Adaptive Personalized Shading Control Strategies To Maximize Occupant Satisfaction While Reducing Lighting Energy Use In Buildings

Jie Xiong
Lyles School of Civil Engineering, Purdue University, West Lafayette, Indiana USA / Center for High Performance Buildings, Ray W. Herrick Laboratories, Purdue University, West Lafayette, Indiana USA, xiong29@purdue.edu

Seungjae Lee
lee1904@purdue.edu

Athanasios Tzempelikos
ttzmepel@purdue.edu

Panagiota Karava
pkarava@purdue.edu

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Personalized Shading Control Strategy to Maximize Occupant Satisfaction while Minimizing Lighting Energy Use by Multi-Objective Optimization

Jie XIONG1,2*, Seungjae LEE1,2, Athanasios TZEMPELIKOS1,2, Panagiota KARAVA1,2

1 Purdue University, Lyles School of Civil Engineering, West Lafayette, Indiana, USA
Email: xiong29@purdue.edu, lee1904@purdue.edu, ttzempel@purdue.edu, pkarava@purdue.edu

2 Ray W. Herrick Laboratories, Purdue University, Center for High Performance Buildings, West Lafayette, Indiana, USA
Email: xiong29@purdue.edu, lee1904@purdue.edu, ttzempel@purdue.edu, pkarava@purdue.edu

* Corresponding Author

ABSTRACT

In this study, a personalized shading control framework is developed to maximize occupant satisfaction while minimizing lighting energy use using a multi-objective optimization scheme. A personalized satisfaction model was developed based on specially-designed experiments in private offices, to quantify the occupant satisfaction level with motorized roller shades by predicting the override probability of occupants considering different variables. Then, a multi-objective optimization algorithm was constructed, considering the shading override probability and predicted lighting energy use as objectives, where the occupants are the decision makers in the final balancing between their personalized comfort limits and energy use considerations. The developed method serves as a prototype study on adaptive shading control with learned personalized comfort profiles and parallel energy use considerations.

1. INTRODUCTION

Occupants play a significant role in energy use of buildings, while they have a strong preference for customized indoor environment. Their perception of controlled environment affects their productivity and well-being. In perimeter building zones with glass facades, shading systems are used as comfort delivery systems under dynamic conditions, affecting daylight provision, view and lighting energy use.

Previous studies (Van Moeseke et al. 2007; Tzempelikos and Athienitis 2007; Nielsen et al. 2011; Shen and Tzempelikos 2012; Grynning 2014) have proven the energy benefits of automated shading control strategies, while occupant dissatisfaction issues with respect to visual comfort could arise with such systems (Reinhart and Voss 2003; Lee et al. 2013). Preventing direct sunlight associated with visual discomfort has been the topic of previous studies, using blind cut-off angles (Tzempelikos, 2013) and sun glare considerations (Guillemin and Morel 2001; Zhang and Birru 2012; Din and Kim 2013), including blind optical properties and overall glare evaluation (Chan and Tzempelikos, 2013). Existing glare indices such as DGI have been used as constraints in optimization studies aiming at reducing energy use (Chaiwiwatworakul et al. 2009; Oh et al. 2012), while Wienold et al. (2011) compared different shading devices and simple rule-based controls through simulation with respect to energy performance and visual comfort. More recently, simple and more advanced model-based shading control strategies for venetian blinds (Chan et al., 2015) and roller shades (Xiong and Tzempelikos, 2016) have been proposed considering overall daylight discomfort glare using detailed optical properties and validated daylight-glare models. Several studies developed probability models of occupant actions of shading and/or lighting with a single variable (Reinhart 2004; Gunay et al. 2014a; Zarkadis et al. 2015; Wang et al. 2016) or multivariate (Haldi and Robinson 2010; Fabi et al. 2015), and incorporated the models in shading and/or lighting control (Gunay et al. 2014b). Gunay et al. (2015) compared the effects on energy consumption of existing behavioral models by simulation, but validation and verification of compared models were not investigated.
There are three main challenges with the current and previous approaches related to “optimal” shading and lighting controls, and considerations of visual comfort, occupant satisfaction, and energy use. First, with very few exceptions that considered occupant preferences of some kind (Guillemin and Molteni, 2002), the standard approach has been to try to satisfy visual comfort criteria using heuristic, model-based or simple occupant-based lighting/shading controls, based on existing indices. However, dissatisfaction with the visual environment, especially in perimeter offices, could still exist even if specific criteria are met, since it depends on several factors, personal and subjective preferences. Moreover, development of shading interaction models are challenging by default, since visual conditions in perimeter zones are dynamic and multivariate, and there is no agreement between different studies. But even when advanced probabilistic models are developed based on short or long-term studies, the studies are specific to the shading type used and space functionality and layout, and there is no standard procedure to quantify the uncertainty involved in this type of models or to guide the selection of the right set of variables (including non-physical variables). Therefore, the development of personalized visual comfort profiles related to shading operation, including a generic set of physical and human variables, are required, with quantified implications on energy use. Second, existing models were developed for the case of manual shading controls (no automation or motorization), which cannot reflect occupant satisfaction and corresponding interactions with motorized shading or fully automated systems. Moreover, the effects of different control interfaces and human variables play a significant role as proven recently (Sadeghi et al., 2016).

