Dynamic Balancing Between Personalized Daylight Preferences and Lighting Energy Use

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Abstract
This paper presents a method to incorporate personalized visual preferences in real-time optimal daylighting control. A personalized shading control framework is developed to maximize occupant satisfaction while minimizing lighting energy use in daylit offices with automated shading systems. Personalized visual satisfaction utility functions were used along with model-predicted lighting energy use to form an optimization framework with two schemes. Variation of results is presented as a function of preference profiles, occupant sensitivity to utility function, and exterior conditions. Finally, we present a new application and an interface to allow occupants to be the final decision makers in real-time balancing between their personalized visual satisfaction and energy use considerations, within dynamic optimal bounds.

Introduction
Occupants play a significant role in the energy use of buildings, while they have a strong preference for a customized indoor environment. The operation of controllable fenestration (daylighting/shading) and electric lighting systems (Jain and Garg, 2018) affects daylight provision, outside view, lighting energy use, as well as overall occupant satisfaction with the visual environment. The standard approach is to satisfy visual comfort criteria based on existing indices or even using fuzzy-logic models (Lah et al., 2006). However, achieving a general visual comfort criterion does not necessarily lead to satisfaction for individuals. Learning visual preference profiles (Guillemin and Molteni, 2002, Xiong et al., 2018) and implementing them in lighting controls can lead to optimized visual environments.

In addition, learning and implementing visual preference models is quite challenging. Previous work on adaptive controls (Guillemin and Molteni, 2002, Gunay et al., 2017) was based on occupant actions, which may not reflect actual occupant satisfaction, since they include the combined effect of many factors (Wang et al., 2016) including discomfort. Also, most previous shading and lighting interaction (or behavioral) models (Haldi and Robinson, 2010, Fabi et al., 2015, Reinhart, 2004, Da Silva et al., 2013, Inkarojrit, 2008, Mahdavi et al., 2008) were developed assuming manually operated systems, which is different from automated operation. The most recent findings (Meerbeek et al., 2014, Sadeghi et al., 2016, Chaibri et al., 2016) show that, for automated lighting and daylighting/shading systems, the effects of “perceived” control, control access and interface play a very significant role on occupant preferences and satisfaction.

Moreover, limited and simple variables (such as work plane illuminance) were considered when developing human interaction models. However, visual preferences depend on a variety of factors, which could be environmental, contextual, psychological or subjective, and may change over time (Galasiu and Veitch, 2006). Therefore, advanced modeling approaches that can consider multiple variables with predicted uncertainty are particularly useful, such as Bayesian inference models (Lindelof and Morel, 2008, Xiong et al., 2018, Sadeghi et al., 2017, 2018). However, these “generalized” visual preference models are challenging to implement since they might not work well for specific individuals in other space layouts, multi-user offices, or controls with conflict in user preferences (Despenic et al., 2017).

Previous studies have considered comfort and energy use in multi-objective optimization (MOO) schemes, with different levels of complexity and formulation types (Nguyen et al., 2014, Carlucci et al., 2015). Typically, more than one objective function is involved, combining at least a measure of energy use and a measure of visual comfort (Ochoa et al., 2012, Ferrarra et al., 2018, Ascione et al., 2016). However, constructing the optimization problem by choosing weights that arbitrarily connect energy and general comfort metrics is debatable. Villa and Labayrade (2013) applied MOO differently, in real-time lighting control – controlling light dimming levels to minimize lighting power while maximizing the modeled satisfaction level obtained from subjective data.

In this study, personalized visual satisfaction utility functions were used along with model-predicted lighting energy use to form an optimization framework in daylit offices with roller shades. We demonstrate the results of a single objective and multi-objective formulation. Unlike previous studies, we apply the MOO by allowing occupants to be the final decision makers in real-time balancing between their personalized visual satisfaction and energy use considerations, within dynamic optimal bounds. Essentially, we present the first method to incorporate personalized visual preferences in optimal daylighting control, without using general occupant behavior models or discomfort-based assumptions.
Methodology

Figure 1 shows the flowchart of the method, which is based on a combination of model-based control and optimization schemes. Lighting energy use (f) is predicted by an integrated daylight-electric lighting model, while the personalized satisfaction level is quantified by a satisfaction utility function (u) inferred from preference data. In our case, u was determined from comparative preference experiments (Xiong et al., 2018). The modeling results then formulate the objectives towards optimal personalized daylighting (shading) control, following two application paths. In the single objective (SOO) path, the satisfaction objective is converted into a constraint when minimizing lighting energy use, resulting in unique optimal conditions, x*, achieved through shading operation, at each time step. In the multi-objective optimization (MOO) path, both objectives are used to provide a set of optimal solutions on a Pareto front at each time step. The optimal points are used to provide a pool of options to the users, who are the final decision makers.

