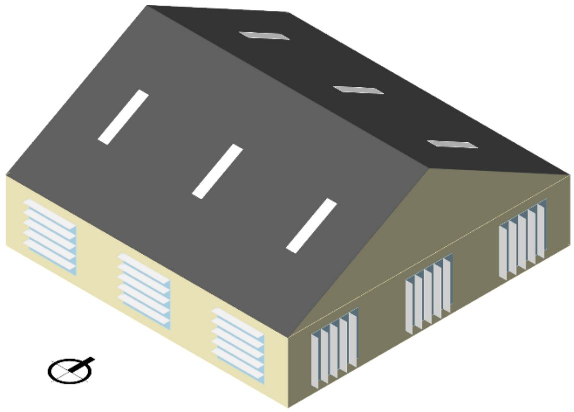
CHAPTER 5: RESULTS

5.1 Baseline Design and Performance

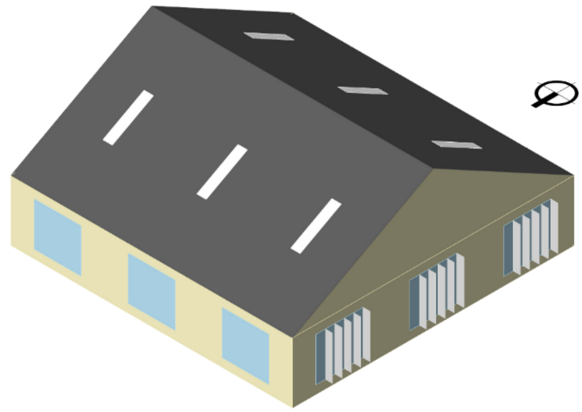
The baseline building geometry is the same for the three representative cities. The building variables are set to the midpoint of all the variable ranges, except the variable for room depth. Room depth variable is set to 0.4 to achieve a square-shape building. Table 5.1 lists the setting values and exact values for all variables. The baseline design is a square shape building with 16.2 feet pitched roof. It has three 10 feet wide windows on its four facades, and three 2 feet wide skylights on the north and south side of the roof. The fins on the east and west façade are 1.5 feet long, and the overhangs on the south façade are 1.4 feet long. Figure 5.1 presents the southeast view and the northwest view of the baseline design.

Table 5.1 Design Variables of Baseline Building

Design Variables	**Variable values**	
	Setting (Range: 0 to 1)	**Actual value [ft.]**
Room Depth	0.4	60.0
Roof Height	0.5	16.2
East West Window Width	0.5	10.0
South Window Width	0.5	10.0
North Window Width	0.5	10.0
East West Fin Length	0.5	1.5
South Overhang Length	0.5	1.4
South Skylight Width	0.5	2.0
North Skylight Width	0.5	2.0



(1) Southeast view



(2) Northwest view

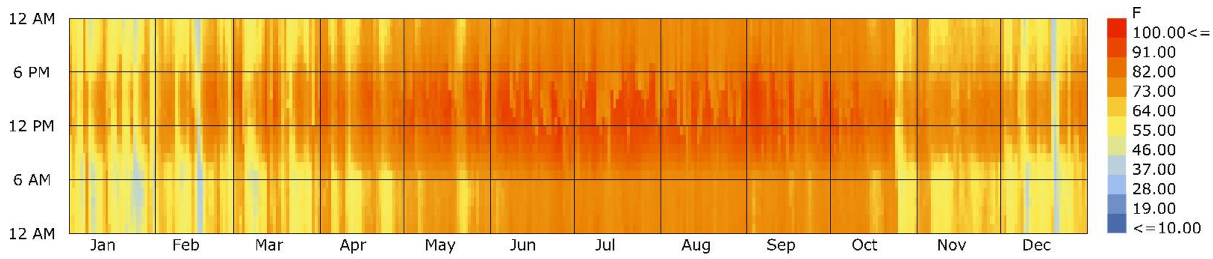
Figure 5.1 Baseline Building Design

The comparison of the temperature and solar altitude of the three representative cities is shown in Figure 5.2 and Figure 5.3.

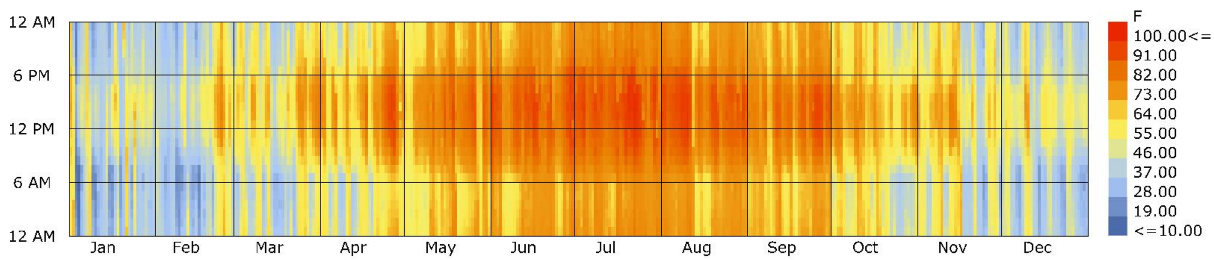
Orlando is in hot-humid climate. It has hot and humid summers and warm and dry winters. During the summer season, high temperatures are typically around 90 °F, while low temperatures are around 70 °F. During the winter season, the temperatures are usually between 50 °F and 70 °F. The weather data used is from the location of Orlando International Airport, and the latitude is 28.43. The sun altitude is 82 degrees at summer solstice (June 21), 61 degrees at equinox (March 20), and 38 degrees at winter solstice (Dec 21).

Raleigh has a mixed-humid climate with four distinct seasons. Summers are hot and humid, and average low and high temperatures are about 65 °F and 85 °F. Winters are generally cool, and average low and high temperatures are about 35 °F and 55 °F. The weather data is from

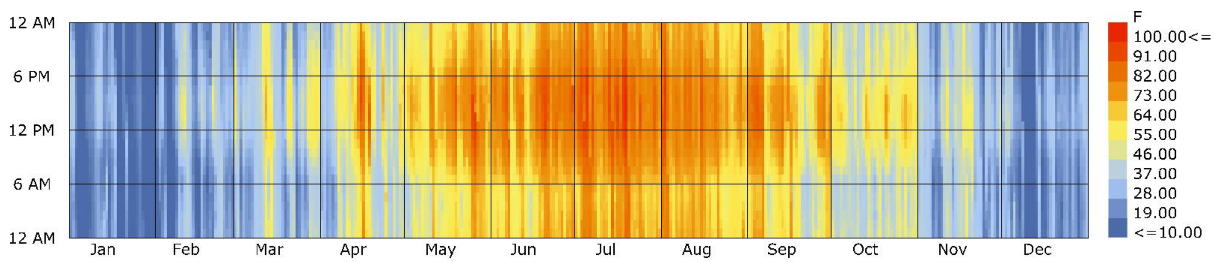
Raleigh-Durham International Airport. The sun altitude is 77 degrees at summer solstice (June 21), 54 degrees at equinox (March 20), and 31 degrees at winter solstice (Dec 21).



(1) Orlando, FL

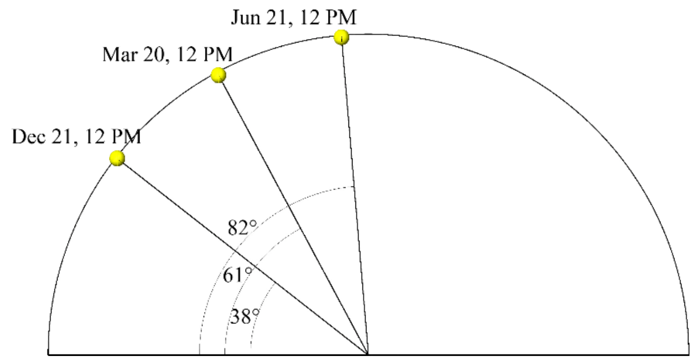


(2) Raleigh, NC

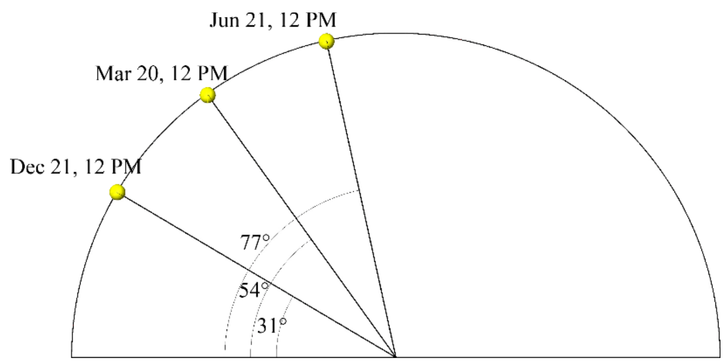


(3) Minneapolis, MN

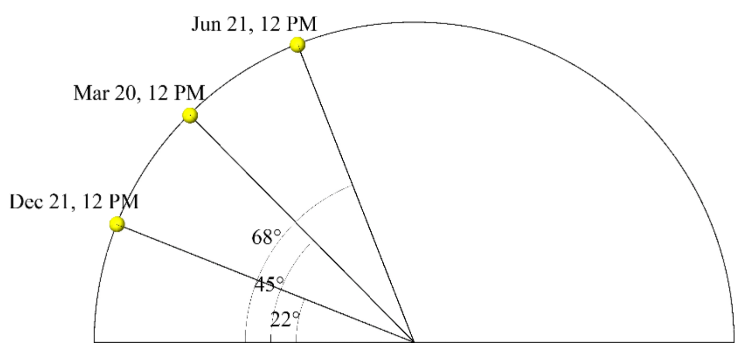
Figure 5.2 Annual Dry Bulb Temperature



(1) Orlando, FL



(2) Raleigh, NC



(3) Minneapolis, MN

Figure 5.3 Solar Altitude

Minnesota has a cold climate with hot summers and cold winters. During summer months, the average low temperatures are around 60 °F, and average high temperatures are around 80 °F. During the winter months, the average low temperatures are around 10 °F, and average high temperatures are around 25 °F. The weather data is from Minneapolis-St.Paul International Airport. The sun altitude is 68 degrees at summer solstice (June 21), 45 degrees at equinox (March 20), and 22 degrees at winter solstice (Dec 21).

Table 5.2 Daylighting and Energy Performance of Baseline Design

<table>
<tr><th colspan="2"></th><th>Orlando, FL</th><th>Raleigh, NC</th><th>Minneapolis, MN</th></tr>
<tr><td rowspan="6">Daylighting Performance Metric [%]</td><td>DA</td><td>80.5</td><td>78.8</td><td>75.7</td></tr>
<tr><td>UDI < 100</td><td>13.3</td><td>15.0</td><td>16.6</td></tr>
<tr><td>UDI 100-2000</td><td>70.7</td><td>69.1</td><td>69.4</td></tr>
<tr><td>UDI > 2000</td><td>16.0</td><td>15.9</td><td>13.9</td></tr>
<tr><td>cDA</td><td>85.0</td><td>83.4</td><td>81.4</td></tr>
<tr><td>sDA</td><td>100.0</td><td>100.0</td><td>100.0</td></tr>
<tr><td rowspan="4">Energy Performance Metric [kBtu/ft^2]</td><td>Cooling EUI</td><td>26.7</td><td>11.2</td><td>4.8</td></tr>
<tr><td>Heating EUI</td><td>2.8</td><td>15.3</td><td>39.9</td></tr>
<tr><td>Lighting EUI</td><td>2.9</td><td>3.2</td><td>3.6</td></tr>
<tr><td>Total EUI (Heating, Cooling, & Lighting)</td><td>32.5</td><td>29.6</td><td>48.4</td></tr>
</table>

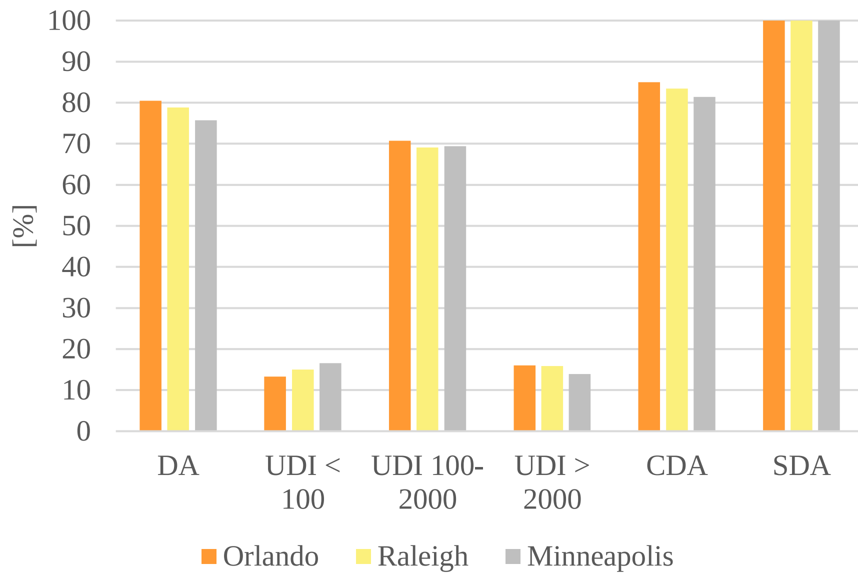


Figure 5.4 Daylighting Performance Metrics of Three Climates

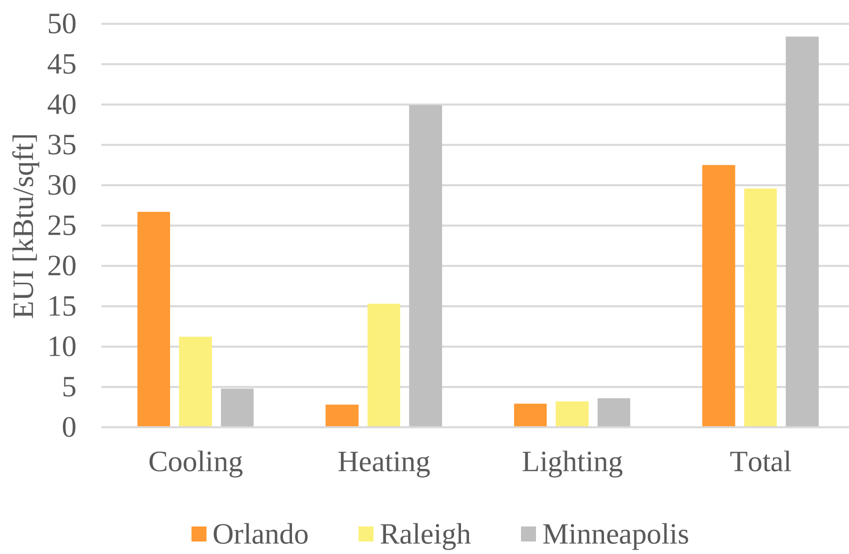


Figure 5.5 Energy Performance Metrics of Three Climates

The daylighting and energy performance metrics of baseline design in three climate zones is listed in Table 5.2, and also illustrated in Figure 5.4 and Figure 5.5. Orlando has the highest DA and cDA, and Minneapolis has the lowest, which can generally represent the overall daylight availability of the three cities. Orlando has the highest UDI > 2000 lux, while Minneapolis has the highest UDI < 100 lux. The UDI 100 - 200 lux are similar at around 70% for the three cities.

The energy performance of the baseline building in the three climate zones also accurately presents the climate features. Orlando has the highest cooling EUI, while Minneapolis has the highest heating EUI. The lighting EUI of the three cases are quite low because of daylighting strategy. Minneapolis has the highest total EUI, and Raleigh has the lowest total EUI.