Finally, the common approach has been to consider visual comfort and energy use in optimization schemes, with different levels of complexity and formulation types. Typically, multi-objective optimization is used that involves more than one objective function, combining a measure of energy use and a measure or metric related to comfort. Most studies related to multi-objective optimization in this field applied the method to building envelope parameters (Manzan and Padovan 2015; Futrell et al. 2015; Carlucci et al. 2015), as MOO usually provides a set of non-dominated alternatives (Pareto front) instead of a deterministic solution. Villa and Labayrade (2012) tried to apply MOO in real-time lighting control – controlling the dimming levels of two luminaires to minimize lighting power demand while maximizing modeled satisfaction level – but the Pareto front of MOO solution was not fully taken advantage of. Cassol et al. (2011) formulated a general optimization problem by assigning weights to two objectives – light provision deviation and energy consumption. However, one could argue that the rationality of constructing the optimization problem and choosing weights that connect energy and comfort are debatable.

A more realistic approach to deal with these problems, including occupant visual comfort and interactions with shading/lighting systems, would be to consider occupant satisfaction with the visual environment as an objective, quantified by specially-designed experiments with occupant interactions and surveys, in order to develop adaptive and personalized shading or lighting control models. If this is combined with energy use considerations for overall optimization, instead of assigning standard weights, variable weight “coefficients” determined by the occupants themselves could be used for realistic and flexible shading control optimization.

In this study, a personalized shading control framework is developed to maximize occupant satisfaction while minimizing lighting energy use using such a multi-objective optimization scheme. A personalized satisfaction model was developed based on specially-designed experiments in private offices, to quantify the occupant satisfaction level with motorized roller shades by predicting the override probability of occupants considering different variables. Then, a multi-objective optimization algorithm was constructed, considering the shading override probability and predicted lighting energy use as objectives, where the occupants are the decision makers in the final balancing between their personalized comfort limits and energy use considerations. The developed method serves as a prototype study on adaptive shading control strategies with learned personalized comfort profiles and parallel energy use considerations.

2. MODELING

2.1 Experiment and Data
A set of experiments were conducted to gather data for developing personal satisfaction models. The experiments were conducted in four private offices of the Herrick Laboratories building at Purdue University from 09/29/2015 – 10/23/2015. The offices are equipped with controllable roller shades and electric lighting systems, as well as comprehensive indoor environment sensing system, for investigating the impact of façade design and control strategies on occupant comfort perception and corresponding behavior. The offices are 3.17m wide by 4.03m deep by 3.1m high, and have a south facing façade with 60% vision area (window-to-wall ratio) and a high performance glazing with 70% normal visible transmittance.
In the experiments, environmental conditions (e.g. vertical and horizontal indoor illuminances, window transmitted illuminance, etc.), states of the shading system (i.e., shading position), and occupancy status were recorded every one minute. Test-subjects were asked to do general work in the office during working hours. For the purpose of learning occupant preferences, the programmed shading control intentionally raises the shades gradually every 30 minutes in order to increase the data collection rate and improve the learning efficiency. The occupants could control the shading system by overriding the system through a web-based control interface, while the override actions and resulting shade positions were continuously monitored. The test subject of each room remained the same during the experiment, and the data used in modeling study is the data of 14-days (non-consecutive) in one office, which consists of 1735 training data points and 2601 test observations.

