SIMULATION-BASED OPTIMIZATION OF WINDOW PROPERTIES BASED ON EXISTING PRODUCTS

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ABSTRACT

Before selecting new windows for a building, consideration of what types of windows will work optimally to improve building energy efficiency is paramount. In this decision process, three key factors are fundamental to assess windows performance: Visual Transmittance (VT), Solar Heat Gain Coefficient (SHGC), and U-factor. However, using low SHGC windows may decrease the building cooling loads, but has the potential to increase both heating and light loads due to the coatings, tints, and films applied to achieve the low SHGC. This paper introduces a genetic algorithm optimization approach to the selection of these three important window properties for the goal of energy efficiency, based upon the glazing product database of the National Fenestration Rating Council (NFRC). End energy use and savings associated with the optimized window properties are compared with baseline models. The findings of this research will benefit designers, contractors, suppliers, property owners and researchers to identify optimum window properties from databases of existing window products, which would help to further improve building energy efficiency.

INTRODUCTION

Windows are an important element in energy efficient building design, and contribute to annual energy consumption, indoor lighting conditions, and view out for occupants. With respect to heating and cooling loads, studies have estimated that about 20-40% of total energy use is attributable to heat loss or gains through building fenestration (Warner, 1995; Bülow-Hübe, 2001; Grynning et al., 2013). In terms of artificial lighting, electrical lighting loads have been demonstrated in some studies as a major building energy end use, accounting for as much as 22% in office buildings and 15% in residential buildings in the U.S. (Pérez-Lombard et al., 2008). In addition to building loads, windows also influence daylighting performance (Ruck, 2006; Doulo et al., 2008), and other non-energy factors, such as view out, visual comfort, work productivity, human physiology and behavior (Edwards et al., 2002; Veitch et al., 2004; Lee, et al., 2013). Therefore, the selection of a proper window system is one of the most important strategies for effectively conserving energy in buildings and improving daylighting performance (Warner, 1995; Galasiu et al., 2006). Before selecting new windows for a building, consideration of what types of windows will work optimally to improve building energy efficiency is paramount. In this decision process, three key factors are fundamental to assess windows performance: Visual Transmittance (VT), Solar Heat Gain Coefficient (SHGC), and U-factor.

- VT: The fraction of visible portion of spectrum transmitted through a window. The higher the VT, the more daylight to be transmitted to the interior, which may offset electric lighting, especially for the spaces with a large lighting demand. It has been reported that window's VT ranges from above 90% to less than 10%, determined by glazing type, number of panes, and glass coatings or films (Commercialwindow, 2016).
- SHGC: The fraction of incident solar radiation transmitted through a window. The lower SHGC (which is mainly used in cooling-dominated weather), the less solar heat gains. One way the low SHGC is achieved through low emissivity (Low-E) coatings.
- U-factor: The rate of heat loss of a window assembly. The lower the U-factor, the greater a window's resistance to heat flow. A low U-factor can be obtained using double or triple panes, air gaps, inert gas fillings, low-e coatings, and others.

The previous work by the authors have been focused on the optimization between SHGC and VT based on the existing window products (Wang et al., 2016). However, that optimization study is limited in hot climates due to the strong conflicting relation between SHGC (cooling loads) and VT (lighting loads). In order to conduct a comprehensive optimization study on broad weather conditions, this research work involves U-factor into the optimization study. Figure 1 shows basic correlations among these three variables and correlated building loads. The dotted lines represent indirect effects of the window's properties on building loads. For instance, internal heat gains due to electric lighting in office buildings may result in a significant proportion of the total cooling load during hot summer months (Lam et al., 1999). In general, these three variables are significantly correlated to building HVAC loads and lighting loads, but there are also other inter-correlations among them.

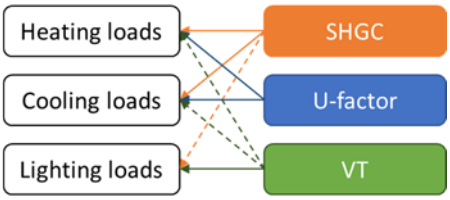

Figure 1. Correlations of the three factors and building loads

1) SHGC vis-à-vis VT

There has long been an interest in using Light-Solar-Gain ratio to analyze the visual properties of glazing systems vis-à-vis solar heat gains and energy conservation in buildings (McCluney et al., 1993; McCluney, 1996). LSG ratio is defined as the ratio between VT and SHGC. A high LSG ratio is considered as an "ideal" window indicator because, while controlling transmitted solar infrared thermal radiation, the ideal window should be able to also transmit as much visible light as possible, to avoid high electrical lighting loads (Correa et al., 2004).