5.2 Optimization Case 1 (Orlando, FL)

5.2.1 Daylighting Optimization

The daylighting optimization process involves 1106 simulations. The population size of the first generation is 200, and the population is 100 for the following generations. There are 10 generations in total. The optimization objective is maximum UDI 100-200 lux. Figure 5.6 shows the optimization process in Galapagos.

Figure 5.7 shows the geometry of the optimal design. The design has square footprint, 5.2 feet high roof, 2.1 feet wide windows on the south, 4 feet wide windows on the east, west, and 8 feet wide windows on the north. The fins are 0.5 feet long, and the overhangs are 2 feet long. The south skylights are 3.2 feet wide, and the north skylights are 1.6 feet wide.

Figure 5.8 shows the UDI at all the sensors in the room. The UDI of baseline model is 70.7. The final optimized UDI is 82.1, which is 16.1% higher than the baseline model. The optimized design variable values are shown in Table 5.3, and the daylighting and energy performance metrics are shown in Table 5.4.

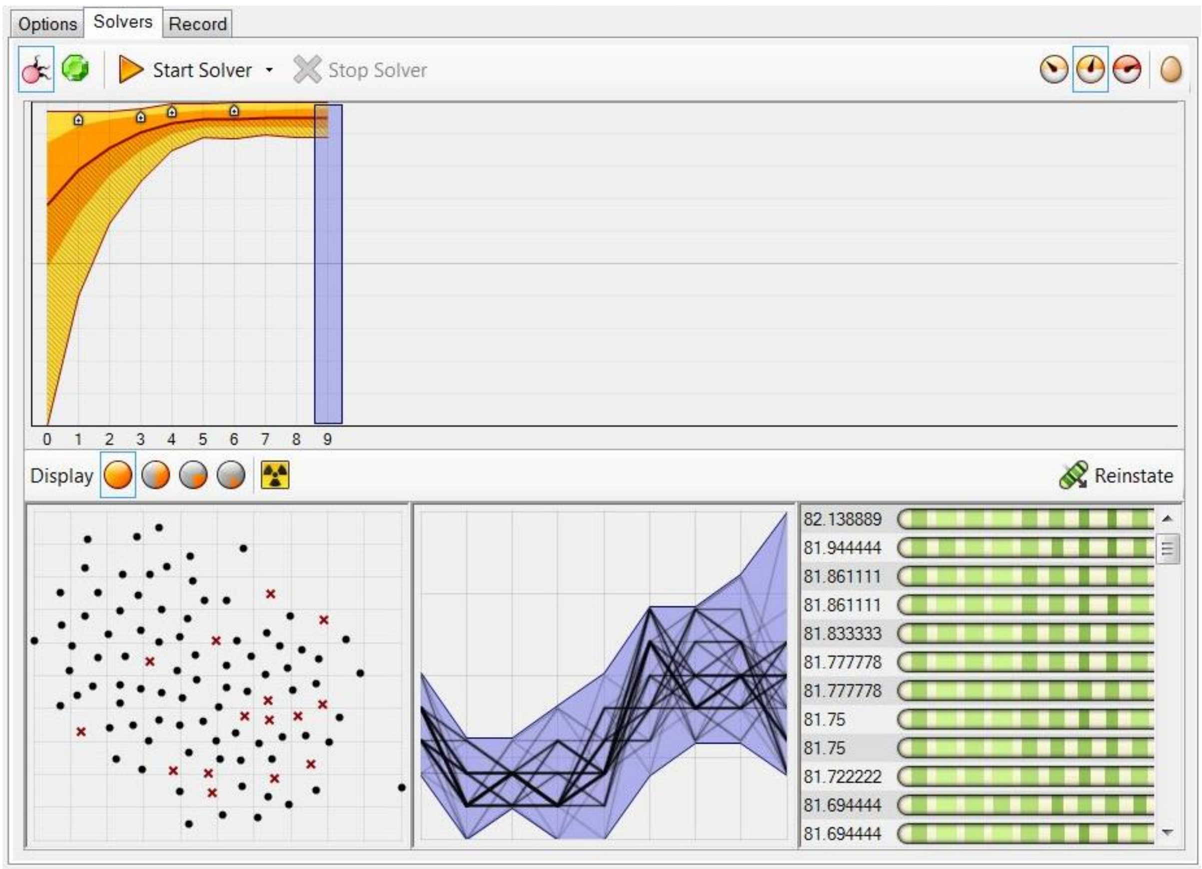


Figure 5.6 Optimization Process in Galapagos (Orlando, FL)

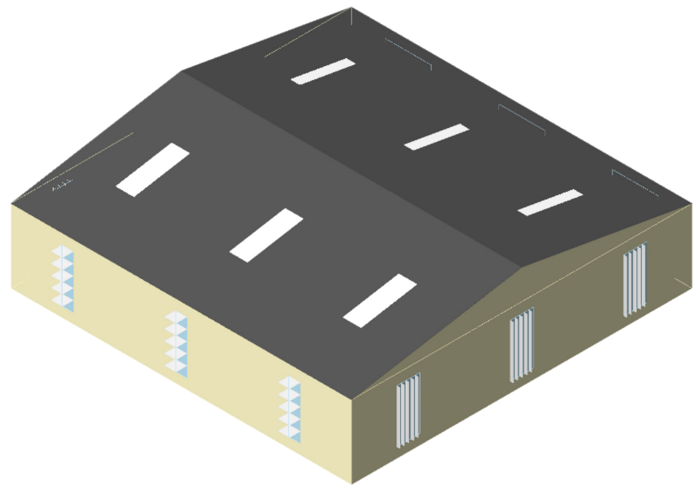


Figure 5.7 Geometry of Optimized Design for Daylighting (Orlando, FL)

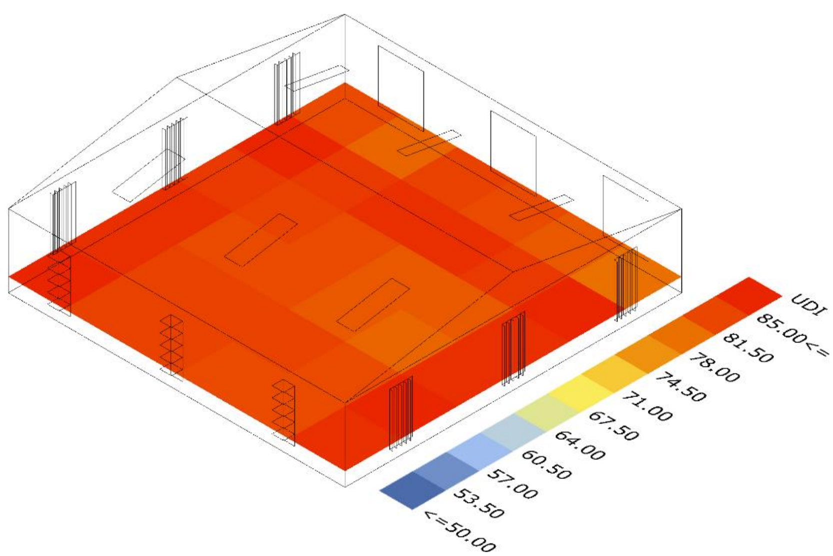


Figure 5.8 Daylighting Performance of Optimized Design (Orlando, FL)

Table 5.3 Variables of Optimized Design (Orlando, FL)

		Setting (Range: 0 to 1)	Actual value [ft.]
Design Variables	Room Depth	0.4	60.0
	Roof Height	0.1	5.2
	East West Window Width	0.2	4.0
	South Window Width	0.1	2.1
	North Window Width	0.4	8.0
	East West Fin Length	0.4	0.5
	South Overhang Length	0.7	2.0
	South Skylight Width	0.8	3.2
	North Skylight Width	0.4	1.6

Table 5.4 Daylighting and Energy Performance of Optimized Design (Orlando, FL)

		Values
Daylighting Performance Metric [%]	DA	73.0
	UDI < 100	16.1
	UDI 100-2000	82.1
	UDI > 2000	1.8
	cDA	81.2
	sDA	100.0
Energy Performance Metric [kBtu/ft^2]	Cooling EUI	21.5
	Heating EUI	2.1
	Lighting EUI	3.3
	Total EUI (Heating, Cooling, & Lighting)	27

5.2.2 Energy Optimization

There are 1213 simulations in the energy optimization process. Same as the previous daylighting optimization setting, the population size of the first generation is 200, and the population is 100 for the following generations. There are totally 11 generations. The optimization objective is minimum total energy load. Figure 5.9 shows the optimization process in Galapagos.

Figure 5.10 shows the geometry of the optimal design. The design footprint is a rectangular shape with the south and north edges slightly longer than the east and west edges. The roof slope is the minimum height. The windows on the east and west are 1.9 feet wide, and the windows on the south are 2.2 feet wide. There are no windows on the north. The fin length is 0, and the overhang length is 1.1 feet. The skylights on the south are 1.6 feet wide, and the skylights on the north are 2.8 feet wide. The overall window sizes are much smaller than the daylighting optimal design.

Figure 5.11 shows the daylighting condition of the room. The baseline EUI is 32.5. The final optimized EUI is 25.6, which is 21.2% lower than the baseline design. The optimized design variable values are shown in Table 5.5, and the daylighting and energy performance metrics are shown in Table 5.6.

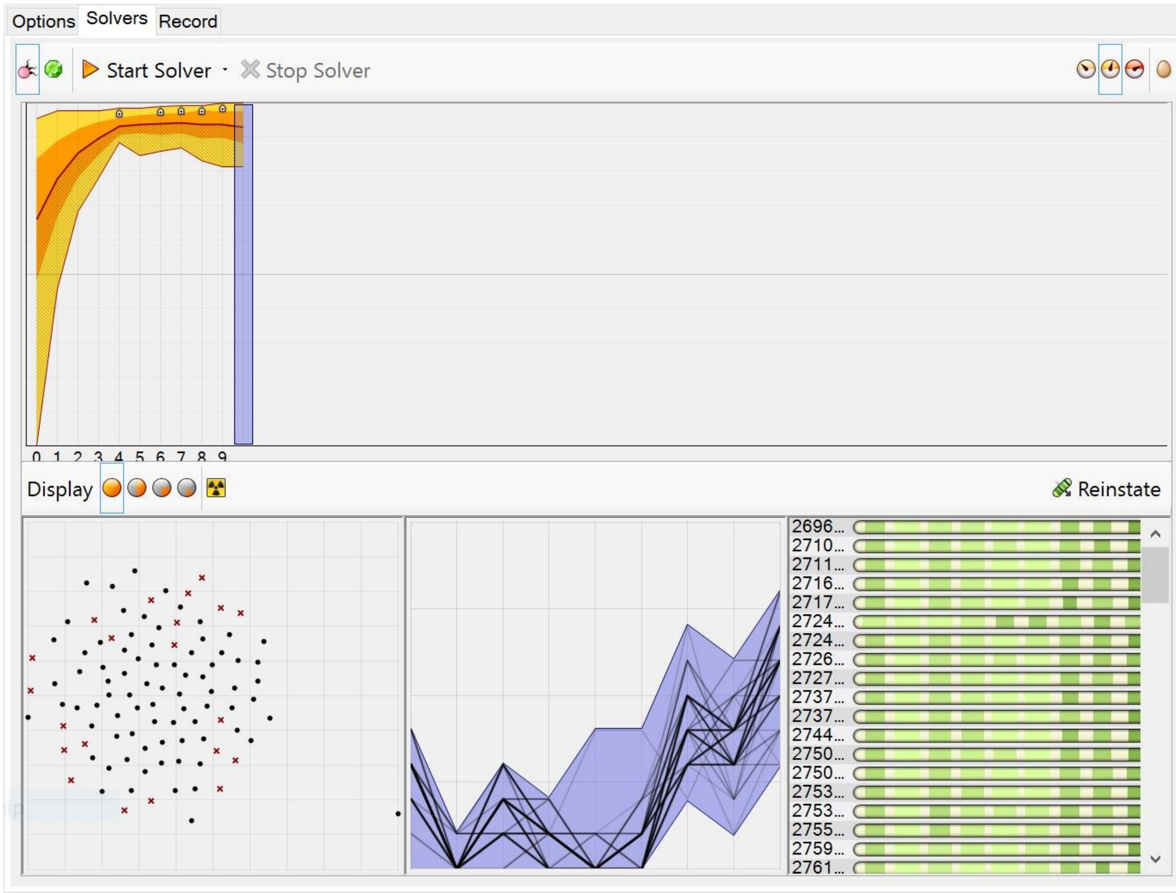


Figure 5.9 Optimization Process in Galapagos (Orlando, FL)

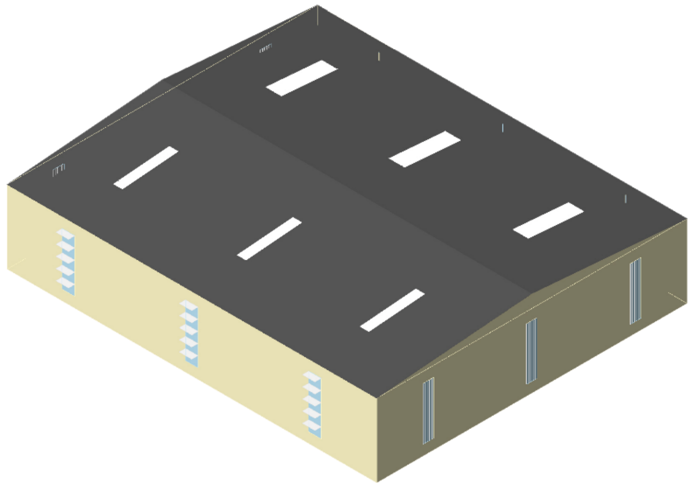


Figure 5.10 Geometry of Optimized Design for Energy (Orlando, FL)

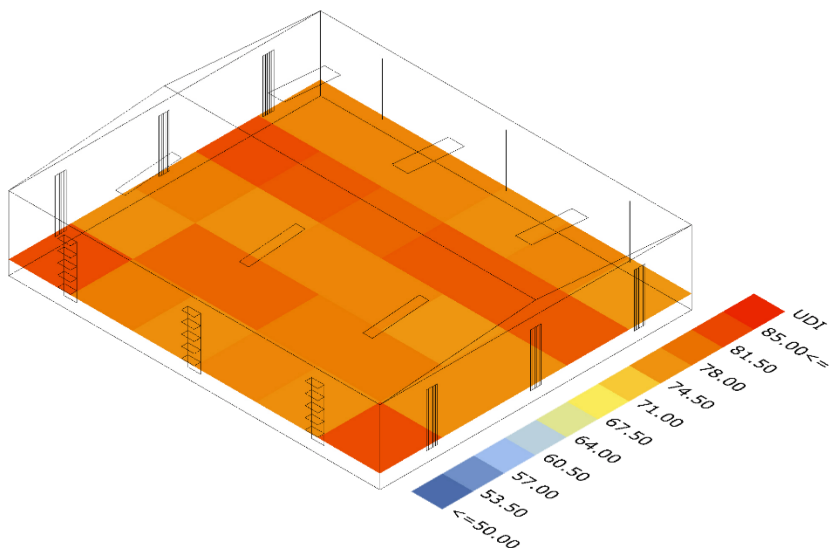


Figure 5.11 Daylighting Performance of Optimized Design (Orlando, FL)

Table 5.5 Variables of Optimized Design (Orlando, FL)

		Setting (Range: 0 to 1)	**Actual value [ft.]**
Design Variables	Room Depth	0.3	55.0
	Roof Height	0	2.3
	East West Window Width	0.1	1.9
	South Window Width	0.1	2.2
	North Window Width	0	0.1
	East West Fin Length	0	0.0
	South Overhang Length	0.4	1.1
	South Skylight Width	0.4	1.6
	North Skylight Width	0.7	2.8

Table 5.6 Daylighting and Energy Performance of Optimized Design (Orlando, FL)

		Values
Daylighting Performance Metric [%]	DA	59.3
	UDI < 100	20.6
	UDI 100-2000	77.1
	UDI > 2000	2.3
	cDA	74.3
	sDA	80.0
Energy Performance Metric [kBtu/ft^2]	Cooling EUI	19.6
	Heating EUI	1.7
	Lighting EUI	4.2
	Total EUI (Heating, Cooling, & Lighting)	25.6

5.2.3 Multi Objective Optimization

There are 897 simulations in the multi-objective optimization process. The optimization objectives are minimum energy load and maximum UDI. Octopus finds the trade-off solutions between the two objectives through the Pareto front.

