Building Geometry Optimization with Integrated Daylighting and Energy Simulation

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Abstract

This paper proposes an approach for building geometry optimization for energy efficiency using parametric design, daylighting and energy simulation, and Genetic Algorithms. This methodology can extensively evaluate building design options and identify design solutions with optimal energy performance in the early design stage. Integrated daylighting and energy simulation is used to evaluate energy efficiency while considering the energy savings through daylighting strategy. A case study building geometry is optimized in six conditions, and different optimization results are found and compared. The relationships between design variables and building performance metrics are also analyzed through linear regression.

Introduction

Buildings account for a great amount of the world's fossil fuel consumption and greenhouse gas emissions (EIA, 2016). Because of the growing concerns for sustainability, the development of high performance buildings is becoming an intense research topic. Daylight in built environment has a significant impact on the comfort, health, mood, and productivity of the occupants (Edwards & Torcellini, 2002). Daylighting is also an important strategy for reducing energy consumption in buildings. Significant energy savings were found in previous studies (Opdal & Brekke, 1995; Lee & Selkowitz, 2006).

However, since daylight modeling and energy modeling are two parallel procedures, precedent building performance optimization studies were typically limited to single domain optimization. Also, the influence of daylight on the energy performance was usually not considered in energy optimization. This methodology utilizes environmental modeling tools Ladybug and Honeybee (Roudsari & Pak, 2013) to incorporate both daylight and energy simulation performance in the optimization process.

The shape and position of windows and shadings can considerably influence the daylighting and energy performance of buildings. However, they were often overlooked in precedent studies. Traditionally, energy simulation result is mainly determined by the size the windows. Buildings with the same window sizes on each façade and the same settings in other areas would have the same energy simulation result even if the shape and position of the windows vary. However, different shape and position of windows result in different interior daylighting condition, which lead to different lighting energy requirement, and even different heating and cooling energy requirement. This study takes this issue into consideration, and focuses on the optimization of the building geometry; specifically, the shape and position of the windows and shadings.

The proposed building geometry optimization approach consists of parametric design, daylighting and energy simulation, and Genetic Algorithms. The optimization process is executed in Rhino and Grasshopper. Rhino is a 3D modeling program, and Grasshopper is a parametric modeling plugin for Rhino. Parametric design is a design approach that uses parameters and functions to create architectural geometry. There are dynamic links between parameters and geometry, so that numerous design options can be easily generated through the modification of design parameters. The daylighting and energy modeling tools are Ladybug and Honeybee, which are plugins for Grasshopper. The daylighting models are exported to Daysim for daylighting simulation and the energy models are exported to EnergyPlus for energy simulation. After the simulation, daylighting and energy performance metrics are imported back to Grasshopper for the optimization process. The optimization engine Galapagos is a component in Grasshopper. The optimization algorithm used in Galapagos is Genetic Algorithm, which is mimicking the natural selection process in biological evolution (Galletly, 1998). Genetic Algorithm is found to be an efficient and reliable algorithm in building performance studies (Machairas, Tsangrassoulis, & Axarli, 2014).

The case study model is an apartment or office unit with 9 design variables. There are 6 different optimization scenarios: apartment unit in east, south, and west orientations, and office unit in east, south, and west orientations. The optimization objective is to find design options with minimum energy loads considering energy savings from daylighting.

Simulation

Simulation Framework

The overall simulation and optimization framework is shown in Figure 1. The building geometry and design parameters are dynamically linked through the parametric model. Then the parametric model goes through the parallel daylighting and energy modeling processes. Daylighting simulation runs first, and the illuminance at the lighting sensor positions for every hour in a year are calculated. Then according to the daylight illuminance, electrical light is turned off or dimmed, and an annual electrical lighting schedule is generated. The lighting schedule is imported to the energy model, and energy simulation runs after the daylighting simulation. The total energy loads in this study is the sum of lighting, heating, and cooling energy. Since equipment loads stays the same for all simulation cases, it is not included in the total energy loads. The optimization process requires two types of input: the genetic input and the fitness input. The genetic input is the design parameter, which controls the building geometry and performance. The fitness input is the total energy loads, which is the building energy performance metric from the energy simulation. The optimization objective is the minimum total energy loads. The optimization engine automatically modifies building parameters and search for design options towards optimal energy performance.