Among current glazing products, except for the ones with spectrally selective coatings, low-SHGC glazing types are achieved by adding a tint or traditional low-e coatings, which also substantially reduce VT values (Commercialwindow, 2016). Although spectrally selective low-e coatings may slightly increase VT under low-SHGC configurations, the VT value still decreases somewhat compared with uncoated glazing or with other high-SHGC glazing types.

2) U-factor vis-à-vis VT

Several techniques can be used to reduce a window's U-factor, such as multiple-pane units with central gap filled with various gases, low-e coatings, and transparent insulation (e.g. honeycomb materials, porous materials). Compared with clear soda-lime glass, these techniques normally reduce visible transmittance, as light needs to pass through multiple transparent layers or coatings. Furthermore, these units often have thicker frames which will affect the overall window's VT according to the NFRC rating method (NFRC, 2016). Table 1 shows a few typical glazing systems' U-factor (in IS units) and VT (Bliss, 2006).

Table 1. Typical glazing U-factors （SI units） and VT (center of glass)

Type of glazing	*U-factor*	*VT*
Single glazing, clear	5.68	0.9
Double glazing, clear	2.84	0.81
Double glazing, low-e	1.99	0.75
Double glazing, low-e, argon	1.65	0.75
Double glazing, spectrally slective low-e, argon	1.42	0.71

As a consequence, a low U-factor may reduce heating and cooling loads but deteriorate daylighting performance, which might increase lighting loads, and internal heat gains from electrical lights. The reduction of SHGC may reduce cooling loads in the summer season, but it also has the potential to increase heating loads in the winter. The energy efficiency effectiveness of selecting different types of window or glazing products is then an obvious optimization problem, also because it varies with other variables such as geographical area, building use, and utility rates.

An approach known as parametric energy simulation has been used in similar optimization problems, to identify "optimal" building shapes, orientations, envelope properties, and other components for improving building energy efficiency. The input of each variable is varied to assess its effect on design objectives, while correlated variables are parametrically changed under the user's definition and design constraints (Nguyen et al., 2014). Due to the iterative nature of the procedure, these methods are often automated by computer programming. The use of such methods is known as simulation-based optimization, which has become an efficient measure to satisfy several stringent requirements of building performance (Wang et al, 2005; Fesanghary et al., 2012; Bambrook et al., 2011; Castro-Lacouture et al., 2009). Although the scientific literature is vast on publications on window or glazing factors influencing building energy use, these studies usually analyze limited number of window models or hypothesized window properties. A systematic research, combining measured properties of existing market products with a large sample number, has been rarely found. In this respect, this paper contributes to existing scientific literature in that it brings the actual existing product directory from NFRC database into the realm of simulation-based optimization studies.

The aim of this research work is to perform a multiple regression analysis of window factors based on the large database of existing window products certified by NFRC, and subsequently integrate this regression model into an *EnergyPlus* simulation-based optimization study, to identify optimal window properties for a given location. Three different U.S. cities representing different climates were selected for this optimization study: Phoenix, AZ; Baltimore, MD; and Chicago, IL. This research adopted Pacific Northwest National Laboratory (PNNL) commercial prototype models (PNNL, 2006), which comply with ASHRAE 90.1-2013 standard, as baseline models. Building energy use and savings, achieved by selecting optimal window properties (VT, SHGC, and U-factor) determined by the optimization process, are analyzed and compared with baseline models.

METHOD

1) Database of Window Products

NFRC developed a nationally recognized rating and labeling system, for the energy performance of windows in the U.S., which provides consumers with a way to compare the thermal and visual properties of windows. Manufacturers who have certified their products through the NFRC Certification Program can be found in the NFRC Certified Products Directory (NFRC, 2014). Through randomly searching and downloading window products, we formed a large database that covers nearly 8,000 different manufacturer product lines and more than 550,000 NFRC-certified fenestration products. Among the properties of each window product, SHGC, VT, U-factor, and emittance were selected from the dataset. Unfortunately, the original NFRC database does not directly provide emittance (E) values for each window product, but instead offers glazing layer numbers and corresponding emittance for each layer (e.g. 0.022(2), 0.76(3)). E was calculated by Eq. (1).

$$E = \frac{1}{1/E_1 + 1/E_2 + \ldots + 1/E_n - (n-1))} \qquad (1)$$

Where E is overall emittance, n is number of layers.