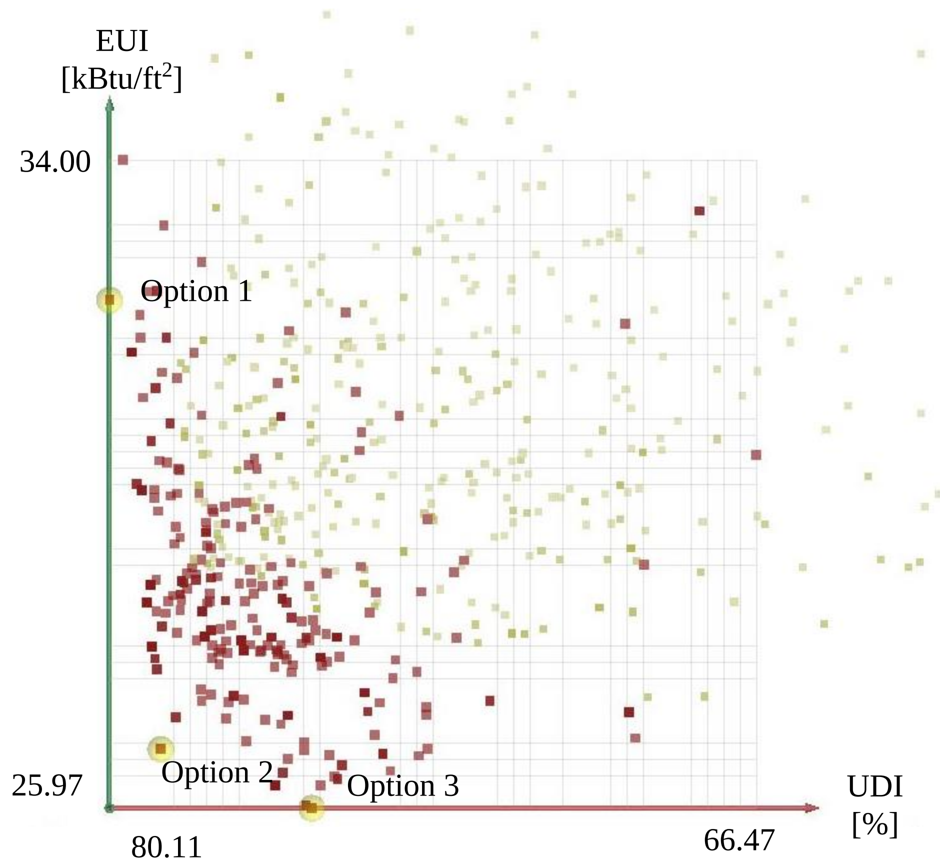
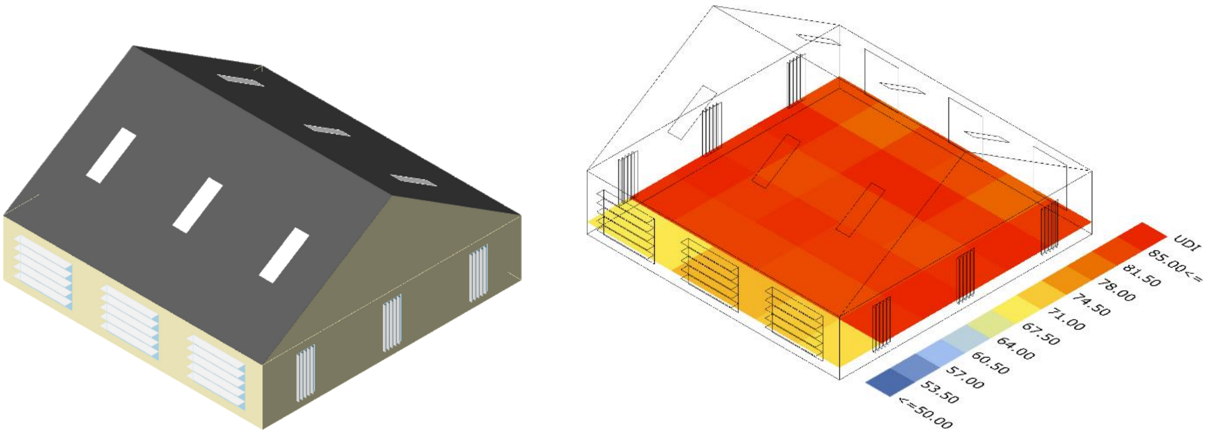
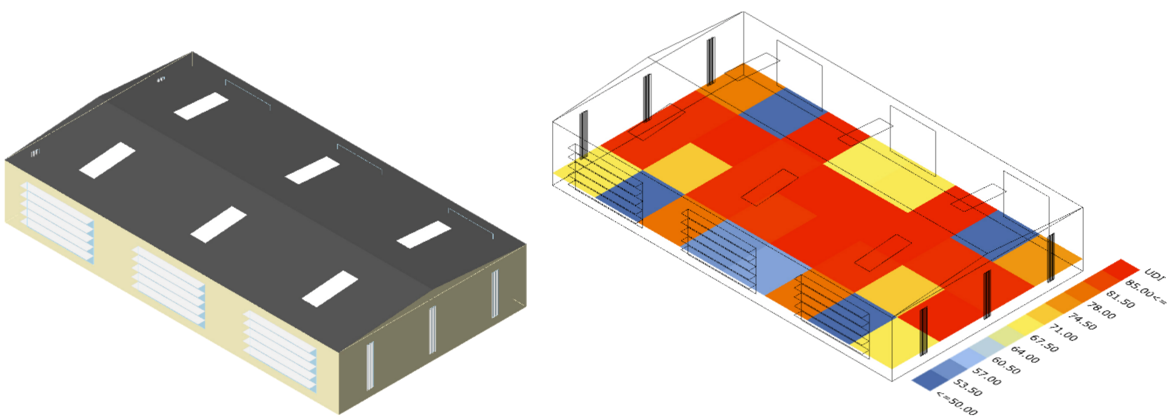


Figure 5.12 Pareto front (Orlando, FL)

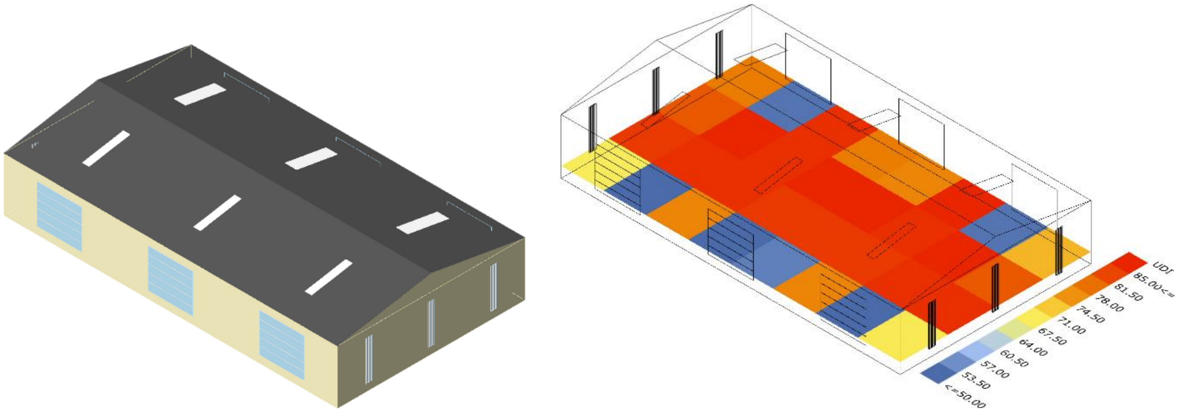
As Figure 5.12 shows, all the dark red color dots present non-dominated solutions found in the optimization process. Three solutions from the Pareto front are selected as examples. Option 1 has the best daylighting performance. Option 3 has the best energy performance. Options 2 has relatively balanced daylighting and energy performance. The geometry of the three options are shown in Figure 5.13. Their variable values and performance metrics are shown in Table 5.7 and Table 5.8.



(1) Option 1 (Best Option for Daylighting)



(2) Option 2 (Balanced Option)



(3) Option 3 (Best Option for Energy)

Figure 5.13 Geometry of Pareto Frontiers (Orlando, FL)

Table 5.7 Variables of Pareto Frontiers (Orlando, FL)

		Option 1 (Best Option for Daylighting)		**Option 2 (Balanced Option)**		**Option 3 (Best Option for Energy)**	
		Setting (Range: 0 to 1)	**Actual value [ft.]**	**Setting (Range: 0 to 1)**	**Actual value [ft.]**	**Setting (Range: 0 to 1)**	**Actual value [ft.]**
Design Variables	Room Depth	0.4	60.0	0.1	45.0	0.1	45.0
	Roof Height	0.6	19.0	0	1.9	0.1	3.9
	East West Window Width	0.2	4.0	0.1	1.6	0.1	1.6
	South Window Width	0.6	12.0	0.6	16.0	0.4	10.7

	North Window Width	0.4	8.0	0.4	10.7	0.4	10.7
	East West Fin Length	0.4	0.5	0.4	0.2	0.3	0.2
	South Overhang Length	0.6	1.7	0.6	1.7	0	0.0
	South Skylight Width	0.8	3.2	0.9	3.6	0.4	1.6
	North Skylight Width	0.6	2.4	0.8	3.2	0.7	2.8

Table 5.8 Daylighting and Energy Performance of Three Options (Orlando, FL)

		Option 1 (Best Option for Daylighting)	**Option 2 (Balanced Option)**	**Option 3 (Best Option for Energy)**
Daylighting Performance Metric [%]	DA	68.1	71.6	71.8
	UDI < 100	16.4	16	15.7
	UDI 100-2000	80.1	79	75.8
	UDI > 2000	3.5	4.9	8.3
	cDA	80.1	81	81.3
	sDA	86.1	100	100
Energy Performance Metric [kBtu/ft^2]	Cooling EUI	25.5	21.1	20.4
	Heating EUI	2.5	2.2	2.1
	Lighting EUI	4.3	3.4	3.4
	Total EUI (Heating, Cooling, & Lighting)	32.3	26.7	26.0

5.2.4 Data Analysis

Linear regression approach is used to model the relationship between design variables and building performance. There are two regression models for each case. One energy performance regression model and one daylighting performance regression model. The data is the combination of all the simulation data from the three optimization processes.

Energy Regression Model

In the first model, total EUI is the dependent variable, and the actual values of 9 design variables are independent variables. The interaction effects between independent variables are not considered. The actual by predicted plot, summary of fit, effect summary, and parameter estimates are shown in Figure 5.14, Table 5.9, Table 5.10, and Table 5.11. The fitted model has R-square of 0.79, which indicates a good fit. The actual by predicted plot also indicates a good match between predicted value and actual value.

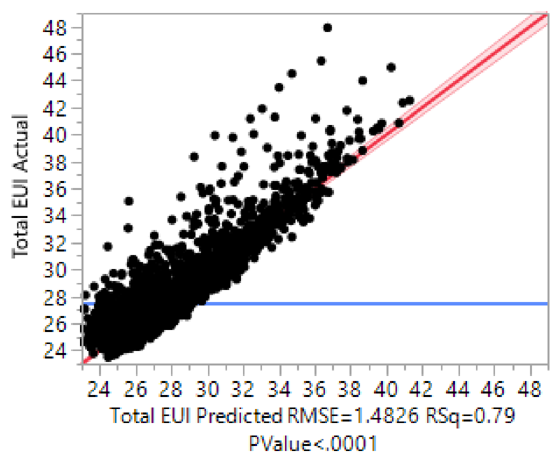


Figure 5.14 Actual by Predicted Plot (Orlando, FL)

Table 5.9 Summary of Fit (Orlando, FL)

RSquare	0.793433
RSquare Adj	0.792853
Root Mean Square Error	1699.765
Mean of Response	31518.02
Observations (or Sum Wgts)	3216

Table 5.10 Effect Summary (Orlando, FL)

Source	LogWorth	PValue
Roof Height	579.507	0.00000
Room Depth	73.363	0.00000
East West Window Width	31.155	0.00000
South Window Width	18.330	0.00000
South Overhang Length	8.366	0.00000
South Skylight Width	8.131	0.00000
North Window Width	3.344	0.00045
North Skylight Width	2.221	0.00601
East West Fin Width	1.991	0.01021

Table 5.11 Parameter Estimates (Orlando, FL)

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	20.092395	0.21299	94.34	<.0001*
Room Depth	0.2180274	0.011664	18.69	<.0001*
Roof Height	0.9431189	0.014647	64.39	<.0001*
East West Window Width	0.3372564	0.02839	11.88	<.0001*
South Window Width	0.1654124	0.018428	8.98	<.0001*
North Window Width	0.0641379	0.018269	3.51	0.0005*
East West Fin Width	0.3839319	0.149378	2.57	0.0102*
South Overhang Length	0.821278	0.139472	5.89	<.0001*
South Skylight Width	-0.608484	0.104963	-5.80	<.0001*
North Skylight Width	-0.256925	0.093468	-2.75	0.0060*

The variables that contribute to the most variance of total energy include roof height, room depth, east west window width, and south window width. All the variables are considered significant in the model.

The relationship between design variables and the energy performance can be found through parameter estimates table (Table 5.11). A positive estimate value indicates a positive relationship, and a negative relationship indicates a negative relationship. The relationship can be also found through data plots. Figure 5.15 shows the plot of total EUI versus two design variables that are the most important in the linear model. Total energy increases with the increase in roof height, and total energy increases with the increase in room depth.