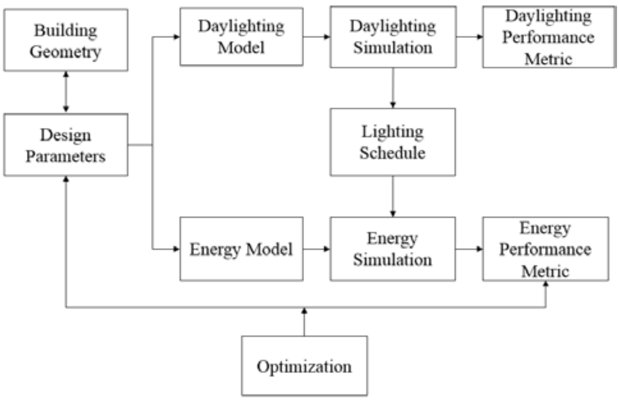


Figure 1: Simulation and optimization framework

Parametric Model

The baseline building model is shown in Figure 2. Each room measures 4.0 m (13.1 ft.) wide, 7.0 m (23 ft.) deep, and 3.0 m (9.8 ft.) high. There is a L-shape shading on the top and left of each window. In the simulation, four neighboring units are modeled. The targeted room is located on the second floor on the left in Figure 2.

The width and height of the room are fixed. The size of the window is also fixed at 3 m^2 (32.29 ft^2). There are 9 design variables controlling the shape and position of the window, shading, and façade. The variable details and their ranges are explained by Figure 3 and Table 1. Each variable is divided into 100 steps within their range, and represented by numbers from 0 to 1. With the combination of different variable values, there are numerous design options, and some examples are presented in Figure 4.

There is a constraint that the height of the window sill should not exceed 1.12 m (44 inch). Besides this constraint, the window can be any rectangular shape, and can be in any position on the facade. The shape of shading is controlled by point A, B and C (Figure 3). Point A moves in x, y, and z directions, while point B and C only moves in y direction. The orientation of the façade (surface DEFG) can be rotated from 20 degrees left to 20 degrees right.