Statistical information on the four variables is presented in Table 2. This table also includes the calculated LSG values which show a deliberate large scatter and ensure that the broadest range of both non-spectrally selective and spectrally selective glazing systems was chosen. SHGC, VT, U-factor (in IS units), E, and LSG span 0.02-0.89, 0.01-0.89, 0.51-6.08, 0.01-0.84, and 0.13-2.46 respectively, indeed indicating glazing systems of very diverse properties and performance.

Table 2. Basic statistics of database used in this work

	SHGC	*VT*	*U-factor*	*E*	*LSG*
Max	0.89	0.89	6.08	0.84	2.46
Min	0.02	0.01	0.51	0.01	0.13
Ave	0.31	0.41	1.70	0.1	1.45
Median	0.27	0.43	1.65	0.03	1.59

Figure 2 presents pair-wise relationships between the variables of the selected sample dataset. From this figure, we can see that both VT and U-factor have approximate linear relationship with SHGC, and the relationship between E and SHGC is quadratic. The correlation matrix of these four variables in Table 3 also indicates that SHGC has strong associations with the other three values. Comparatively, the other three variables are not strongly inter-correlated (except for the relationship between E and U-factor).

Table 3. Correlation matrix of the four variables

	SHGC	VT	E	U-factor
SHGC	1	0.71	0.50	0.40
VT	0.71	1	0.11	0.075
E	0.50	0.11	1	0.72
U-factor	0.40	0.075	0.72	1

Based on these results, we built several regression models by taking SHGC as response (dependent variable), and the other three as predictors (independent variable), which forms $SHGC = f(VT, U, E)$. The process of determining the coefficients of regression models for an equation is known as training the model. For this research, a stepwise search algorithm was developed for parameter optimization. A selected set of values of the parameter was supplied to the algorithm. Finally, the parameter that yielded the maximum accuracy was selected. The statistical index used to evaluate the accuracy of the generated models was Mean Squared Prediction Error (MSPE).

$$MSPE = ave\{(predicted\ SHGC - actual\ SHGC)^2\} \qquad (2)$$

2) Reference Models and Simulation Inputs

The U.S. Department of Energy (DOE), in conjunction with three of its national laboratories, developed commercial reference buildings, formerly known as commercial building benchmark models. These reference buildings play a critical role in the program's energy modeling software research by providing complete descriptions for whole building energy analysis using EnergyPlus simulation software. In this study, we adopted the *small office building model* (Figure 3) simulated for the three representative cities mentioned above. This reference model for each city was generated by PNNL and complies with ASHRAE 90.1-2013 energy efficiency standard, the latest available version. Table 4 shows the basic information of the selected reference models.

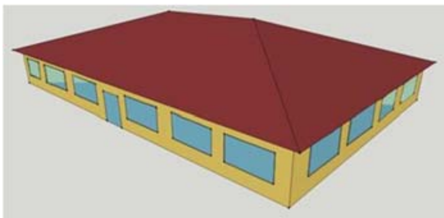

Figure 3. PNNL prototypical office model

Table 4. Basic information of the reference models

Total Floor Area (sqaure meters)	511			
Aspect Ratio	1.5			
Number of Floors	1			
Window Fraction (Window-to-Wall Ratio)	24.4% for South and 19.8% for the other three orientations (Window Dimensions: 2.7 m x 1.5 m. punch windows for all façades)			
Floor to floor height (m)	3			
Floor to ceiling height (m)	3			
Climatic zone (U.S.)	2A	3C	4B	5A
Roof R-value (IS)	R-6.7	R-6.7	R-8.6	R-8.6
Wall R-value (IS)	R-2.3+ R-0.7 c.i.	R-2.3+ R-0.7 c.i.	R-2.3+ R-0.7 c.i.	R-2.3+ R-1.8 c.i.
Window U-factor (IS)	2.56	2.33	2.16	1.99
Window SHGC	0.25	0.25	0.26	0.26