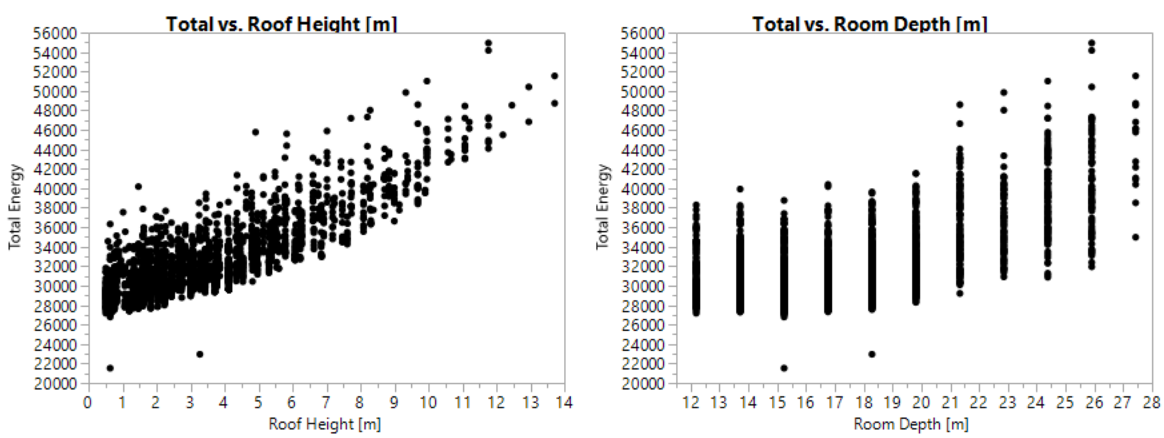


Figure 5.15 Plots of Total Energy against Design Variables (Orlando, FL)

Daylighting Regression Model

In the second model, Useful Daylighting Illuminance (UDI 100-2000 Lux) is the dependent variable, and the actual values of 9 design variables are independent variables. The actual by predicted plot, summary of fit, effect summary, and parameter estimates are shown in Figure 5.16, Table 5.2, Table 5.13, and Table 5.14. R-square of the model is 0.50, which indicates the fit is not as good as the first model. From the actual vs predicted plot, it is found that the prediction is not accurate at higher UDI values. The actual value is sometimes much lower than the predicted value. The design variables have different effect on the daylighting and energy performance. For example, roof height shows strong relationship with total energy, but shows almost no relationship with UDI. The plots of the two most influential design variables are shown in Figure 5.17.

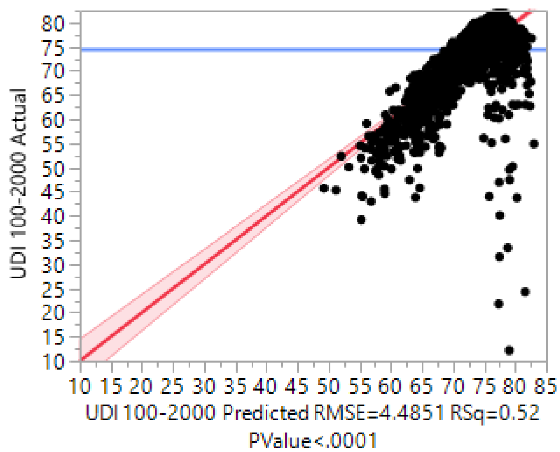


Figure 5.16 Actual by Predicted Plot (Orlando, FL)

Table 5.12 Summary of Fit (Orlando, FL)

RSquare	0.524648
RSquare Adj	0.523314
Root Mean Square Error	4.485061
Mean of Response	74.52989
Observations (or Sum Wgts)	3216

Table 5.13 Effect Summary (Orlando, FL)

Source	LogWorth	PValue
East West Window Width	272.782	0.00000
South Window Width	55.782	0.00000
East West Fin Width	47.485	0.00000
North Window Width	39.251	0.00000
South Overhang Length	26.902	0.00000
Room Depth	5.667	0.00000
North Skylight Width	2.731	0.00186
Roof Height	2.054	0.00884
South Skylight Width	0.472	0.33704

Table 5.14 Parameter Estimates (Orlando, FL)

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	82.792012	0.644334	128.49	<.0001*
Room Depth	-0.167518	0.035286	-4.75	<.0001*
Roof Height	-0.116083	0.044311	-2.62	0.0088*
East West Window Width	-3.356094	0.085886	-39.08	<.0001*
South Window Width	-0.900702	0.055749	-16.16	<.0001*
North Window Width	-0.741548	0.055267	-13.42	<.0001*
East West Fin Width	6.7045179	0.451898	14.84	<.0001*
South Overhang Length	4.6390394	0.42193	10.99	<.0001*
South Skylight Width	0.3048834	0.317532	0.96	0.3370
North Skylight Width	0.8806807	0.282759	3.11	0.0019*

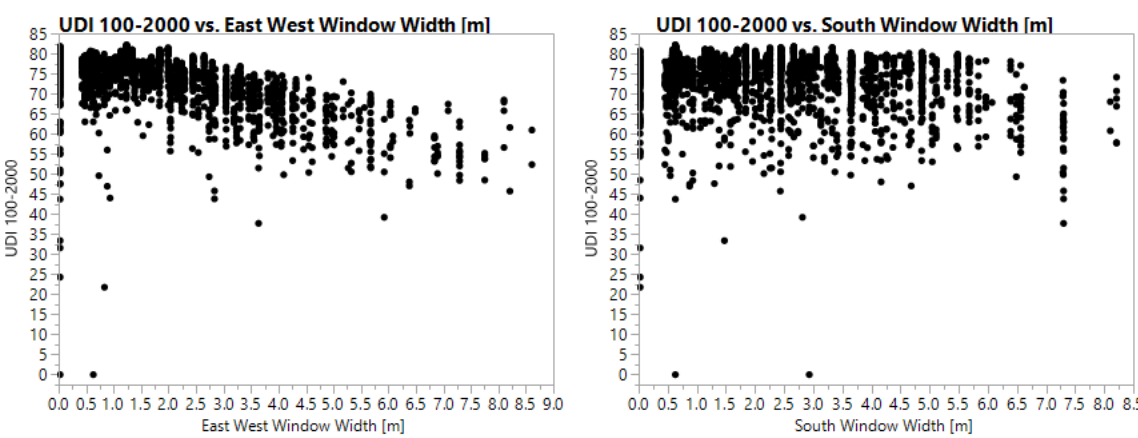


Figure 5.17 Plot of UDI against Design Variables (Orlando, FL)

5.3 Optimization Case 2 (Raleigh, NC)

5.2.1 Daylighting Optimization

The daylighting optimization process involves 1224 simulations. Figure 5.19 shows the optimization process in Galapagos. The geometry of the optimal design and its daylighting performance are shown in Figure 5.20 and Figure 5.21.

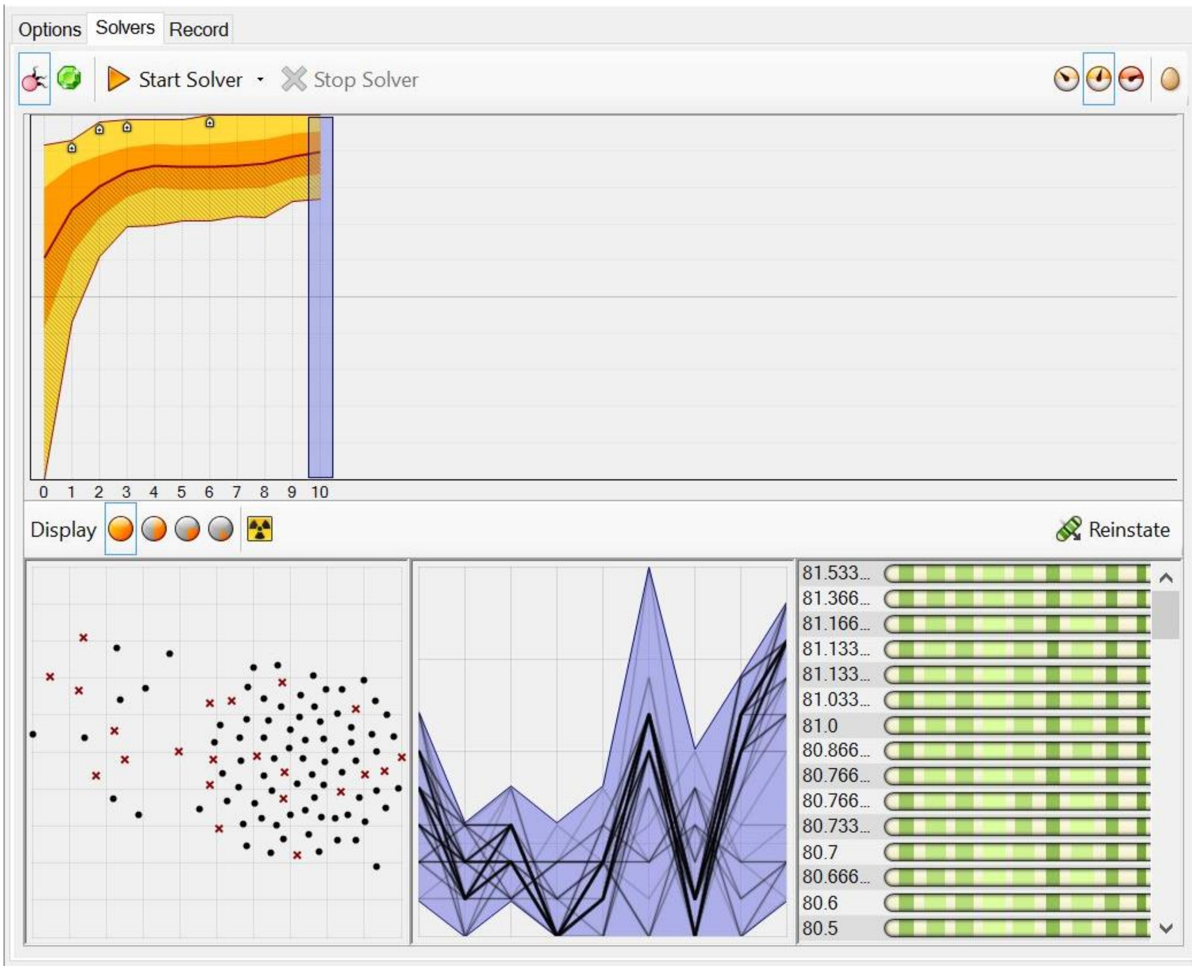


Figure 5.18 Optimization Process in Galapagos (Raleigh, NC)

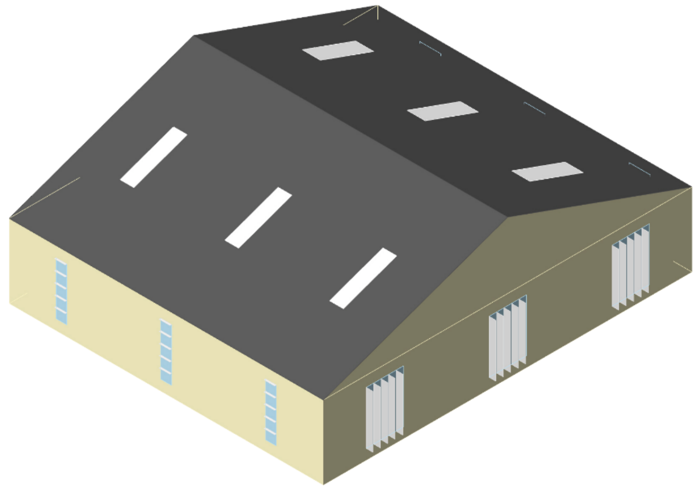


Figure 5.19 Geometry of Optimized Design for Daylighting (Raleigh, NC)

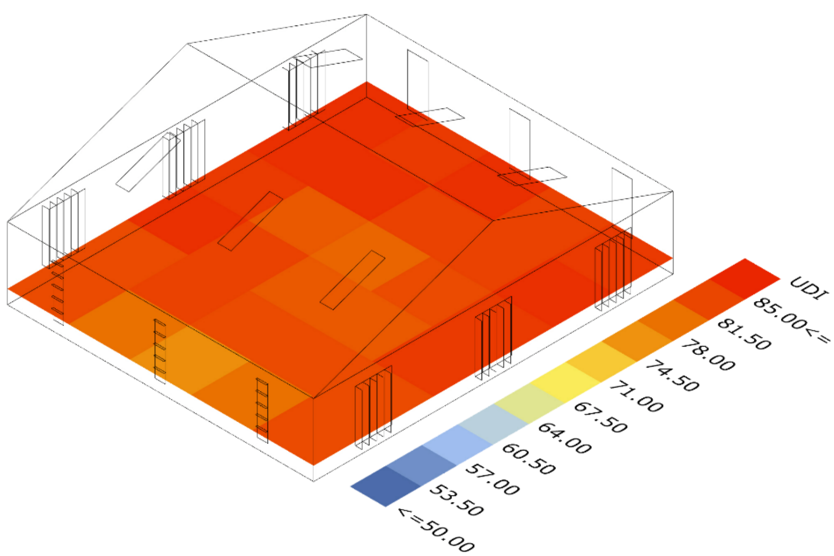


Figure 5.20 Daylighting Performance of Optimized Design (Raleigh, NC)

Table 5.15 Variables of Optimized Design (Raleigh, NC)

		Setting (Range: 0 to 1)	**Actual value [ft.]**
Design Variables	Room Depth	0.5	65.0
	Roof Height	0.3	11.6
	East West Window Width	0.3	6.5
	South Window Width	0.1	1.9
	North Window Width	0.2	3.7
	East West Fin Length	0.6	1.2
	South Overhang Length	0.1	0.3
	South Skylight Width	0.6	2.4
	North Skylight Width	0.8	3.2

Table 5.16 Daylighting and Energy Performance of Optimized Design (Raleigh, NC)

		Values
Daylighting Performance Metric [%]	DA	71.2
	UDI < 100	17.2
	UDI 100-2000	81.5
	UDI > 2000	1.3
	cDA	79.8
	sDA	100.0
Energy Performance Metric [kBtu/ft^2]	Cooling EUI	9.4
	Heating EUI	13.1
	Lighting EUI	3.7
	Total EUI (Heating, Cooling, & Lighting)	26.2

The optimized geometry is similar as the daylighting optimization case in Orlando. The design footprint is close to a square shape. It has 11.6 feet high roof, 1.9 feet wide windows on the south, 6.5 feet wide windows on the east, west, and 3.7 feet wide windows on the north. The fins are 1.2 feet long, and the overhangs are 0.3 feet long. The south skylights are 2.4 feet wide, and the north skylights are 3.2 feet wide.

The UDI of the baseline design in Raleigh is 69.1. The final optimized UDI is 81.5, which is 17.9% higher than the baseline model. The optimized design variable values are shown in Table 5.15, and the daylighting and energy performance metrics are shown in Table 5.16.

5.2.2 Energy Optimization

There are 1147 simulations in the energy optimization process. Figure 5.22 shows the optimization process in Galapagos. Figure 5.23 shows the geometry of the optimal design. The design footprint is a rectangular with longer edge at the south and north orientation. Figure 5.24 shows the daylighting condition of the room.

The final optimized EUI is 22.6. Compared to the EUI of 29.6 from the baseline design, there is 23.6% reduction. The optimized design variable values are shown in Table 5.17, and the daylighting and energy performance metrics are shown in Table 5.18.