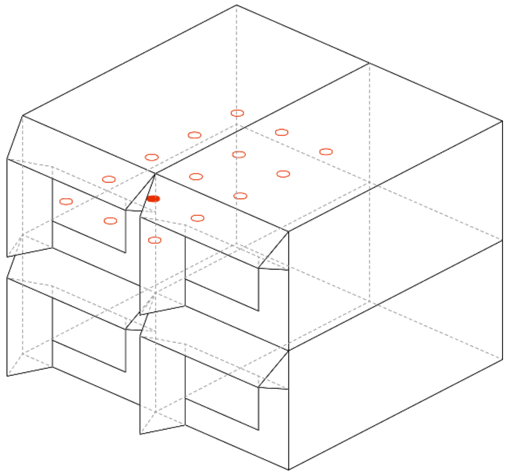


Figure 2: Baseline model

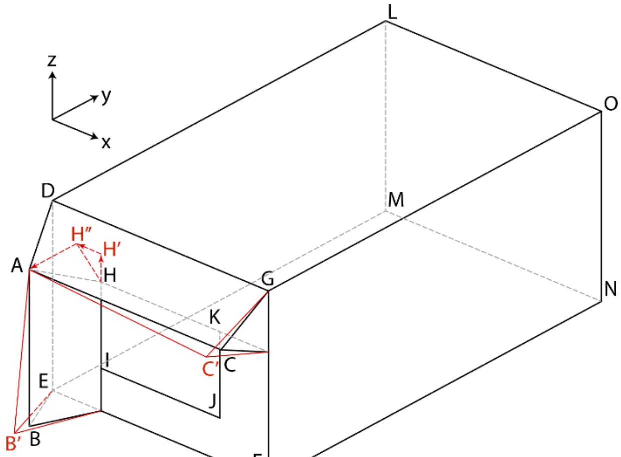


Figure 3: Design variables

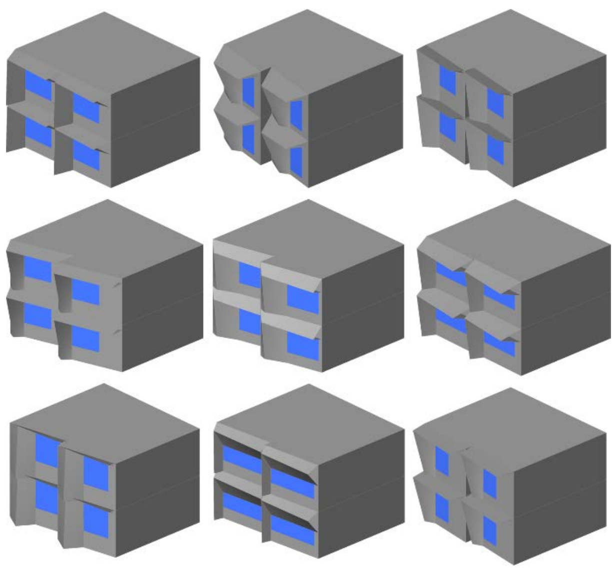


Figure 4: Some design alternatives

Table 1: Design variables and ranges

No.	Design Variables	Variables Details	Range	
			Lower Limit	Upper Limit
1	Façade orientation	The orientation of surface DEFG	20 degrees left	20 degrees right
2	Window shape parameter	The width of the window/the height of the window	0.3	5.3
3	Window position X	The horizontal position of the window: distance between KJ and GF	0	When the window edge HI touches the wall edge DE
4	Window position Z	The vertical position of the window: distance between IJ and EF	0	1.12 m or when the window edge HK touches the wall edge DG
5	Shading A-X	How point A moves in x direction: the distance between point H' and point H"	0	When point A is on surface DEML
6	Shading A-Y	How point A moves in y direction: the distance between point A and point H"	0	2 m
7	Shading A-Z	How point A moves in z direction: the distance between point H and point H'	0	When point A is 0.5 m above surface DGOL
8	Shading B	The distance between point B and point B'	When point B' is on surface DEFG	When point B' is 1 m away from point B
9	Shading C	The distance between point C and point C'	When point C' is on surface DEFG	When point C' is 1 m away from point C