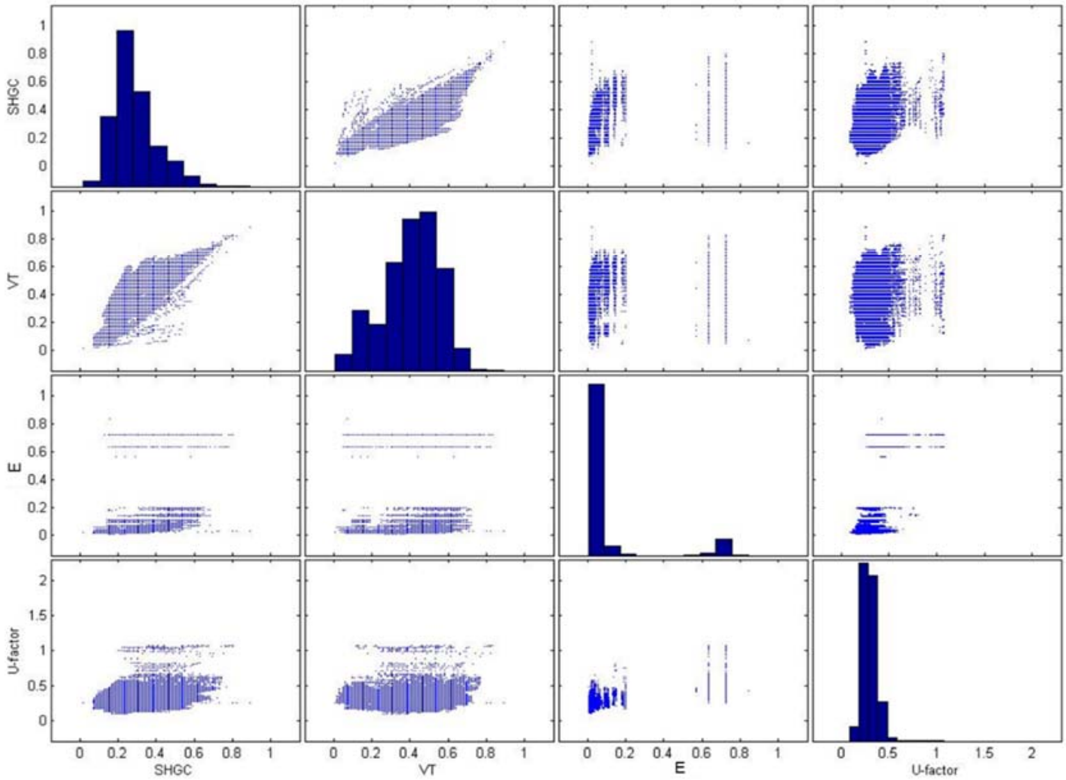

Figure 2. Pair-wise relationships between the variables

3) Optimization Approach

In the field of simulation-based optimization, Genetic Algorithms (GA) have attracted much research interest in sustainable building design and have been used to search the best design options of a building in the Mediterranean area (Znouda et al., 2007), the optimal conceptual design settings for life cycle cost and energy (Wang et al., 2005), the optimal external venetian blinds and overhangs for both energy and daylighting distribution (Manzan, 2014.), and other design goals. The optimization software used was GENE_ARCH, which uses *EnergyPlus* (version 8.0) as its simulation engine, and Pareto Genetic Algorithms for multi-objective optimization (Caldas, 2008). GENE_ARCH was developed to help architects in the creation of energy-efficient and sustainable architectural solutions, by using goal-oriented or inverse design, a method that allows the user to set building performance goals and have the software search a given design space for architectural solutions that respond to those requirements (Caldas et al., 2003).

This study did not apply Pareto optimization but a single fitness value. The objective used was minimizing annual energy consumption, including spacing heating, cooling, ventilating, and lighting loads. Based on our assumption, SHGC, U-factor and VT are in conflict with each other in terms of heating and cooling loads, and lighting loads. With the exception of SHGC, U-factors, and VT of windows, all other properties and components of the existing reference models remain unchanged. This ensures that the optimal combination of SHGC, U-factor, and VT can be identified.