Figure 5.21 Optimization Process in Galapagos (Raleigh, NC)

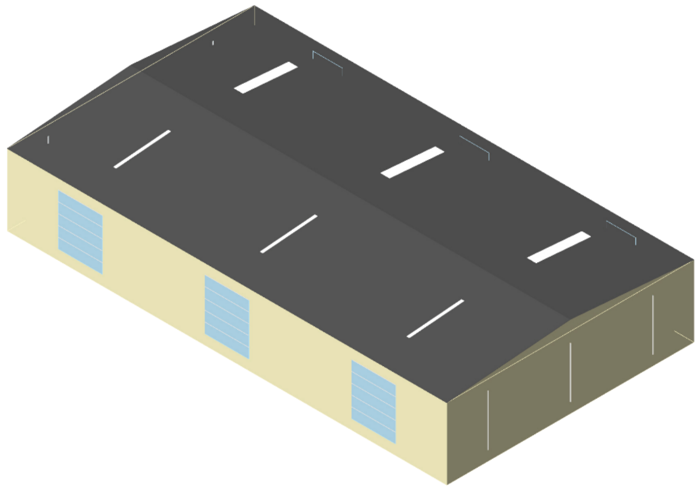


Figure 5.22 Geometry of Optimized Design for Energy (Raleigh, NC)

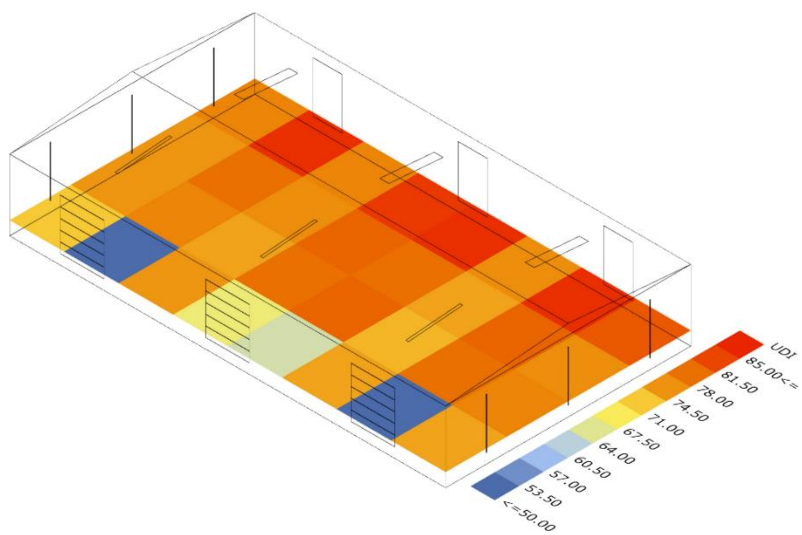


Figure 5.23 Daylighting Performance of Optimized Design (Raleigh, NC)

Table 5.17 Variables of Optimized Design (Raleigh, NC)

		Setting (Range: 0 to 1)	**Actual value [ft.]**
Design Variables	Room Depth	0.1	45.0
	Roof Height	0.0	1.9
	East West Window Width	0.0	0.1
	South Window Width	0.3	8.0
	North Window Width	0.2	5.4
	East West Fin Length	0.2	0.0
	South Overhang Length	0.0	0.0
	South Skylight Width	0.1	0.5
	North Skylight Width	0.4	1.6

Table 5.18 Daylighting and Energy Performance of Optimized Design (Raleigh, NC)

		Values
Daylighting Performance Metric [%]	DA	59.5
	UDI < 100	20.8
	UDI 100-2000	74.1
	UDI > 2000	5.1
	cDA	74.4
	sDA	75.0
Energy Performance Metric [kBtu/ft^2]	Cooling EUI	7.4
	Heating EUI	10.6
	Lighting EUI	4.7
	Total EUI (Heating, Cooling, & Lighting)	22.6

5.2.3 Multi Objective Optimization

This multi-objective optimization process includes 1002 simulations. Figure 5.25 shows the Pareto front formed by non-dominated solutions. Three examples are chosen again for best daylighting performance, best energy performance, and balanced performance. Their geometry is shown in Figure 5.26. The variable values, and the performance metrics of the three options are listed in Table 5.19 and Table 5.20.

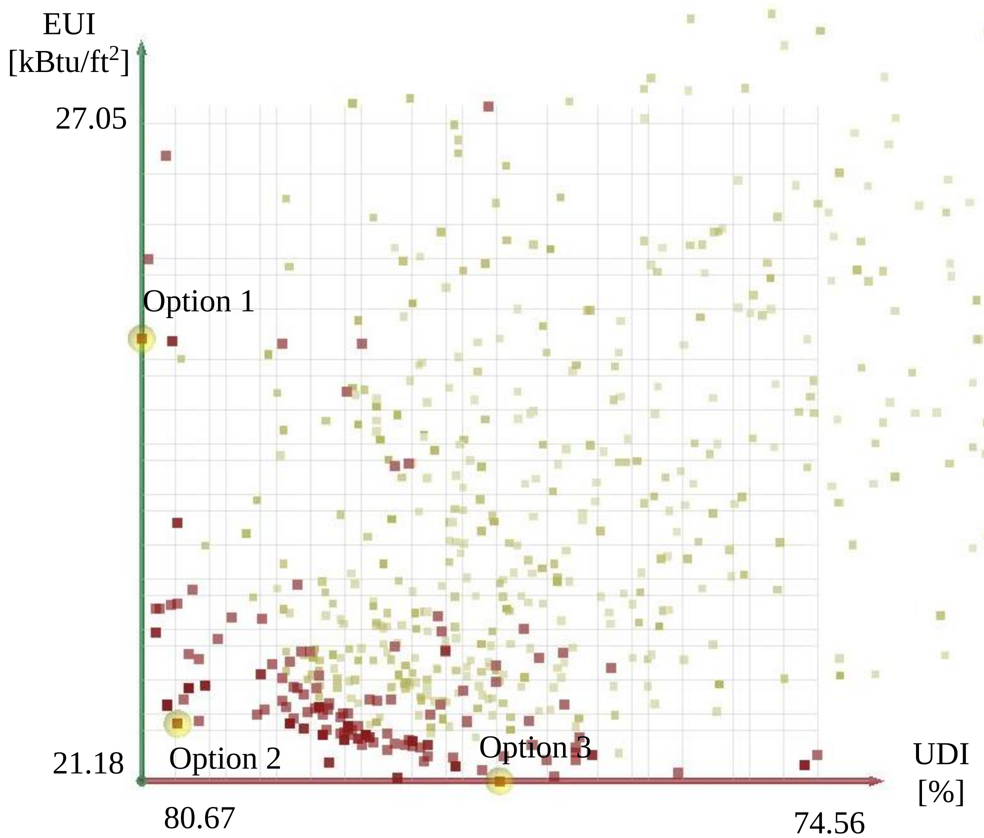
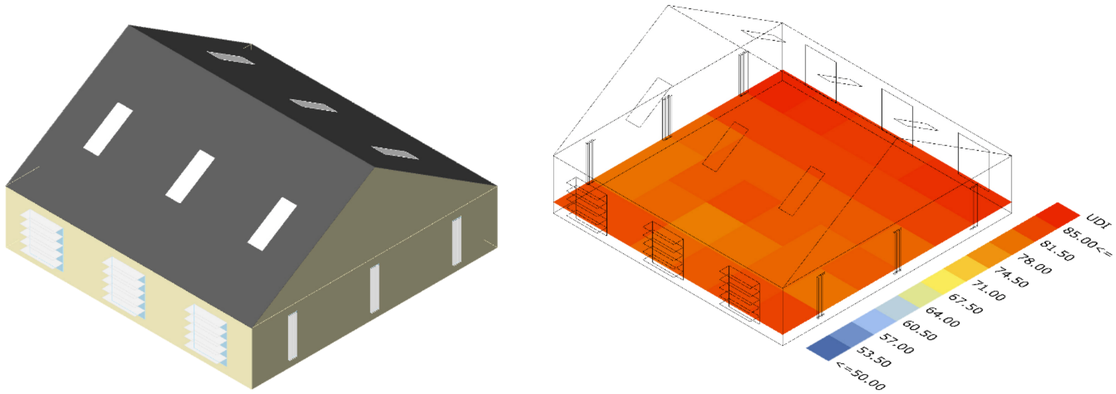
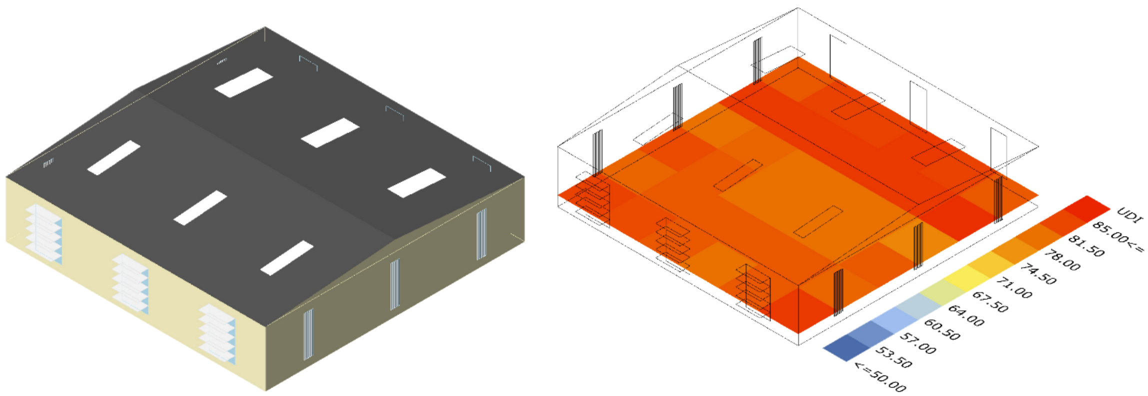


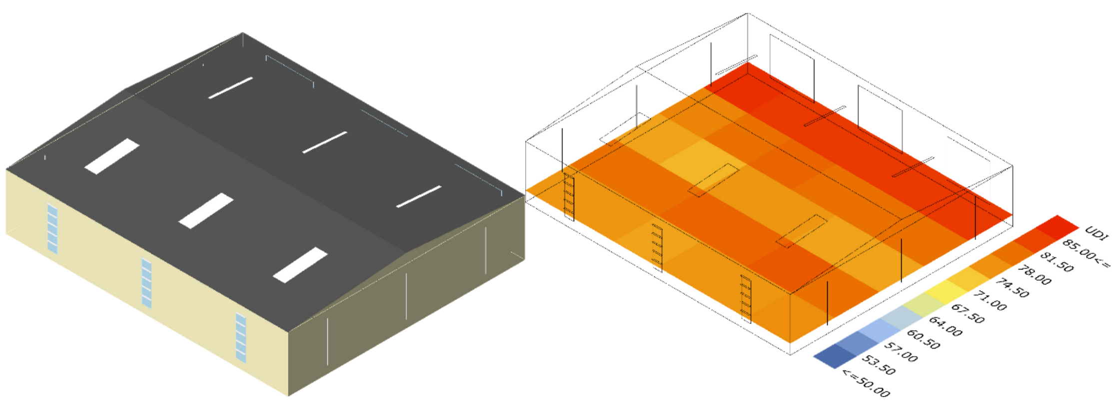
Figure 5.24 Pareto frontier (Raleigh, NC)



(1) Option 1 (Best Option for Daylighting)



(2) Option 2 (Balanced Option)



(3) Option 3 (Best Option for Energy)

Figure 5.25 Geometry of Pareto Frontiers (Raleigh, NC)

Table 5.19 Variables of Pareto Frontiers (Raleigh, NC)

		Option 1 (Best Option for Daylighting)		**Option 2 (Balanced Option)**		**Option 3 (Best Option for Energy)**	
		Setting (Range: 0 to 1)	**Actual value [ft.]**	**Setting (Range: 0 to 1)**	**Actual value [ft.]**	**Setting (Range: 0 to 1)**	**Actual value [ft.]**
Design Variables	Room Depth	0.4	60.0	0.4	60.0	0.3	55.0
	Roof Height	0.6	19.0	0	2.5	0	2.3
	East West Window Width	0.1	2.1	0.1	2.1	0	0.1
	South Window Width	0.4	8.0	0.3	6.0	0.1	2.2
	North Window Width	0.4	8.0	0.2	4.0	0.5	10.9
	East West Fin Length	0.7	0.4	0.1	0.1	0.7	0.0
	South Overhang Length	0.9	2.5	0.9	2.5	0.1	0.3
	South Skylight Width	0.9	3.6	0.6	2.4	0.7	2.8
	North Skylight Width	0.8	3.2	0.9	3.6	0.1	0.5

Table 5.20 Daylighting and Energy Performance of Pareto Frontiers (Raleigh, NC)

<table>
<tr><th colspan="2"></th><th>Option 1 (Best Option for Daylighting)</th><th>Option 2 (Balanced Option)</th><th>Option 3 (Best Option for Energy)</th></tr>
<tr><td rowspan="6">Daylighting Performance Metric [%]</td><td>DA</td><td>68.5</td><td>69.0</td><td>59.2</td></tr>
<tr><td>UDI < 100</td><td>18.4</td><td>18.4</td><td>21.1</td></tr>
<tr><td>UDI 100-2000</td><td>80.7</td><td>80.3</td><td>77.4</td></tr>
<tr><td>UDI > 2000</td><td>1.1</td><td>1.4</td><td>1.6</td></tr>
<tr><td>cDA</td><td>78.1</td><td>78.3</td><td>74.3</td></tr>
<tr><td>sDA</td><td>100.0</td><td>100.0</td><td>70.0</td></tr>
<tr><td rowspan="4">Energy Performance Metric [kBtu/ft²]</td><td>Cooling EUI</td><td>8.9</td><td>7.6</td><td>6.8</td></tr>
<tr><td>Heating EUI</td><td>13.0</td><td>10.6</td><td>10.2</td></tr>
<tr><td>Lighting EUI</td><td>3.4</td><td>3.5</td><td>4.2</td></tr>
<tr><td>Total EUI (Heating, Cooling, & Lighting)</td><td>32.3</td><td>26.7</td><td>26.0</td></tr>
</table>

5.2.4 Data Analysis

The same regression method for the energy and daylighting performance are applied to the optimization data in Raleigh.

Energy Regression Model

The actual by predicted plot, summary of fit, effect summary, and parameter estimates are shown in Figure 5.26, Table 5.21, Table 5.22, and Table 5.23. The fitted model has R-square of 0.89. The variables that contribute to the most variance of total energy include roof height, east west window width, north window width, and south window width. South overhang length and north skylight width are not significant in the model.

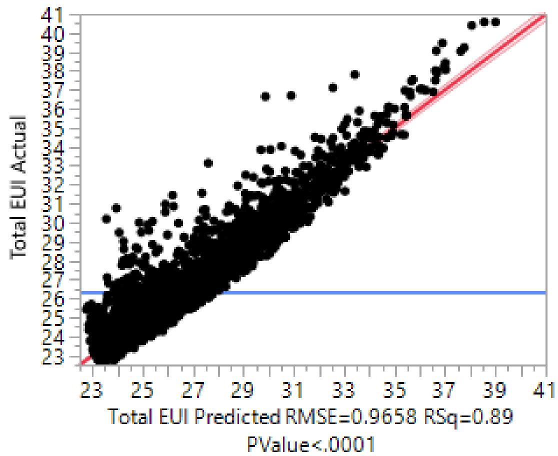


Figure 5.26 Actual by Predicted Plot (Raleigh, NC)

Table 5.21 Summary of Fit (Raleigh, NC)

RSquare	0.890466
RSquare Adj	0.890172
Root Mean Square Error	0.965786
Mean of Response	26.34394
Observations (or Sum Wgts)	3367

Table 5.22 Effect Summary (Raleigh, NC)

Source	LogWorth		PValue
Roof Height	795.569		0.00000
East West Window Width	286.991		0.00000
North Window Width	94.366		0.00000
South Window Width	54.253		0.00000
Room Depth	18.631		0.00000
East West Fin Width	6.022		0.00000
South Skylight Width	2.144		0.00719
North Skylight Width	0.049		0.89245
South Overhang Length	0.018		0.95872

Table 5.23 Parameter Estimates (Raleigh, NC)

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	21.06122	0.122441	172.01	<.0001*
Room Depth	0.0645488	0.007131	9.05	<.0001*
Roof Height	0.7285409	0.008956	81.35	<.0001*
East West Window Width	0.8322506	0.020751	40.11	<.0001*
South Window Width	0.1891668	0.011893	15.91	<.0001*
North Window Width	0.2883039	0.013492	21.37	<.0001*
East West Fin Width	0.5078981	0.103428	4.91	<.0001*
South Overhang Length	-0.004046	0.078158	-0.05	0.9587
South Skylight Width	-0.165187	0.061413	-2.69	0.0072*
North Skylight Width	-0.007244	0.053576	-0.14	0.8924

Figure 5.27 shows the plot of total energy versus two design variables that are the most important in the linear model. Total energy increases with the increase of the roof height, and total energy increases with the increase of the window width on the east and west.