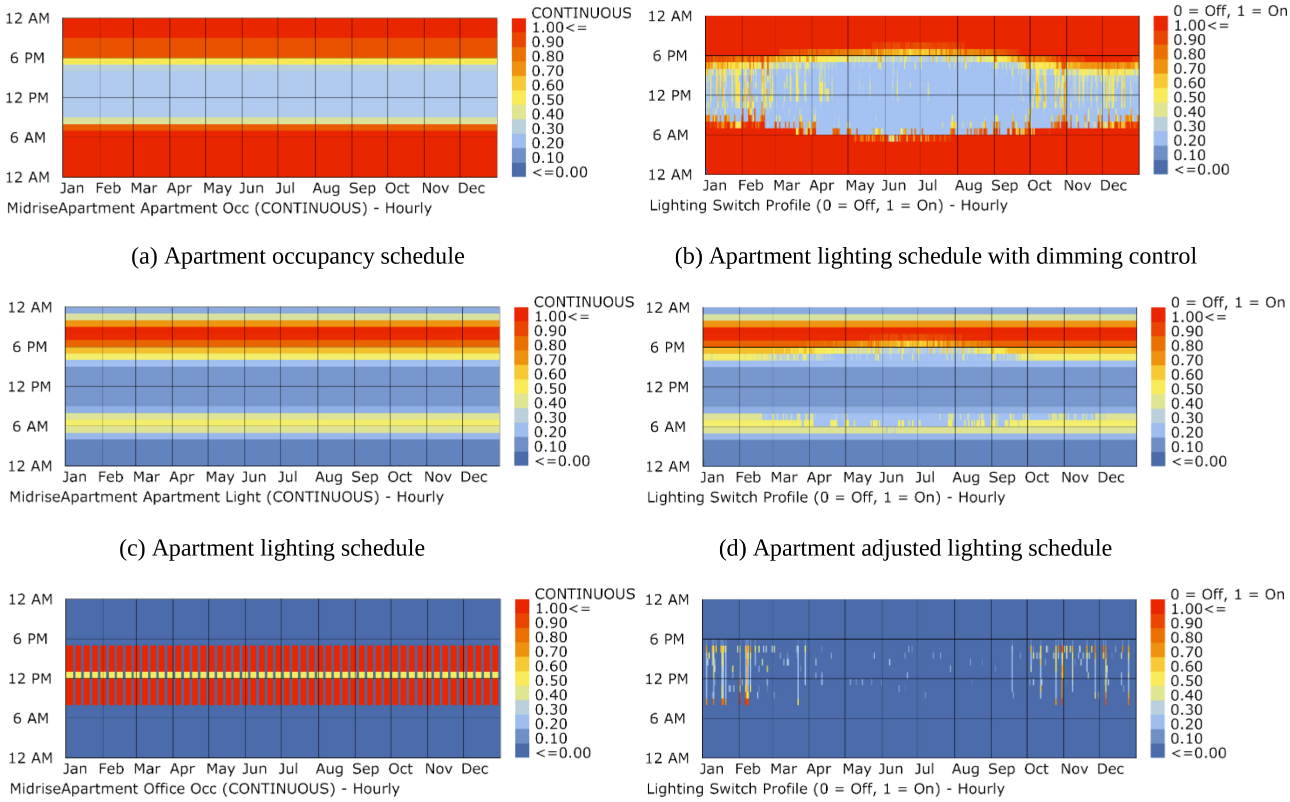
Simulation Setting

The building is located in Atlanta, Georgia. For daylighting simulation, the ceiling, floor, interior walls, and shading use Radiance opaque materials. Their reflectance are respectively 0.8, 0.2, 0.5, and 0.8. The window uses Radiance glass material with visible transmittance of 0.65. 15 daylighting sensors are evenly placed inside the room on the height of 0.8 m (31.5 inch) (Figure 2). Annual illuminance data obtained from the 15 sensors are used to generate daylighting performance metrics UDI. UDI (Useful Daylight Illuminance) is defined as the 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 usually divides the illuminance values into three ranges, 0-100 lux, 100-2000 lux, and over 2000 lux. Illuminance between 100 and 2000 lux is considered useful. In this case, UDI is calculated as the average of the UDI (between 100 and 200 lux) at 15 sensor locations, and it is used to represent the overall daylighting condition of the room.

The middle sensor from the second row (shown as solid red circle in Figure 3) is used as the dimming sensor. The target illuminance of the space is 300 Lux. Electric light would adjust its energy intensity according to the illuminance at the sensor. If the illuminance is above 300 Lux, electric light would be considered turned off. An annual lighting schedule would be generated based on the illuminance of 8760 hours in a year.

However, there is one problem with the lighting schedule generated by current version (0.0.60) of Honeybee. When Honeybee generates the lighting schedule with dimming controls, it would assume the light is 100% on during occupied hours. For example, Figure 5(a) shows the occupancy schedule of midrise apartment, Figure 5(b) shows the lighting schedule with dimming control generated by Honeybee. The light is 100% on at night hours, which is not an accurate representation of light use. To modify this problem, A Python component is added in Grasshopper to compare the original lighting schedule and the lighting schedule with dimming control, and take the minimum value from each hour throughout the year and output an adjusted lighting schedule. Figure 5(c) shows the original lighting schedule of midrise apartment. Figure 5(d) shows the adjusted lighting schedule generated through the python component, which presents the light use condition more accurately. This problem is not obvious in the office condition, since the occupancy schedule and lighting schedule are similar. Figure 5(e) and (f) show the occupancy schedule and adjusted lighting schedule for the office.

Apartment buildings have moderate lighting needs between 6 am to 8 am in the morning, and intense lighting needs from 5 pm to 11 pm at night. Office buildings have intense lighting requirement from 8 am to 5 pm at weekdays. Comparing the adjusted lighting schedule for the apartment (Figure 5(d)) and office (Figure 5(f)), it is obvious that electrical light can be turned off for most of the time in the office case. In the apartment case, only in mornings and evenings in the summer time daylight is sufficient. Therefore, daylighting strategy has more potential for energy savings in office buildings.



(a) Apartment occupancy schedule

(b) Apartment lighting schedule with dimming control

(c) Apartment lighting schedule

(d) Apartment adjusted lighting schedule

(e) Office occupancy schedule

(f) Office adjusted lighting schedule

Figure 5: Lighting schedules

The adjusted lighting schedule is imported to the energy model so that the impact of daylighting on energy simulation is considered. For energy simulation, the model uses OpenStudio template midrise apartment - apartment, and midrise apartment – office for different simulation scenarios. The EnergyPlus materials for the model are default materials defined by Honeybee. The exterior roof, exterior wall, exterior window, exterior floor, interior wall, and interior floor have the U-Value of 0.26, 0.08, 0.42, 0.10, 0.45, 0.26 (Btu/h·ft^{2}·°F). The energy simulation output includes annual lighting energy loads, cooling energy loads and heating energy loads of the case study room.

Optimization Setting

The optimization engine is Galapagos, which is a built-in evolutionary solver of Grasshopper. The design variables are connected to the genetic input of the solver, and the total energy loads is connected to the fitness input of the solver. The optimization objective is the minimum total energy loads. The population of each generation is 50, with 4 times multiplication for the first generation. Galapagos evaluates the relationship between design variables and building performance, and it can narrow down the ranges of design variables that contribute to less energy loads through each generation of data. The optimization process is usually stopped at a certain time constraint or when the building performance stops to improve in a few generations. Another grasshopper plug-in TT Toolbox records the input and output of each simulation process, and the data is exported to an Excel file for further analysis. The six optimization scenarios are based on the same building geometry and follow the same process. The only difference is the orientation of the geometry and the simulation template.