In the GENE_ARCH interface, both VT, U-factor, and E were set as independent variables. Although their discretization is determined by the user, their actual value is automatically generated by GENE_ARCH; SHGC was a dependent variable, resulting from the regression equation: $SHGC = f(VT, U, E)$. The values generated for each variable were then used to guide different window selections. The optimal window properties identified by GENE_ARCH, and corresponding energy use (HVAC and lighting loads), were then compared with the original reference models.

RESULTS

1) Multiple Regression Model

Based upon the aforementioned methods, we firstly built the following five regression models. Among these five models, Model A is the simplest one, which has linear terms. The most complicated model we considered in our analysis is Model E, which includes all the quadratic terms and intersections.

Model A: $SHGC = \beta_0 + \beta_1 VT + \beta_2\, E + \beta_3 U + \varepsilon$

Model B: $SHGC = \beta_0 + \beta_1 VT + \beta_2\, E + \beta_3 U + \beta_2\, E^2 + \varepsilon$

Model C: $SHGC = \beta_0 + \beta_1 VT + \beta_2\, E + \beta_3 U + \beta_4\, E^2 + \beta_5 VT *\ E + \varepsilon$

Model D: $SHGC = \beta_0 + \beta_1 VT + \beta_2\, E + \beta_3 U + \beta_4\, E^2 + \beta_5 VT *\ E + \beta_6\, VT^2 + \varepsilon$

Model E: $SHGC = \beta_0 + \beta_1 VT + \beta_2\ E + \beta_3 U + \beta_4\ E^2 + \beta_5 VT *\ E + \beta_6\ VT^2 +\ \beta_7 VT * U + \beta_8 E * U + \beta_8\ U^2 + \varepsilon$

The following step was to randomly divide the whole dataset, which has 555,383 samples, into three parts: training set, validation set, and test set. We randomly chose 50% (277,692 samples) of the dataset as the training set, which was used to fit the model, 25% (138,846 samples) as the validation set, which was used to calculate Mean Squared Prediction Error (MSPE) for model selection, and the remaining 25% part (138,845 samples) as the test set, which was used for the assessment of the model. After that, we used the training set to fit these models, and used the validation set to find the MSPE for each model, as shown in Table 5. Even though Model D and Model E are more complex than Model C, they do not have a better performance in prediction. Thus, Model C was selected as the final model.

Table 5. Summary of the five regression models

Model	***A***	***B***	***C***	***D***	***E***
MSPE	0.0038	0.0024	0.0023	0.0023	0.0023

The fitted function for Model C is:

$$SHGC = 0.023 + 0.44 * VT + 1.88 *\ E + 0.002 * U - 2.38 *\ E^2 + 0.28 * VT *\ E \qquad (3)$$

The R-Square of the above model is 0.81, which means 81 percent of variability in SHGC can be explained using these three predictors. We also tested the accuracy of the final model. As shown in Figure 3, the goodness of fit for the training and testing data of the final model is graphically illustrated in the left and right plots, respectively. Data points are in general very close to the red line, which is the locus where there is no error between the predicted and the actual values, showing a quite accurate fit for the model. Moreover, the scatter of data points is almost similar in both plots in Figure 4. Therefore, it can be inferred that the model does not suffer from problems of under fitting or over fitting (both over and under fitting lead to poor predictions on test data sets).

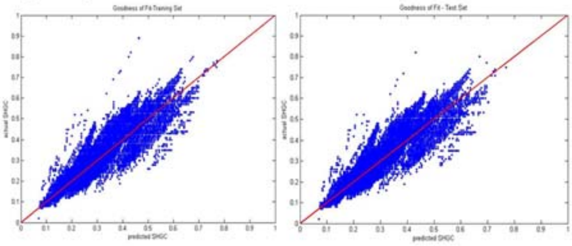

Figure 4. Fit goodness for the training data (left) and testing data (right)

2) Optimal Window Selection and Energy Results

The above multivariate regression model $SHGC = f(VT, U, E)$ was then integrated into GENE_ARCH. The algorithm was run for 200 generations; the population size was 25 individuals, with a total of 5,000 simulations for each city. Optimal window settings were identified, as shown in relation to the original window properties in the reference models in Table 6.