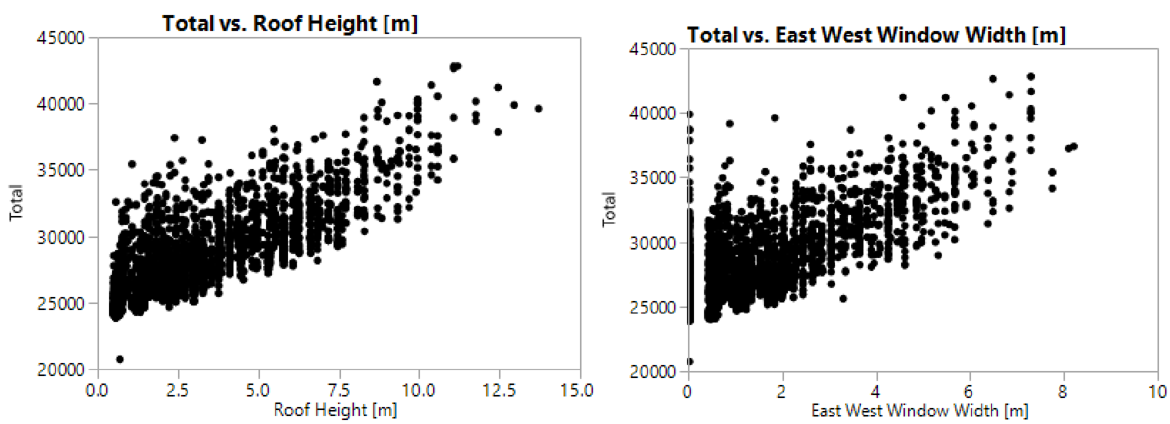


Figure 5.27 Plots of Total Energy against Design Variables (Raleigh, NC)

Daylighting Regression Model

The Actual by predicted plot, summary of fit, effect summary, and parameter estimates are shown in Figure 5.28, Table 5.24, Table 5.25, and Table 5.26. R-square of the model is 0.60. The plots of the most influential design variables are shown in Figure 5.29.

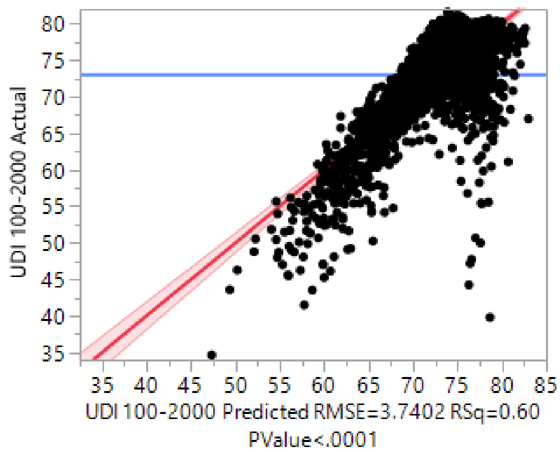


Figure 5.28 Actual by Predicted Plot (Raleigh, NC)

Table 5.24 Summary of Fit (Raleigh, NC)

RSquare	0.604589
RSquare Adj	0.603529
Root Mean Square Error	3.740178
Mean of Response	73.06555
Observations (or Sum Wgts)	3367

Table 5.25 Effect Summary (Raleigh, NC)

Source	LogWorth	PValue
East West Window Width	326.864	0.00000
South Window Width	159.912	0.00000
South Overhang Length	85.379	0.00000
East West Fin Width	45.073	0.00000
North Window Width	22.546	0.00000
North Skylight Width	8.002	0.00000
South Skylight Width	4.944	0.00001
Roof Height	1.138	0.07279
Room Depth	0.736	0.18346

Table 5.26 Parameter Estimates (Raleigh, NC)

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	77.084002	0.474175	162.56	<.0001*
Room Depth	0.0367444	0.027618	1.33	0.1835
Roof Height	-0.062249	0.034684	-1.79	0.0728
East West Window Width	-3.49139	0.080361	-43.45	<.0001*
South Window Width	-1.314681	0.046057	-28.54	<.0001*
North Window Width	-0.523141	0.05225	-10.01	<.0001*
East West Fin Width	5.7770331	0.400543	14.42	<.0001*
South Overhang Length	6.1288375	0.302683	20.25	<.0001*
South Skylight Width	1.0454664	0.237833	4.40	<.0001*
North Skylight Width	1.1921931	0.207483	5.75	<.0001*

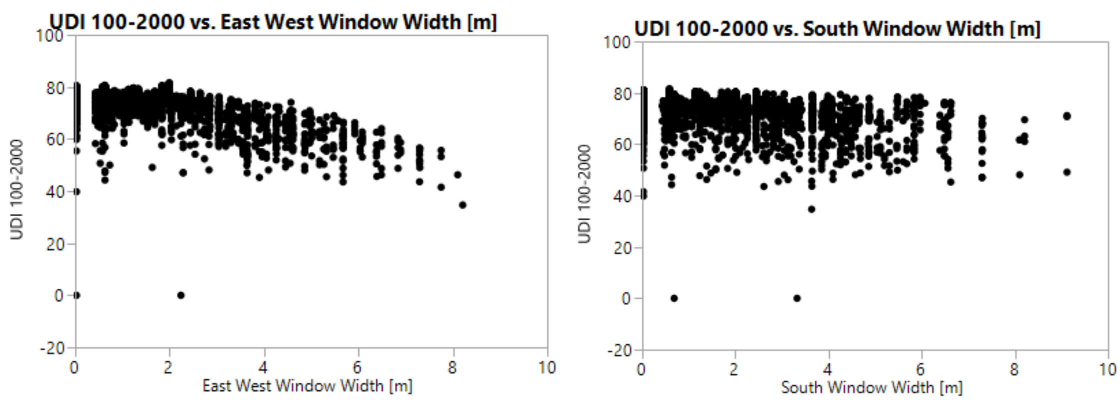


Figure 5.29 Plot of UDI against Design Variables (Raleigh, NC)

5.4 Optimization Case 3 (Minneapolis, MN)

5.3.1 Daylighting Optimization

The daylighting optimization process involves 1106 simulations. Figure 5.30 shows the optimization process in Galapagos. The geometry of the optimal design and its daylighting performance are shown in Figure 5.31 and Figure 5.32. The UDI of baseline design is 69.4.

The final optimized average UDI is 77.5, which is 11.7% higher than the baseline model. The optimized design variable values are shown in Table 5.27, and the daylighting and energy performance metrics are shown in Table 5.28.

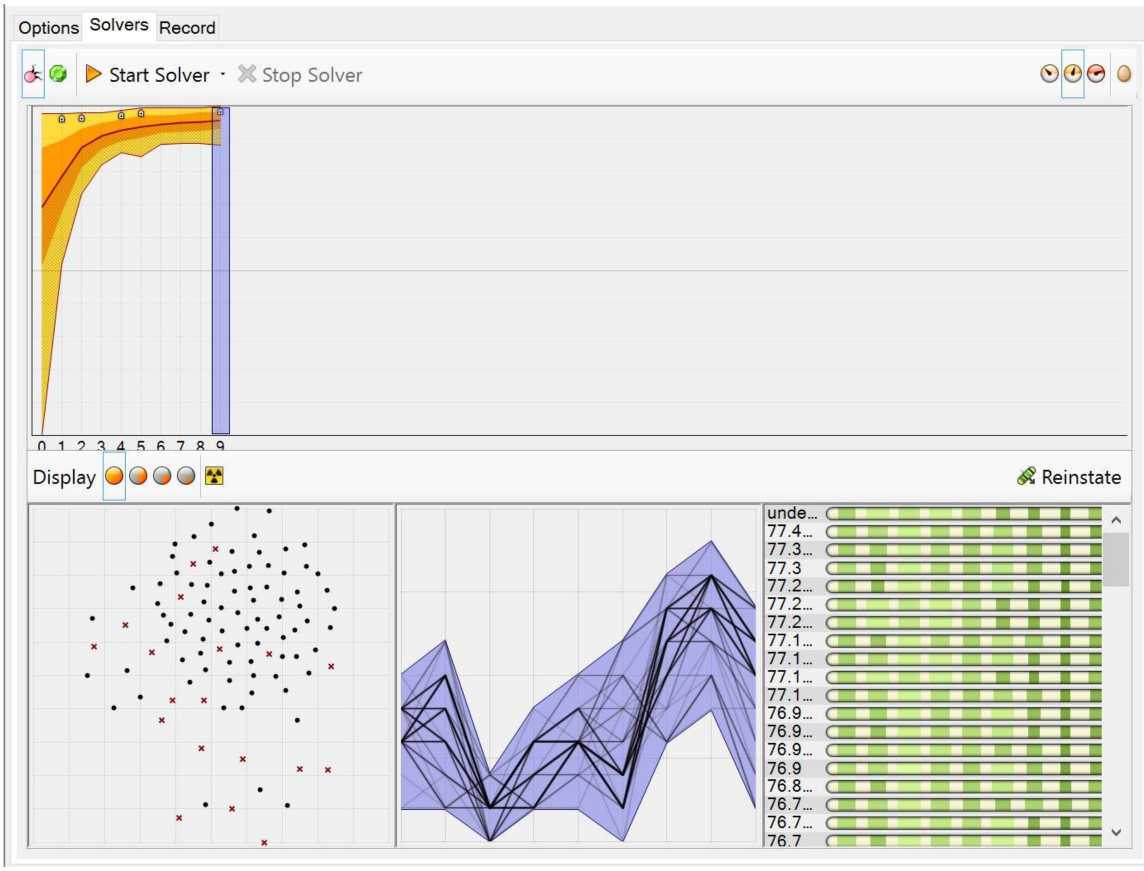


Figure 5.30 Optimization Process in Galapagos (Minneapolis, MN)

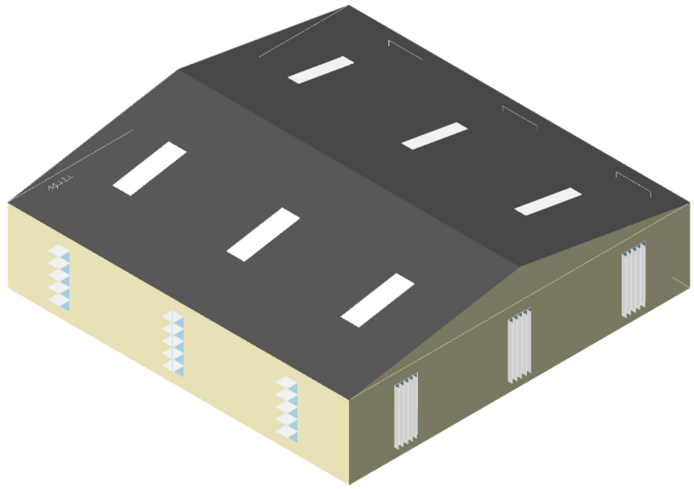


Figure 5.31 Geometry of Optimized Design for Daylighting (Minneapolis, MN)

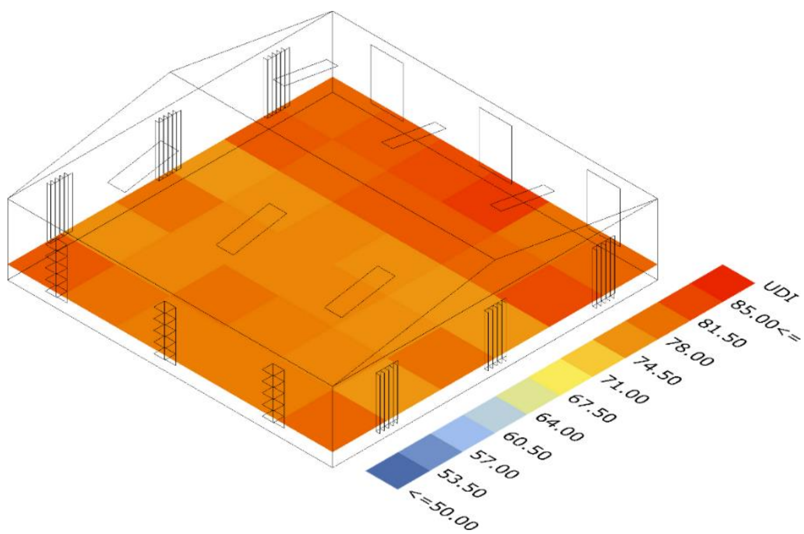


Figure 5.32 Daylighting Performance of Optimized Design (Minneapolis, MN)

Table 5.27 Variables of Optimized Design (Minneapolis, MN)

		Setting (Range: 0 to 1)	**Actual value [ft.]**
Design Variables	Room Depth	0.4	60.0
	Roof Height	0.1	5.2
	East West Window Width	0.2	4.0
	South Window Width	0.1	2.1
	North Window Width	0.3	6.0
	East West Fin Length	0.6	0.7
	South Overhang Length	0.7	2.0
	South Skylight Width	0.8	3.2
	North Skylight Width	0.5	2.0

Table 5.28 Daylighting and Energy Performance of Optimized Design (Minneapolis, MN)

		Values
Daylighting Performance Metric [%]	DA	64.1
	UDI < 100	20.9
	UDI 100-2000	77.5
	UDI > 2000	1.4
	cDA	75.4
	sDA	100.0
Energy Performance Metric [kBtu/ft^2]	Cooling EUI	3.4
	Heating EUI	31.7
	Lighting EUI	4.3
	Total EUI (Heating, Cooling, & Lighting)	39.5

5.3.2 Energy Optimization

There are 1105 simulations in the energy optimization process. Figure 5.33 shows the optimization process in Galapagos. The geometry of the optimal design and its daylighting performance are shown in Figure 5.34 and Figure 5.35. The EUI of the baseline design is 48.4. The final optimized EUI is 36.2, which is 25.2% lower than the baseline design. The optimized design variable values and the daylighting and energy performance metrics are shown in Table 5.229 and Table 5.30.