Optimization Results

Each optimization process involves about 1000 simulations, and each process is stopped at the simulation time of about 12 hours. Table 2 shows the optimized design geometry for the 6 scenarios. The design variable values of baseline and optimized design are shown in Table 3. From the optimization result, it can be found that even though the apartment cases and office cases have different loads and schedules, the optimized design geometry show great similarities.

The optimized designs in south orientation have relatively narrow windows. The window is on the upper left corner of the façade. The horizontal and vertical shadings are small and up tilted. The orientation of the facade is the south. The optimized designs in the east and west orientations have wide windows and large shadings. The shadings of the west rooms are even larger than the east rooms. The windows are in the left side of the façade, but the height of the windows vary greatly for the four cases, which needs further investigation. The west facade is rotated to the northwest, while the east facade is rotated towards the southeast. Also, point C in the shading is far away from the façade, and point B in the shading is close to the façade.

Table 2: Optimized designs

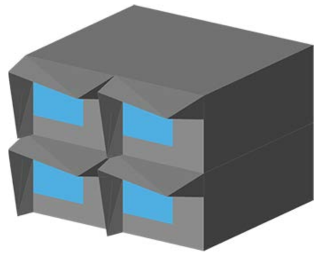
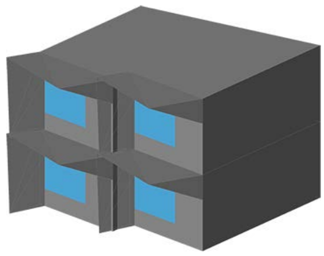
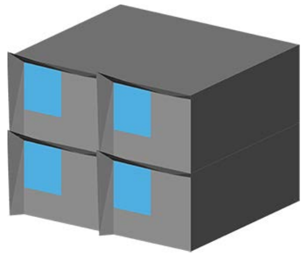
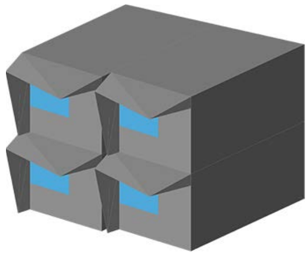
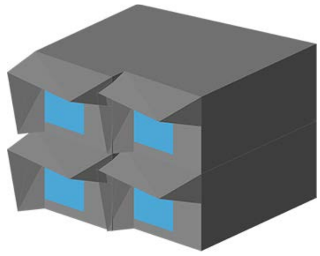
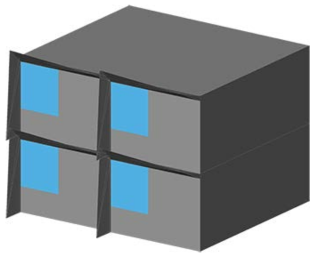
	West	East	South
Apartment			
Office			

Table 3: Design variables of baseline and optimized designs

	Baseline Design	Optimized Design					
		East Office	West Office	South Office	East Apartment	West Apartment	South Apartment
Facade Orientation	0.50	0.29	0.22	0.52	0.48	0.13	0.51
Window Shape Parameter	0.40	0.32	0.35	0.22	0.42	0.41	0.22
Window Position X	0.50	0.8	0.75	0.97	0.8	0.85	0.76
Window Position Z	0.60	0.91	0.34	0.89	0.67	0.6	0.92
Shading A-X	0.50	0.05	0.89	0.58	0.56	0.54	0.63
Shading A-Y	0.50	0.65	0.74	0.33	0.66	0.85	0.3
Shading A-Z	0.30	0.13	0.42	0.89	0.47	0.79	0.77
Shading B	0.50	0.27	0.38	0.53	0.31	0.58	0.26
Shading C	0.50	0.96	0.87	0.74	1.00	0.96	0.83