Table 6. GENE_ARCH optimized window properties in relation to reference values

	Reference Models			***Optimized Models***		
	VT	SHGC	U	VT	SHGC	U
Miami	0.28	0.23	3.52	0.20	0.14	1.14
Memphis	0.28	0.23	3.18	0.48	0.24	0.85
Chicago	0.28	0.22	2.38	0.52	0.26	0.79

Figure 5 presents HVAC and lighting energy use for the optimal window VT and SHGC values for each city, and compares their energy use with the three reference models. Energy savings range between ~7.1-8.2GJ for the selected office model. As expected, energy savings happen in these three cities, where the optimized VT, U, and SHGC factors are obviously away from the standard values. Mixed climate conditions in Chicago and Memphis achieved slightly higher energy savings compared with hot climate conditions in Miami. It also can be seen from this figure that the electrical lighting energy savings by increasing window's VT were not as high as what we expected. The main reasons are two-fold: one is related to the value of "% Zone covered by Lighting Sensor Area", which is only ~24% percentage in the DOE prototypical reference models. This can significantly reduce the utilization of daylight. Another reason is involved in lighting control schemes which are set as "Stepped" in all reference models. Compared with continuous lighting control with dimming electrical lights, stepped control modes using discrete blocks can adversely dampen the daylighting effects. However, since the objective of this research is to demonstrate our proposed simulation-based optimization method based on existing window products, an accurate comparison between optimized window factors and standard window factors in reference models was essential. Thereby, we adopted the same settings of lighting sensor zone percentage and control modes in our optimized models. The further savings by manipulating these settings will be focus of future research work.

Finally, we searched the identified optimal VT, U-factor, and SHGC values in the original database of the NFRC certified product directory, and a few window products with similar properties were easily confirmed as existing glazing products available in the market.

CONCLUSION

We conducted a GA optimization study to seek best VT and SHGC window properties for three different US cities. The database of NFRC certified products was used to generate a multivariate regression model which was subsequently used as input into GENE_ARCH for optimization. Resulting combinations of VT, U-factor, and SHGC were

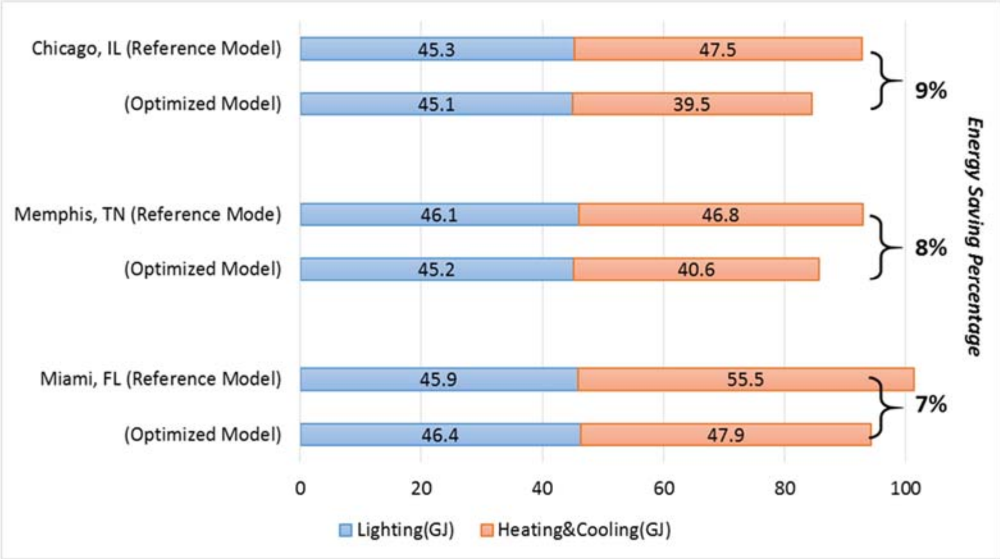

Figure 5. Energy savings of the optimized window settings in comparison to reference models

compared with reference models that meet ASHRAE 90.1-2013.

Research findings based on a small office model indicate apparent energy savings by the selection of optimal window properties. As discussed, in this work we adopted the same lighting control scheme and lighting sensor controlled area that exist in the reference models, which technically decrease the daylighting effects on building lighting loads. Furthermore, the building typology used, with small window openings and internal electrical lighting requirements, can also degrade the resulting energy savings. Higher energy savings may be found for buildings with large fenestration areas and high electrical lighting demands. Future work will be conducted for different building types and daylighting control methods. Also, the comparisons to other optimization tools, such as JEPlus and EA will be conducted.

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