Figure 5.33 Optimization Process in Galapagos (Minneapolis, MN)

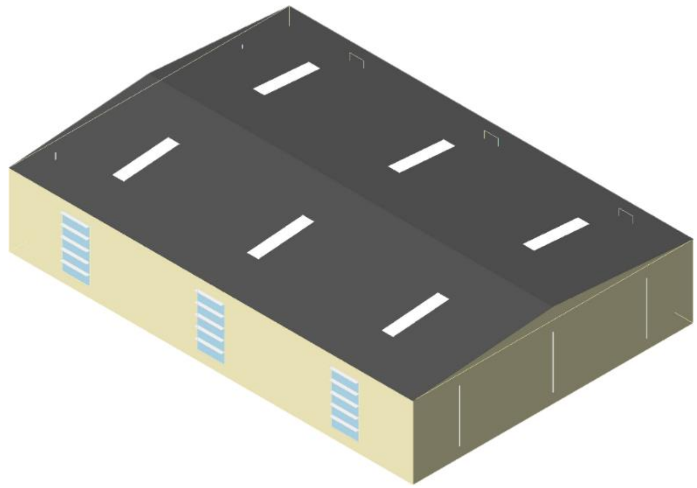


Figure 5.34 Geometry of Optimized Design for Energy (Minneapolis, MN)

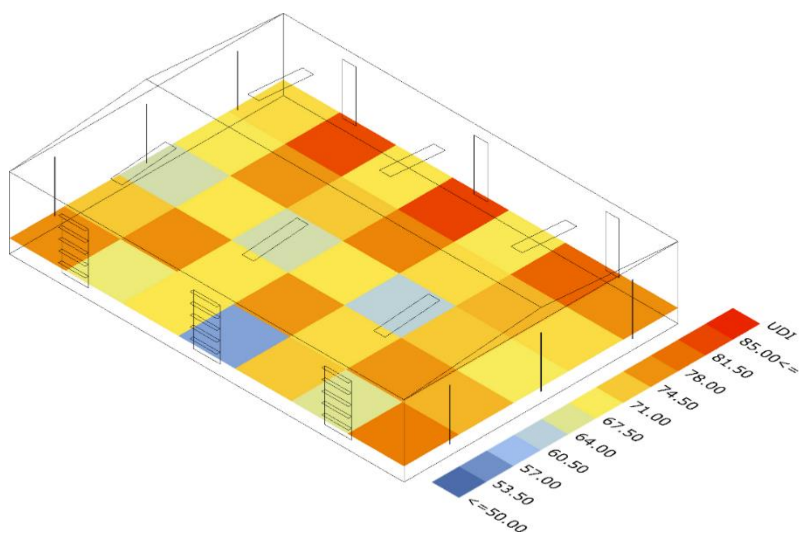


Figure 5.35 Daylighting Performance of Optimized Design (Minneapolis, MN)

Table 5.29 Variables of Optimized Design (Minneapolis, MN)

		Setting (Range: 0 to 1)	**Actual value [ft.]**
Design Variables	Room Depth	0.2	50.0
	Roof Height	0	2.1
	East West Window Width	0	0.1
	South Window Width	0.2	4.8
	North Window Width	0.1	2.5
	East West Fin Length	0.2	0.0
	South Overhang Length	0.2	0.6
	South Skylight Width	0.5	2.0
	North Skylight Width	0.5	2.0

Table 5.30 Daylighting and Energy Performance of Optimized Design (Minneapolis, MN)

		Values
Daylighting Performance Metric [%]	DA	49.7
	UDI < 100	26.9
	UDI 100-2000	70.5
	UDI > 2000	2.5
	cDA	67.5
	sDA	48.6
Energy Performance Metric [kBtu/ft^2]	Cooling EUI	2.9
	Heating EUI	27.5
	Lighting EUI	5.8
	Total EUI (Heating, Cooling, & Lighting)	36.2

5.3.3 Multi Objective Optimization

There are totally 905 simulations in the optimization process. Figure 5.36 shows the Pareto front formed by non-dominated solutions. Three examples are chosen for best daylighting performance, best energy performance, and balanced performance. Their geometries are shown in Figure 5.37. The variable values, and the performance metrics of the three options are listed in Table 5.31 and Table 5.32.

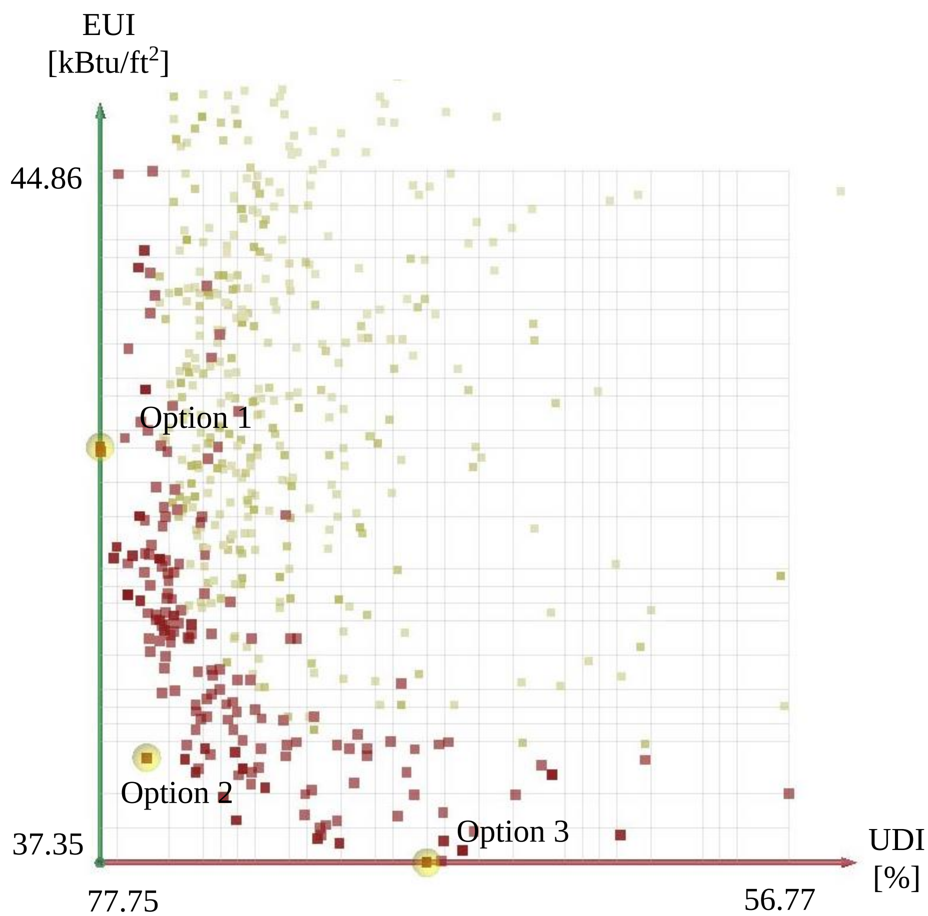
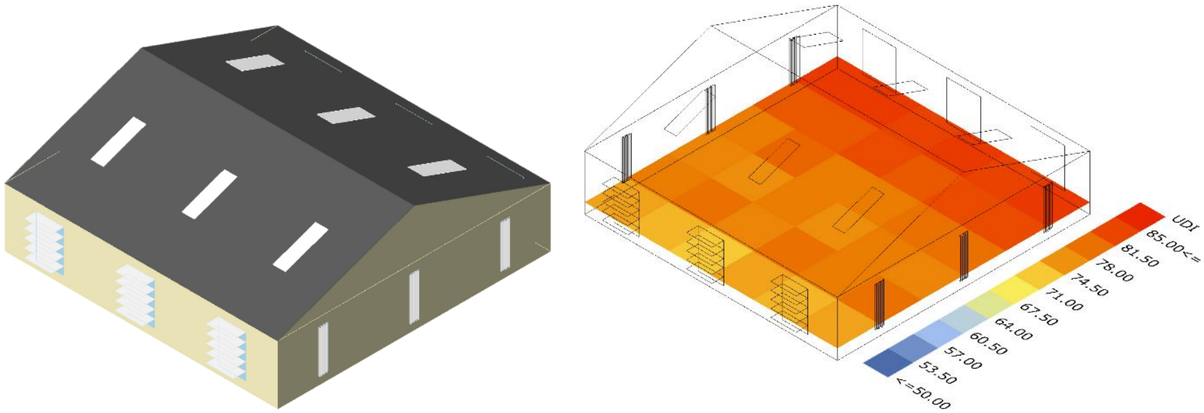
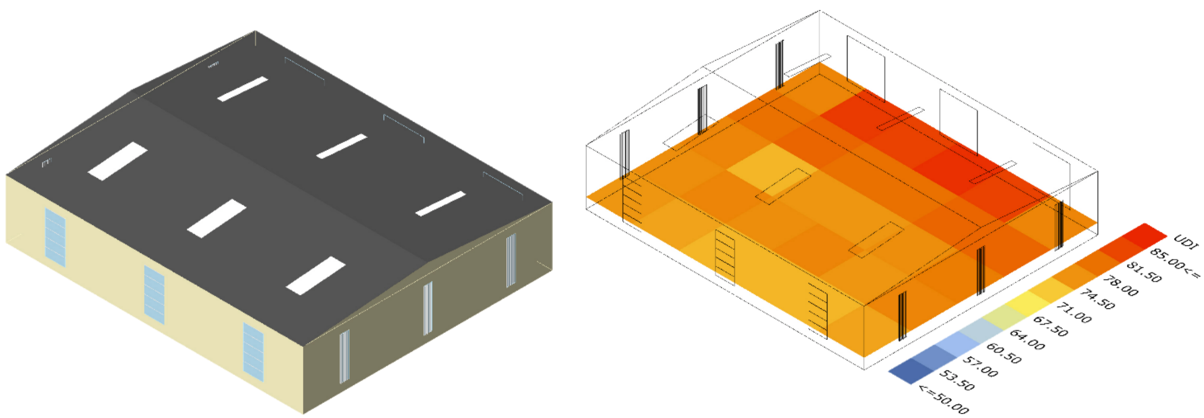


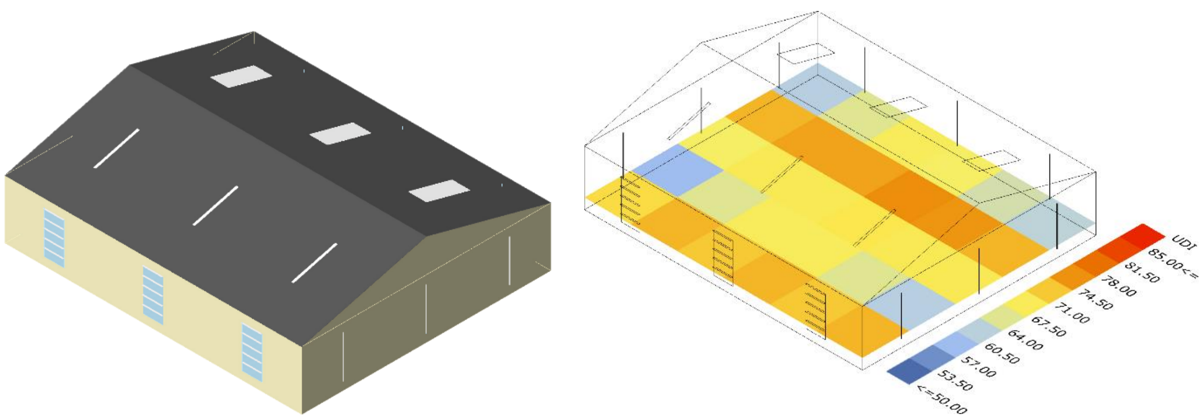
Figure 5.36 Pareto frontier (Minneapolis, MN)



(1) Option 1 (Best Option for Daylighting)



(2) Option 2 (Balanced Option)



(3) Option 3 (Best Option for Energy)

Figure 5.37 Geometry of Pareto Frontiers (Minneapolis, MN)

Table 5.31 Variables of Pareto Frontiers (Minneapolis, MN)

		Option 1 (Best Option for Daylighting)		**Option 2 (Balanced Option)**		**Option 3 (Best Option for Energy)**	
		Setting (Range: 0 to 1)	**Actual value [ft.]**	**Setting (Range: 0 to 1)**	**Actual value [ft.]**	**Setting (Range: 0 to 1)**	**Actual value [ft.]**
Design Variables	Room Depth	0.4	60.0	0.3	55.0	0.3	55.0
	Roof Height	0.3	10.7	0	2.3	0.2	7.3
	East West Window Width	0.1	2.1	0.1	1.9	0	0.1
	South Window Width	0.3	6.0	0.2	4.4	0.2	4.4
	North Window Width	0.4	8.0	0.4	8.7	0	0.1
	East West Fin Length	0.5	0.3	0.2	0.1	0.5	0.0
	South Overhang Length	1	2.8	0	0.0	0.1	0.3
	South Skylight Width	0.7	2.8	0.8	3.2	0.1	0.5
	North Skylight Width	0.9	3.6	0.3	1.3	1	4.0

Table 5.32 Daylighting and Energy Performance of Pareto Frontiers (Minneapolis, MN)

		Option 1 (Best Option for Daylighting)	**Option 2 (Balanced Option)**	**Option 3 (Best Option for Energy)**
Daylighting Performance Metric [%]	DA	64.5	67.7	41.5
	UDI < 100	21.0	19.7	30.1
	UDI 100-2000	77.8	76.3	67.8
	UDI > 2000	1.2	3.8	2.2
	cDA	75.3	77.2	63.0
	sDA	100	100	26.67
Energy Performance Metric [kBtu/ft^2]	Cooling EUI	3.6	3.2	3.0
	Heating EUI	33.9	30.9	28.0
	Lighting EUI	4.4	4.3	6.4
	Total EUI (Heating, Cooling, & Lighting)	41.9	38.5	37.3

5.3.4 Data Analysis

The same regression method for the energy and daylighting performance are applied to the optimization data in Minneapolis.

Energy Regression Model

The actual by predicted plot, summary of fit, effect summary, and parameter estimates are shown in Figure 5.38, Table 5.33, Table 5.34, and Table 5.35. The fitted model has R-square of 0.97, which is better than the model from the previous two cities. The variables that contribute to the most variance of total energy include roof height, east west window width, north window width and south window width. Figure 5.39 shows the plot of total energy versus two design variables that are the most important in the linear model.