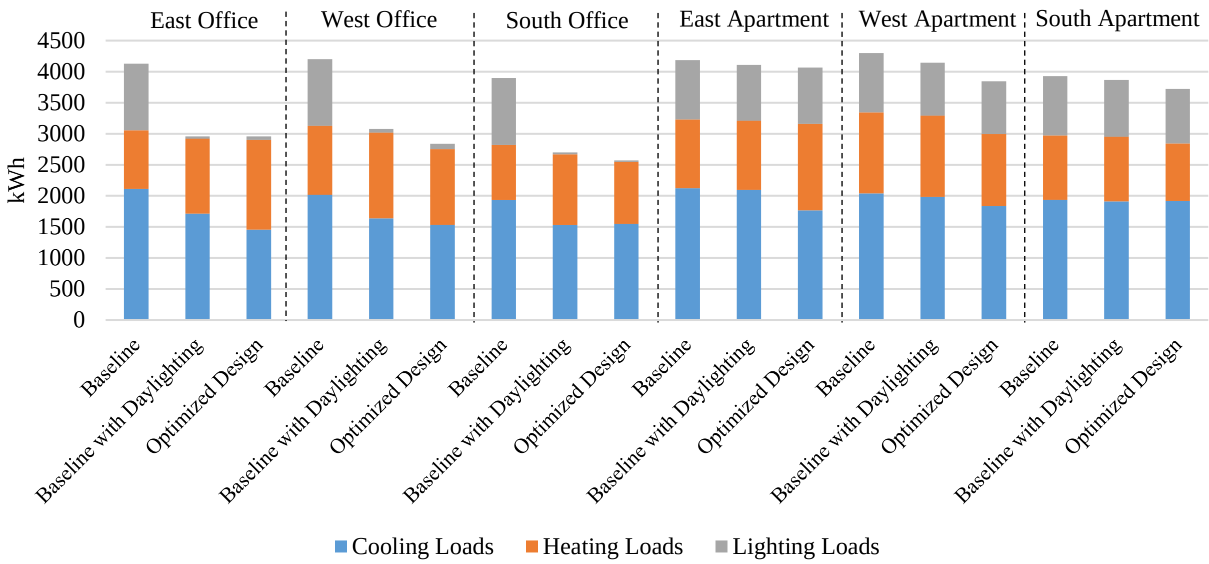


Figure 6: Energy loads comparison

Table 4: Energy loads comparison

		East Office	West Office	South Office	East Apartment	West Apartment	South Apartment
Baseline Design	**Cooling Energy (kWh)**	2,016	2,110	1,931	2,040	2,123	1,933
	Heating Energy (kWh)	1,109	944	889	1,303	1,108	1,040
	Lighting Energy (kWh)	1,075	1,075	1,075	954	954	954
	Total Energy (kWh)	4,200	4,129	3,894	4,297	4,184	3,927
Baseline Design with Daylighting	**Cooling Energy (kWh)**	1,635	1,712	1,526	1,984	2,097	1,911
	Heating Energy (kWh)	1,386	1,210	1,143	1,311	1,111	1,042
	Lighting Energy (kWh)	57	35	28	850	898	909
	Total Energy (kWh)	3,078	2,957	2,698	4,144	4,106	3,863
	Percentage decrease from baseline design	26.7%	28.4%	30.7%	3.6%	1.9%	1.6%
Optimized Design With Daylighting	**Cooling Energy (kWh)**	1,531	1,454	1,549	1,833	1,767	1,913
	Heating Energy (kWh)	1,219	1,448	996	1,160	1,389	929
	Lighting Energy (kWh)	85	54	22	851	911	875
	Total Energy (kWh)	2,836	2,955	2,567	3,844	4,067	3,718
	Percentage decrease from baseline design with daylighting	7.9%	0.1%	4.9%	7.3%	1.0%	3.8%

Figure 6 and Table 4 present the energy performance comparison of the baseline design, baseline design with daylighting, and optimal design with daylighting for the 6 scenarios. As shown, the energy savings are significant from daylighting application alone without optimization. It achieved about 30% energy savings in office buildings and about 1-3% energy savings in apartment buildings. With the reduction in lighting energy, there is also reduction in cooling energy and increase in heating energy.

The energy savings from optimized designs vary greatly for different orientations, but similar for different building types. The energy savings are about 7% in west oriented cases, 4% in south oriented cases, and only below 1% in east oriented cases. Of the three orientations, the south oriented rooms are the most energy efficient, both before and after optimization. One interesting observation is that the baseline cases with west orientation require more energy than the east orientation. However, after optimization, the cases with west orientation have better energy performance than east orientation. One probable reason is that the baseline design happens to be more energy efficient for east orientation, and it is more difficult to be improved.

Analysis

Besides finding optimal design options, the analysis of the relationship between design variables and performance metrics is also important. Since the analysis methods for 6 scenarios follow the same process, only the office case with west orientation is presented as an example.

Through the plotting of the data, linear relationship between design variables and performance metrics is observed. Therefore, linear regression is an appropriate analysis technique. Statistical analysis software JMP Pro 12 is used to fit linear regression models.