2.2 Integrated Daylight, Electric-light and Lighting Energy Model

A validated hybrid ray-tracing and radiosity daylight model (Chan and Tzempelikos, 2012) was used for daylight simulation. The model combines the accuracy of forward ray tracing for direct light with the computational efficiency of radiosity for diffuse light entering the space and interior reflections. Angular direct-direct and direct-diffuse light transmission through roller shades is calculated using the semi-empirical model by Kotey et al. (2009), which has been validated using integrated sphere measurements and full-scale experiments (Chan et al., 2015). Beam and diffuse (sky and ground-reflected) transmitted illuminance through the window (calculated or measured by sensors for real-time control, or TMY3 data for an annual analysis) are required as inputs to the daylight model. At each time step, these quantities are obtained by processing the readings of one exterior sensor (direct-diffuse ratio of horizontal solar radiation) and two interior sensors (total transmitted radiation and total transmitted illuminance). The daylight simulation results are then used as required inputs in electric lighting model and developed personal satisfaction model. Electric lights dimming levels were determined in electric lighting model based on a work plane illuminance set point (500 lx in this study) and the simulated work plane illuminance (on the calculation grid), by mapping dimming levels and work plane illuminance provided by lights. The lighting power and energy consumption can then be computed based on determined dimming levels. The integrated daylight, electric-light and energy model based on models above can be mathematically expressed as:

\[
[\text{Power}, Y] = E(SP, X)
\]

where \(\text{Power}\) is the predicted lighting power density consumption (W/m²); \(Y\) is the simulated results from daylight model which are also required inputs for the developed personal satisfaction model; \(SP\) is the shade position; \(X\) is the measurement inputs used for daylight model.

2.3 Personal Satisfaction (Override) model

2.3.1 Model Development: The personal satisfaction model developed in this study aims at predicting the satisfaction level of occupant by quantifying the override probability distribution with different shading positions given a set of measured physical conditions. The override model is developed by logistic regression method. Considering that the same physical variable could have reverse effects on shade lowering and raising actions (e.g. high illuminance triggers lowering action while low illuminance leads to raising), two separate models were first developed for predicting lowering and raising probabilities respectively, and then the overall override model was inferred by probability theory:
\[ P(\text{lowering}) = \frac{\exp(\beta_1 x_i + \alpha_i)}{1 + \exp(\beta_1 x_i + \alpha_i)} \]  
\[ P(\text{raising}) = \frac{\exp(\beta_2 x_r + \alpha_r)}{1 + \exp(\beta_2 x_r + \alpha_r)} \]  
\[ P(\text{override}) = 1 - (1 - P(\text{lowering}))(1 - P(\text{raising})) \]

where \( x_i \) and \( x_r \) are input variables; \( \beta_1, \alpha_i, \beta_2, \text{and} \alpha_r \) are parameters trained based on experimental data, and shall be different with different occupants.

The input variables were selected based on prior knowledge and sensitivity analysis. To assist in reliable regression results and comparative studies, all the input variables are normalized (e.g. vertical illuminance is normalized by constant 5000 lx, and all values higher than 5000 is set to 1).

The first prior belief is that shade position (SP) should be included in the model, based on the common sense that when shades are already fully closed/open, the probability of lowering/raising action should be 0, and the probability of raising/lowering action would be higher than other positions. Second, at least one illuminance value (transmitted illuminance TI, vertical illuminance VI or work plane illuminance WI) should be selected as they indicate the amount of light perceived by occupants.

Global sensitivity analysis was conducted to investigate the sensitivities of different illuminance values with override action. Sobol’ indices (Sobol’ 1990; Saltelli et al. 2000) were computed with six alternative models (lowering and raising models using normalized SP with VI, SP with WI and SP with TI) to quantify the influence of variables on override prediction, as shown in Figure 2.

**Figure 2:** Total Sobol’ indices of (a) lowering model with PSP and PVI, (b) raising model with PSP and PVI, (c) lowering model with PSP and PWI, (d) raising model with PSP and PWI, (e) lowering model with PSP and PTI, (f) raising model with PSP and PTI

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It can be seen that vertical illuminance and work plane illuminance have similar effect on both lowering and raising models, while transmitted illuminance has little impact on lowering and smaller effect on raising. As vertical illuminance on the eye can better represent the light incident on the occupant (and is used in glare indices such as DGP), it was selected as the input variable in both lowering and raising models.