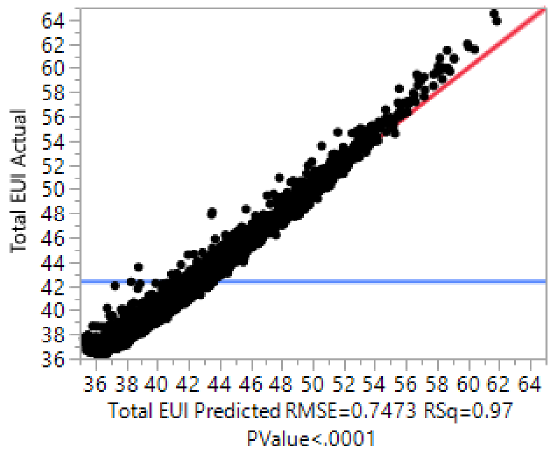


Figure 5.38 Actual by Predicted Plot (Minneapolis, MN)

Table 5.33 Summary of Fit (Minneapolis, MN)

RSquare	0.973154
RSquare Adj	0.973076
Root Mean Square Error	0.747255
Mean of Response	42.43958
Observations (or Sum Wgts)	3113

Table 5.34 Effect Summary (Minneapolis, MN)

Source	LogWorth		PValue
Roof Height	1439.397		0.00000
East West Window Width	1007.430		0.00000
North Window Width	769.089		0.00000
South Window Width	420.682		0.00000
North Skylight Width	50.006		0.00000
Room Depth	26.693		0.00000
South Overhang Length	6.639		0.00000
South Skylight Width	6.069		0.00000
East West Fin Width	2.641		0.00229

Table 5.35 Parameter Estimates (Minneapolis, MN)

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	32.731732	0.093929	348.47	<.0001*
Room Depth	0.0521022	0.004757	10.95	<.0001*
Roof Height	1.1164536	0.007346	151.99	<.0001*
East West Window Width	1.667789	0.016124	103.44	<.0001*
South Window Width	0.5261883	0.010172	51.73	<.0001*
North Window Width	0.775233	0.009551	81.16	<.0001*
East West Fin Width	0.2576307	0.084392	3.05	0.0023*
South Overhang Length	-0.317229	0.061179	-5.19	<.0001*
South Skylight Width	0.2256341	0.045742	4.93	<.0001*
North Skylight Width	0.7231791	0.047401	15.26	<.0001*

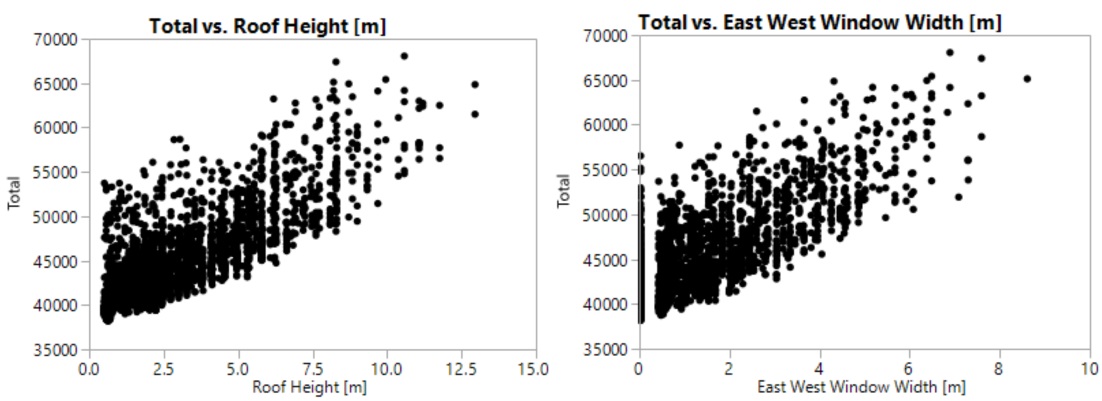


Figure 5.39 Plots of Total Energy against Design Variables (Minneapolis, MN)

Daylighting Regression Model

The actual by predicted plot, summary of fit, effect summary, and parameter estimates are shown in Figure 5.40, Table 5.36, Table 5.37, and Table 5.38. R-square of the model is 0.45. The plots of the most influential design variables are shown in Figure 5.41.

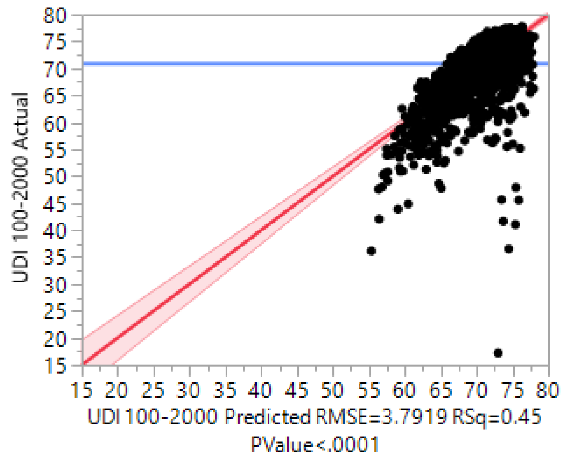


Figure 5.40 Actual by Predicted Plot

Table 5.36 Summary of Fit (Minneapolis, MN)

RSquare	0.449378
RSquare Adj	0.447781
Root Mean Square Error	3.791948
Mean of Response	71.05608
Observations (or Sum Wgts)	3113

Table 5.37 Effect Summary (Minneapolis, MN)

Source	LogWorth	PValue
East West Window Width [m]	164.251	0.00000
South Window Width [m]	100.340	0.00000
South Shading [m]	54.738	0.00000
East West Shading [m]	14.629	0.00000
South Skylight [m]	13.361	0.00000
North Skylight [m]	8.338	0.00000
North Window Width [m]	6.643	0.00000
Roof Height [m]	1.886	0.01299
Room Depth [m]	0.388	0.40940

Table 5.38 Parameter Estimates (Minneapolis, MN)

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	71.101126	0.476646	149.17	<.0001*
Room Depth [m]	0.019916	0.024139	0.83	0.4094
Roof Height [m]	0.092647	0.037276	2.49	0.0130*
East West Window Width [m]	-2.382193	0.081819	-29.12	<.0001*
South Window Width [m]	-1.143445	0.051618	-22.15	<.0001*
North Window Width [m]	0.2514052	0.048469	5.19	<.0001*
East West Shading [m]	3.4097184	0.428245	7.96	<.0001*
South Shading [m]	4.9689505	0.310453	16.01	<.0001*
South Skylight [m]	1.7607314	0.23212	7.59	<.0001*
North Skylight [m]	1.4138622	0.240536	5.88	<.0001*

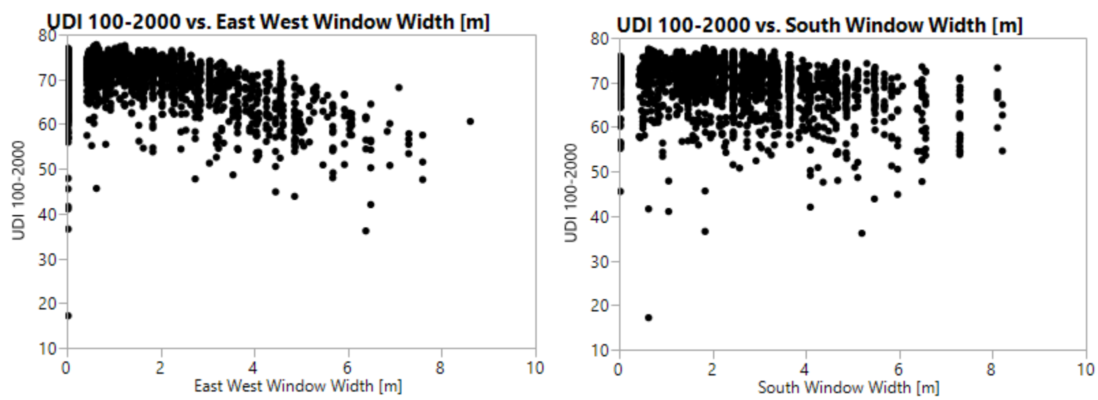


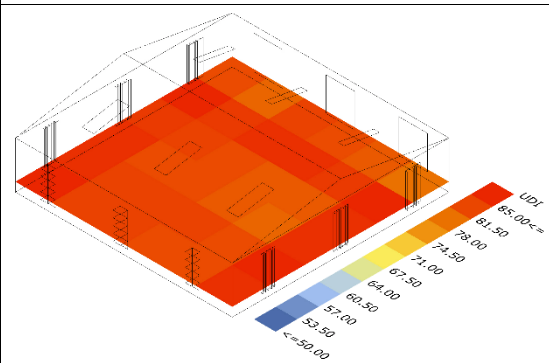
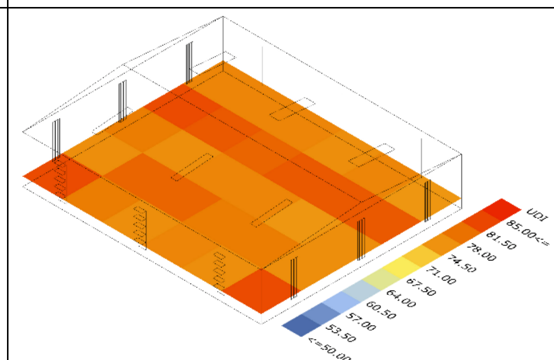
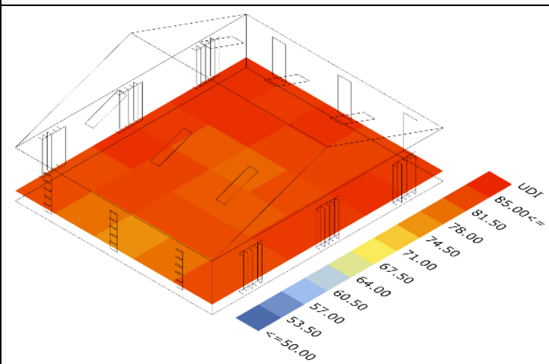
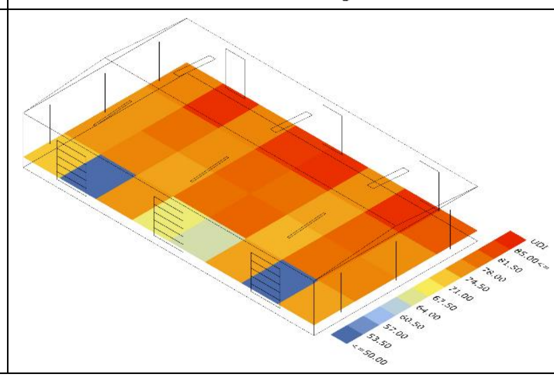
Figure 5.41 Plot of UDI against Design Variables (Minneapolis, MN)

5.4 Comparison of Three Cases

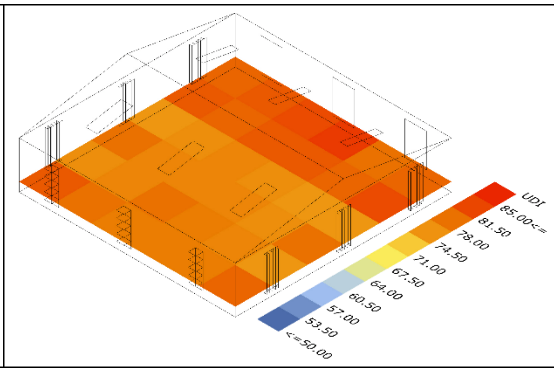
Table 5.39 shows the comparison of the optimized design geometries for daylighting or energy optimization. The building geometries for best daylighting performance have the characteristics of square foot print, low roof slope, middle sized windows on all four facades, and relatively large skylights. Building geometries for the best energy performance have wider facade on the south and north, nearly flat roof, wider windows on south and north, small or no windows on the east and west, and the skylights are relatively smaller.

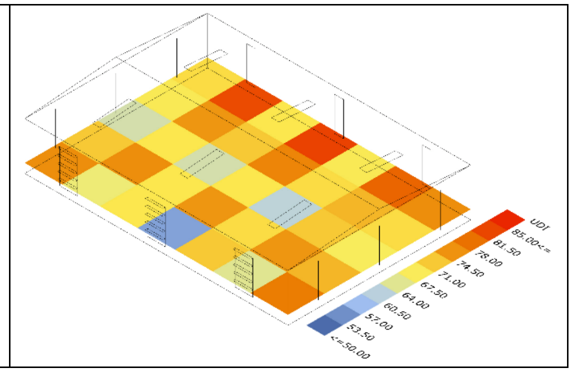
Some features of the optimized building geometry are specific to this building design. For example, because of the locations of skylight, square shaped building makes the distribution of daylight more evenly in the space, so daylight optimal designs are all square shaped. Some features are in accordance with prevalent passive design strategies. For example, smaller facade area and smaller window on the east and west can reduce the unnecessary heat gain into the space and make the building more energy efficient.

Table 5.39 Comparison of Optimized Design

	Daylighting Optimization	Energy Optimization
Orlando, FL		
Raleigh, NC		

Minneapolis, MN





Daylighting and energy optimization processes all achieved significant performance improvement. The results are listed in Table 5.40 and Table 5.41. The largest daylighting performance improvement is found in Orland, and the largest energy performance improvement is found in Minneapolis.

Table 5.40 Comparison of Daylighting Optimization Results

	Orlando, FL	**Raleigh, NC**	**Minneapolis, MN**
Baseline UDI [%]	70.7	69.1	69.4
Optimized UDI [%]	82.1	81.5	77.5
Improvement	16.1%	17.9%	11.7%

Table 5.41 Comparison of Energy Optimization Results

	Orlando, FL	**Raleigh, NC**	**Minneapolis, MN**
Baseline EUI [kBtu/sqft]	32.5	29.6	48.4
Optimized EUI [kBtu/sqft]	25.4	22.6	36.2
Improvement	21.8%	23.6%	25.2%

The regression models for the energy performance generally have good fit, which is because of the strong linear relationship between some design variables and energy load, such as the roof height and window width. The regression models are generally not fit well for the daylighting performance cases, which is because the relationship between UDI and design variables are not linear. The most important variables on energy and daylighting performance are found to be different. Also, the variables are different for different climate zones.

Table 5.42 Comparison of Energy Regression Models

	Orlando, FL	**Raleigh, NC**	**Minneapolis, MN**
R-Square	0.81	0.89	0.97
Most Important Variables	Roof Height Room Depth South Window Width East West Window Width	Roof Height East West Window Width North Window Width South Window Width	Roof Height East West Window Width North Window Width South Window Width

Table 5.43 Comparison of Daylighting Regression Models

	Orlando, FL	**Raleigh, NC**	**Minneapolis, MN**
R-Square	0.56	0.60	0.45
Most Important Variables	East West Window Width South Window Width North Window Width South Overhang Length	East West Window Width South Window Width South Overhang Width East West Fin Length	East West Window Width South Window Width South Overhang Width East West Fin Length

CHAPTER 6: CONCLUSIONS

6.1 Conclusions

This research proposed a building performance optimization process during the early stages of design. The optimization process involves parametric design, daylighting simulation, energy simulation, and Genetic Algorithms. This process allows designers to extensively explore building design alternatives, accurately evaluate daylighting and energy performance of each design, and automatically find designs options with optimal performance.

Extensive literature demonstrated the benefits of daylighting for occupants' health and buildings' energy efficiency, whereas the optimization of both daylighting and energy performance was not properly considered in precedent optimization studies. This research integrated daylighting and energy simulation process, and it was able to evaluate energy efficiency while considering the admission of daylight.

The applicability and effectiveness of this approach were tested through three optimization cases in different climate. Each case included three optimization processes: daylighting optimization, energy optimization, and multi-objective optimization. Through the optimization processes, this method successfully demonstrated the ability to adapt to various design environments, and provide design solutions with significant performance improvement. As a result, this method can be considered a valid approach.

The analysis of optimization data in the three optimization cases also revealed general building performance features in hot, mixed, and cold climate zones. These findings can also be used to further provide design guidelines for sustainable buildings.

6.2 Limitations

The optimization is a complex process, so this method requires advanced computational design ability, energy modelling experience, and proficiency in multiple programs. It is still not ready for architects to seamlessly incorporate into their design process.

The optimization algorithm in this research, genetic algorithm, randomly selects individuals from the current population and uses them as parents to produce the children for the next generation. Because of the random selection process, it is normal that each optimization process generates different design options with different performance. The optimal design found through each optimization process is one of the best options. Mathematically, the global optimal design cannot be found.

The methodology relies heavily on computational power. The optimization time of each scenario is between 24 to 48 hours depending on the speed of the computer processor, even though the case study model has a simple geometry. Also, this optimization process involves multiple programs. Complicated design model could make the data transfer between programs broke and make the optimization process stopped. Therefore, further technical support is needed to deal with more advanced design problems.

6.3 Future Studies

Further work is needed on expanded optimization objectives, including cost, thermal comfort, visual comfort, energy generation, building life cycle performance, etc. Multi-objective optimization is also needed to evaluate multiple performance metrics simultaneously.

Future work also includes the application of this optimization process on real architectural design projects, which could be design projects in architectural design firms or student design works.

Finally, future research is the examination of optimization algorithms and the development of optimization tools. Desired optimization tool should have graphical user interface, powerful optimization algorithms, accurate optimization result, and reduced the optimization time. Multi-disciplinary cooperation is needed in this process.

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