In the first model is the energy regression model. Total energy is the dependent variable, and the 9 design variables are independent variables. The interaction effects between independent variables are not considered. The fitted model has R-square of 0.79, which indicates a good fit. The parameter estimates table (Table 5) shows the influence of design parameters on energy performance. The variables that contribute to the most variance of total energy include window position Z, window shape parameter, and façade orientation. Only the effect of window position X is not significant in the model. The exact relationship between design variables and the daylighting performance can be found through data plots. Figure 7 shows the plot of total energy versus three design variables that are the most important in the linear model. Total energy decreases as window position moves higher. Total energy increases as the window shape parameter is larger, which means the window is wider, but the minimum energy is achieved when window shape parameter is about 1.2. Total energy increases as the façade rotates away from the center, but the energy difference is not obvious when the angle is between 0 and 10 degrees.

In the second model is the daylighting regression model. Useful Daylighting Illuminance (UDI 100-2000 lux) is the dependent variable, and the 9 design variables are independent variables. R-square of the model is 0.77, which is also a good fit. The parameter estimates table (Table 6) shows different features from the first model. Shading A-Z, Shading A-X, and Façade orientation are not significant in the model. Facade orientation shows strong relationship with total energy, but show almost no relationship with UDI. Also, shading A-X is not significant in the daylighting regression model, but it is rather important in the energy regression model. The plots of the most influential design variables are shown in Figure 8. UDI increases as window moves higher. UDI decreases as window becomes wider. There is no obvious linear relationship between shading A-Y and UDI from the data plot even though it is significant in the model.

Data plots also reveal the relationship between different dependent variables (Figure 9). For example, the total energy has strong positive relationship with cooling energy, and it has strong negative relationship with heating energy. The relationship between total energy and UDI seems to be quadratic, and the minimum total energy is found when UDI is around 50.

Linear regression approach shows the influence of design variables and the results illustrate the overall data tend, and provide preliminary design suggestions. However, it is not accurate enough for prediction and finding optimal designs.

Table 5: Parameter estimates of the first model

Term	Estimate	Std Error	t Ratio	Prob>|t|
Window Position Z	-160.8028	8.478144	-18.97	<.0001*
Window Shape Parameter	44.329391	4.414274	10.04	<.0001*
Facade Orientation	3.5938509	0.423659	8.48	<.0001*
Shading A-Z	43.416554	5.704077	7.61	<.0001*
Shading A-X	62.495889	10.36041	6.03	<.0001*
Shading A-Y	23.067863	5.028924	4.59	<.0001*
Shading C	-12.51268	4.079395	-3.07	0.0022*
Shading B	13.260656	5.251029	2.53	0.0117*
Window Position X	-4.007947	8.107708	-0.49	0.6212

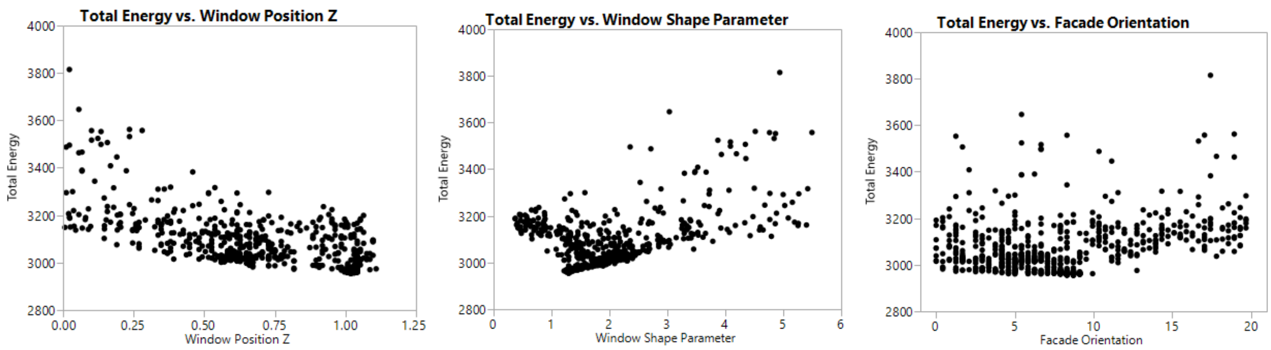


Figure 7: Plot of total energy vs. design variables

Table 6: Parameter estimates of the second model

Term	Estimate	Std Error	t Ratio	Prob>|t|
Window Position Z	28.382128	0.688155	41.24	<.0001*
Window Shape Parameter	-5.628223	0.358298	-15.71	<.0001*
Shading A-Y	-5.98803	0.408188	-14.67	<.0001*
Shading C	-3.9628	0.331117	-11.97	<.0001*
Window Position X	-4.410472	0.658088	-6.70	<.0001*
Shading B	2.206854	0.426216	5.18	<.0001*
Shading A-Z	-0.4815	0.462989	-1.04	0.2986
Shading A-X	-0.599681	0.840935	-0.71	0.4760
Facade Orientation	0.0150382	0.034388	0.44	0.6620