2.3.2 Modeling Results and Evaluation: Logistic regression was implemented with experiment data based on selected variables and model structure.

\[
P(\text{lowering}) = \frac{\exp(2.9735SP + 0.21VI - 5.3485)}{1 + \exp(-2.1882SP - 24.9413VI - 2.9023)} \quad (5)
\]

\[
P(\text{raising}) = \frac{\exp(-2.1882SP - 24.9413VI - 2.9023)}{1 + \exp(-2.1882SP - 24.9413VI - 2.9023)} \quad (6)
\]

\[
P(\text{override}) = 1 - (1 - P(\text{lowering})) (1 - P(\text{raising})) \quad (7)
\]

The lowering and raising models are visualized in Figure 3.

The red and black dots represent the mean frequencies of training and test data, respectively, and the vertical lines indicate the corresponding uncertainty (standard deviation) from data noise and number of observations. From the left figure it can be seen that the lowering action is mainly determined by SP, but not really sensitive with VI. The raising model shows curved surface as expected in the right figure. The observations (red and black dots and lines) are accordant with the models in general, with a few noticeable deviations due to data sparsity (long uncertainty bars).

3. MULTI-OBJECTIVE OPTIMIZATION

3.1 Formulation of the Optimization Problem
3.1.1 Variables and Objectives: The controlled variables of the multi-objective optimization problem is simply one-dimensional shading position, ranged from 0 to 1 (0 – fully open; 1 – fully closed).

The objective of the optimization problem is to maximize the satisfaction of occupant by minimizing the probability of override action, while minimizing lighting energy use. Therefore the two objective functions are derived based on the energy model and developed override model.

As the override model predicts the probability of override every one minute (given the experimental data), the magnitude of the prediction is very low in most of the cases – due to the fact that an occupant cannot be dissatisfied and operate shades every minute. Therefore, a longer analysis horizon is preferred for optimization, to enlarge the output value of the “satisfaction” objective function for more reliable optimization distinction, by inferring the joint probability of any override in the time horizon (15 minute in this study) based on assumptions of independency of the action probabilities at serial time steps and fixed outdoor conditions in the time horizon:
The energy objective function should also utilize the 15-minute horizon to predict the average power density consumed. By assuming constant outdoor conditions in 15 minutes, the average power density is the power density at current time step:

$$P_{\text{in} \, 15 \text{min}} = \frac{\sum_{i=1}^{15} \text{Power}(t_i)}{15} = \text{Power}(t)$$

Then the optimization problem can be mathematically expressed as:

$$\min_{SP \in \mathcal{X}} \{\text{Power}(SP, X), P(SP, Y)\}$$

where \(\text{Power}(SP, X)\) is the average power consumption in 15 minutes simulated by energy model given shade position \(SP\) and inputs \(X\) for integrated model; \(P(SP, Y)\) is the joint probability of override in 15 minute predicted by personal satisfaction model with shade position \(SP\) and inputs \(Y\), which is calculated from the integrated model.

### 3.1.2 Optimization Strategy and Algorithm

The integrated model and personal satisfaction model, as well as the multi-objective optimization were implemented in Matlab R2014a. Several toolbox options of different algorithms are provided by Matlab aiming at multi-objective optimization. However the optimization objectives in this study are dependent – personal satisfaction model requires inputs simulated from integrated model – and dependent objectives are not supported by most of algorithms. To address the dependency problem, daylight model needs to run in both the energy model and the personal satisfaction model separately, which is inefficient.

To compromise between computation efficiency and accuracy, a straightforward search strategy was adopted to solve the multi-objective optimization problem. As continuous shade position can be approximated by dividing the full range into a specific number of discrete positions, and very small changes in roller shade position makes no difference in application with respect to energy consumption and occupant comfort perception, the controlled variable is pre-defined with discrete options as a feasible set (e.g. 21 positions with every 5% increments). In the optimization process, two objective models run with all the shade position options, and objective values are provided through the whole feasible region. The optimization solutions are determined by comparing all the feasible objectives in the way of Pareto optimality (if there exists no feasible solution that minimizes two objective simultaneously):

$$x \text{ is not a Pareto solution if there exist } x^* \text{ such that } f_1(x^*) \leq f_1(x) \text{ and } f_2(x^*) < f_2(x).$$

The discretization of shade position depends on the continuity requirement of shading control and efficiency demand of optimization algorithm. For example, 11 shade positions (10% increments) result in short computation time, while 101 positions (1% increments) approximate continuous change of roller shades very well. In this study, 11 shade positions are pre-defined with 10% increments from 0 to 1:

$$SP \in \{0, 0.1, 0.2, \ldots, 1\}$$

### 3.2 Results and Discussions

The developed optimization algorithm was implemented on the experiment training data (7 days) for preliminary theoretical evaluation of the performance. A 15-minute interval was set for the data in accordance with the time horizon of the optimization algorithm, which resulted in optimization results of 115 time steps. The outdoor
conditions (measured transmitted illuminance values) of these time steps are shown in Figure 4 for analysis reference. The illuminance values can roughly indicate different types of weather conditions from cloudy and partly cloudy (day 1, 2, 3, 7) to sunny (day 4, 5, 6). Transmitted illuminances around step 90 are close to 0 corresponding to data collected at sunset.

**Figure 4: Measured transmitted illuminances**

3.2.1 Representative Pareto Fronts: Figure 5 shows the Pareto fronts of optimization results of three representative time steps – step 2 (day 1), step 36 (day 3) and step 86 (day 5). The numbers next to the Pareto optimal or feasible points correspond to the values of controlled variable – shade position (0 – fully open, 1 – fully closed). The number of feasible points, including Pareto optimal, is equal to the number of pre-defined shade positions (11 in this study) in the optimization algorithm, and is kept constant. As can be seen, the number of Pareto solutions and corresponding optimal objectives vary with different time steps, depending on the shape of feasible region (boundary) in objective space. Figure 5 (b) represents the most general cases, where several Pareto optimal points are located at the left side of the “U-shape”, corresponding to partly open shade positions. Figure 5 (a) represents the cases with strictly convex feasible boundary, where the complete left “valley” is the Pareto front (from fully to partly open positions). Figure 5 (c) shows the case when a single global optimal could be achieved.

**Figure 5: Representative feasible solutions and Pareto Fronts – (a) step 2; (b) step 86; (c) step 36**

3.2.2 Tolerance in Objective: Due to large window-to-wall ratio and south-facing facade of the test offices, the lighting power consumed with different shade positions sometimes has very slight difference, which can be seen from Figure 5 (b), where the Pareto points close to the axis have differences that can hardly be noticed. To address this problem, a tolerance could be set in comparison of power objectives while searching for the Pareto optimal:
In this way, points with negligible differences in power consumption but higher override probability would be filtered out as not a Pareto solution. In this study, a tolerance of 0.1 W/m² in power objective is investigated as such difference is insignificant in lighting control. Comparison of Pareto fronts with and without tolerance is shown in Figure 6, using data from the same time step. As can be seen, three Pareto optimal points without significant difference in power consumption are eliminated.

3.2.3 Analysis of Pareto Solutions: The numbers of Pareto solutions of every time step are shown in Figure 7. As can be seen, cases with single optimal (one solution) are rare (only once) without tolerance but more often with tolerance, due to stricter definition of Pareto optimal. The maximum number of Pareto solutions is 7 in this study, appearing with cloudy conditions (low transmitted illuminances). By comparing outdoor conditions in Figure 4 with Figure 7, the trend that sunny condition leads to less Pareto solutions can be concluded.
Figure 8 shows the Pareto solution range of every time step with and without tolerance. As can be seen, the Pareto optimal shade positions range from 0 to 0.8 in both scenarios, which means that the shades are never fully closed (SP=1) even in sunny conditions, indirectly indicating the energy saving potential of the developed optimization algorithm. Intermediate shade positions (0.3 – 0.6) are determined as Pareto solutions more frequently than extreme shade positions. The range of Pareto solutions is narrowed with tolerance as expected.

3.2.4 Analysis of Pareto Optimal: The ranges of Pareto optimal objectives of every time step without and with 0.1 W/m² tolerance are shown in Figure 9 and Figure 10. The Pareto optimal power density ranges from 0 to approximately 3.5 W/m², except for peak power consumed (around 6 W/m²) when it’s nearly dark outside. Average Pareto optimal power consumption is higher in cloudy conditions as expected. The Pareto optimal override probability ranges from 0.2 to 0.75, and the range is larger with cloudy conditions compared to sunny conditions. The Pareto optimal power objective ranges are similar with and without small tolerance, while Pareto optimal override probability range is narrowed with tolerance.