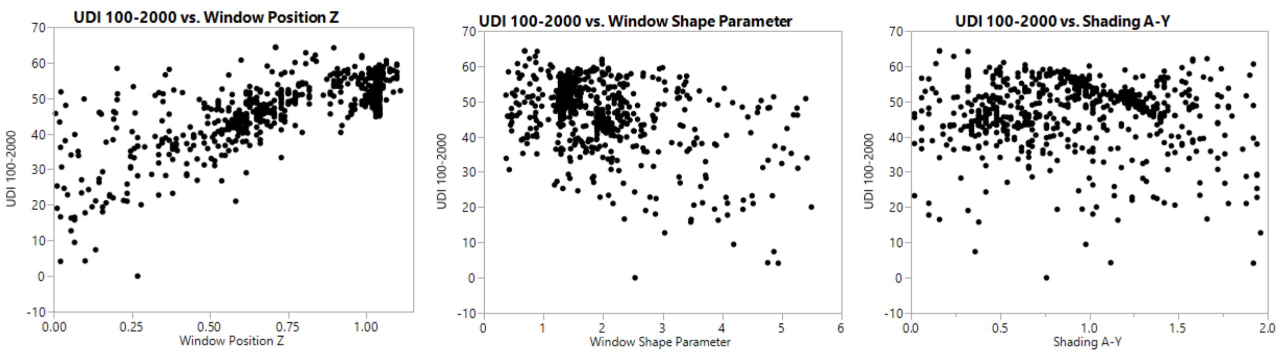


Figure 8: Plot of UDI vs. design variables

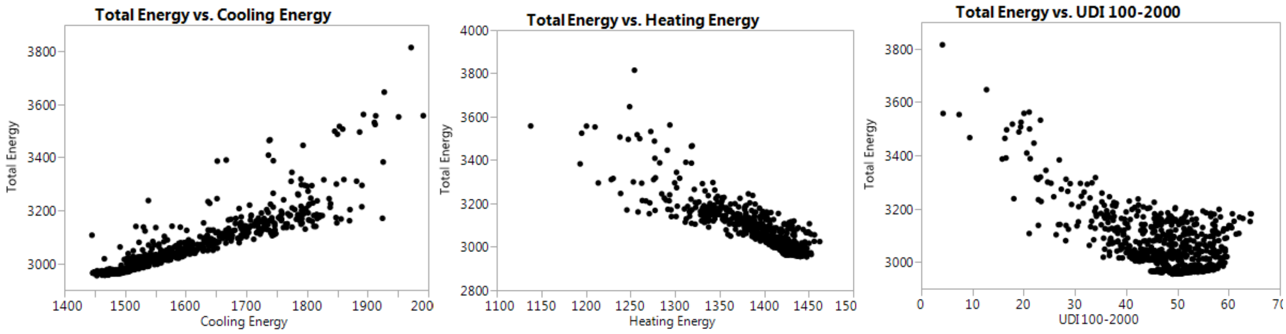


Figure 9: Plot of dependent variables

Conclusion

This paper proposes a building geometry optimization method for energy performance with integrated daylighting and energy simulation, which can more accurately present buildings' energy performance compared to traditional energy simulation. This approach is applied to a single room optimization for window and shading geometry. In the 6 optimization scenarios, this methodology successfully finds different optimized design solutions and achieves different amount of improvement on energy performance. The effects of design variables and the relationship between design variables and performance metrics are found through regression analysis.

However, there are still limitations of this methodology. First, this optimization process is complicated and time consuming. It is currently only appropriate for simple design problems. Second, this approach finds several different optimized design options in different optimization process, and the ultimate best design is not guaranteed to be found. Third, the optimization result is only valid for the specific design scenario. Special attention is needed when providing design suggestions based on the features of optimal design and relationships between design variables and building performance.

Further work is needed on extended optimization objectives, such as the cost, thermal comfort, visual comfort, energy generation, building life cycle performance, etc. Multi-objective optimization is important to evaluate multiple performance metrics simultaneously. Future work is also needed on the comparison of different optimization algorithms on building geometry optimization problems.

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