Figure 9: Range of Pareto optimal lighting power (left) and range of Pareto optimal override probability (right) without tolerance
3.3 Framework of Multi-Objective Optimization Application in Shading Control

The optimization process is designed for application of shading control in perimeter zones of buildings with glass facades. As multi-objective optimization usually provides a set of Pareto solutions, it is challenging to select a single “optimal” point for the control system from the solution set. This selection is equivalent to assigning weights \( w_1, w_2 \) for objectives in multi-objective optimization so that a normal single-objective optimization problem is formed:

\[
\min_{SP \in \mathbb{R}^d} w_1 \text{Energy}(SP, X) + w_2 P(SP, Y)
\]

where \( w_1, w_2 \) will lead to the selected Pareto optimal.

However such weighting of objectives is questionable when considering evaluation of the trade-off between them, especially for personalized control. Therefore, instead of fixing weights for the optimization, variable weight “coefficients” determined by the occupants themselves are introduced.

The idea is to provide various control options which enable the decision maker (occupant or user) to tune the trade-off of different objectives by themselves – but in all cases within the developed personalized satisfaction “limits”. For example in this study, a pool of options in Pareto front from most comfort corresponding to minimum probability of override to most energy-saving corresponding to minimum lighting energy use could be provided in every time step, in a way similar to slide bar (Figure 11).
Since the number of solutions in Pareto front varies with different time steps, the slide bar consists of a variable number of options, or even only one option when there is a single global minimum for the multi-objective optimization. Further research is required on how to assign changing number of Pareto solutions to the slide bar.

4. CONCLUSION AND FUTURE WORK

This study presents the development of a personalized shading control strategy and the application framework aiming at maximizing personal occupant satisfaction while minimizing lighting energy consumption with automated shading systems, using a multi-objective optimization algorithm. A set of experiments with human subjects in private offices were conducted to develop shading override probability models for quantifying the occupant satisfaction with the visual environment using automated shading. The override probability prediction along with predicted lighting energy use were taken as objectives in the multi-objective optimization algorithm to provide a set of Pareto solutions. Finally, occupants or users are allowed to choose from the Pareto solutions based on subjective preferences. The override probability model was developed by combining separately-built lowering and raising models trained by multivariate logistic regression, and the input variables were selected based on global sensitivity analysis. Quantitative evaluation method for probability function is required for evaluating the performance of developed models. Further quantitative evaluation of developed models is required such as Jensen–Shannon divergence method.

The multi-objective optimization strategy utilizes enlarged time horizon based on serial-independency and fixed condition assumptions to improve the reliability of optimization. Pre-defined finite controlled variables and straightforward search strategies were adopted as optimization algorithm for better efficiency without sacrificing accuracy. The developed optimization algorithm was implemented on part of experimental data for evaluation. Three representative Pareto fronts are shown and compared, and tolerance was introduced in the power objective function in optimization for practical application. Results of Pareto solutions and optimal points show the effectiveness of tolerance, and trends that cloudy conditions lead to more Pareto solutions as well as larger Pareto optimal override probability ranges. Extreme shade positions are less likely to be in Pareto front and energy savings potential can be inferred from that high shaded window fraction (high SP) is not preferred in Pareto solutions. The application framework of developed personal shading control strategy using multi-objective optimization strategy was introduced. Instead of assigning fixed weights on multiple objectives without specific reasons, complete Pareto solutions are provided as pool of options and decision is left to occupants or users. In this way, in contrast with existing optimization studies, the occupants are the decision makers in the final balancing between their personalized comfort limits and energy use considerations.

The developed method serves as a prototype study on adaptive shading control strategies with learned personalized comfort profiles and parallel energy use considerations. It is a preliminary step for application of multi-objective optimization strategy in integrated building control. Future work includes developing adaptive learning satisfaction or preference models, as well as new strategies for constructing pools of options given varying numbers of Pareto solutions. The developed strategy needs to be investigated and evaluated by application in more buildings and also considering feedback from occupants. Objectives and controlled variables of the control framework are not only limited in lighting energy, visual comfort and shade position, but also extended to energy consumed in building, overall comfort and indoor environment control.

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