![Figure 1: Overall methodology flowchart.](image)

Integrated Daylighting and lighting energy use 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 light transmittance through windows and complex fenestration systems are enabled (Chan et al., 2015). At each time step, incident beam and diffuse illuminance on the window (calculated for simulation or measured for real-time control) are used to compute transmitted beam and diffuse daylight. Xiong and Tzempelikos (2016) showed how this approach can be used for real-time, model-based shading control, which is partially used in this work. Interior daylight distributions are calculated along with vertical illuminance on the eye of the observer (an input to preference models) and dynamic glare metrics as required. Electric lighting is controlled based on work plane illuminance levels, using a set point. Lighting energy use is then directly computed from light dimming levels at each time step. For a given set of exterior conditions, the shading position (SP) determines indoor daylight illuminances, including vertical illuminance (E_v), and the predicted lighting power at each calculation step. Therefore, SP is the control variable.

Personalized visual satisfaction model

A method for developing personalized visual satisfaction profiles in daylit offices using Bayesian inference (Xiong et al., 2018) was utilized. Experimental measurements with human subjects were used to collect comparative visual preference data in single-occupancy private offices with dimmable electric lights and automated roller shades. The preference learning process starts with constructing the likelihood function, using a probit model structure. The probability of an occupant preferring visual condition q over r given their satisfaction utility function (u) values is (Guo et al., 2010):

\[ p(q > r|u(q), u(r), \sigma) = \Phi \left( \frac{u(q) - u(r)}{\sqrt{2}\sigma} \right) \] (1)

where \( \Phi(\cdot) \) is the standard Normal cumulative distribution function (CDF), which serves the role of a sigmoid function: \( \Phi(z) = \int_{-\infty}^{z} \phi(y)dy \) with \( \phi(y) = \frac{1}{\sqrt{2\pi}}e^{-\frac{y^{2}}{2}} \) being the probability density (PDF) of a standard Normal. The \( \sigma \) parameter captures how sensitive the individual is to the utility \( u(\cdot) \). If \( \sigma \) is large, the individual is insensitive to the utility. A parametrized Gaussian bell form was adopted for the utility function:

\[ u(x; \mu, \Sigma) = \exp \left( -\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right) \] (2)

where \( x \) are the model variables, \( \mu \) is a d-dimensional vector indicating the location of the peak (mostly preferred conditions), and \( \Sigma \) is a positive definite matrix defining the shape of the function. Using the utility function and the pairwise comparative data following Bayes’ rule, we can obtain posterior distributions using Sequential Monte Carlo sampling and infer distinct visual satisfaction profiles (Xiong et al., 2018).

Two inferred personalized satisfaction utility functions, reflecting different overall visual preference characteristics discovered for each person, are used in this study. The profiles are presented as a function of two variables: \( E_v \) and SP. In addition, sky condition is used as...
a binary variable (cloudy vs. sunny) since utility functions were found to strongly depend on sky type. This method is generic and can include multiple variables and their combinations. The normalized posterior medians of the two inferred satisfaction utilities (namely profiles A and B), plotted as a function of $E_v$ and SP, are shown in Fig. 2. The shape of the utilities is different, reflecting different preferences. Under given outside conditions, $E_v$ is determined by the shading position using the predictive lighting model. Therefore, the satisfaction utility is eventually a function of SP. For other shading systems (e.g., blinds), the rotation angle would be a variable instead of shade position.

![Figure 2. Posterior median of two inferred satisfaction utilities (Ev-SP model).](image)

**Optimization**

The inferred personalized utility functions and the modeling results are used in an optimization framework to maximize visual satisfaction while reducing lighting energy use. Here we present two approaches (Fig. 1). The first approach is to formulate two objectives (occupant satisfaction and lighting energy use) and use them in a multi-objective optimization scheme. The second approach converts one of the objectives (occupant satisfaction) into a constraint and formulates a single-objective optimization problem (minimizing energy).

**Multi-Objective Optimization (MOO)**

The two objective functions are derived based on the daylighting-lighting model and the inferred satisfaction model at each time step. Fig. 3 shows the transfer flowchart of variables between daylighting, lighting and satisfaction models, as well as the multi-objective optimization were implemented in Matlab. A fast and efficient simple enumeration method was adopted. The controlled variable SP can be pre-defined with discrete options as a feasible set. To compromise between computation efficiency and accuracy, 11 shade positions are pre-defined with 10% increments $SP \in \{0, 0.1, 0.2...1\}$. In the MOO process, the two objective models run with all possible shade positions at each time step, and objective values are provided through the discretized feasible region. At each time step, SP does not belong to a Pareto solution if there is $SP'$ that dominates it, i.e.:

$$\min_{SP} \left\{ -u(SP) \right\} \quad f(SP) \leq \tau$$  

(3)

![Figure 3. Models and variables transfer flowchart in multi-objective optimization.](image)

**Single-Objective Optimization (SOO)**

In the SOO scheme, the objective is to minimizing lighting energy while maintaining occupant satisfaction level near the maximum. The satisfaction objective is converted to a constraint, using the personalized visual preference profiles and a relative tolerance ($\varepsilon$) of the maximum utility value. In addition, the randomness factor $\sigma$ is considered in the satisfaction constraint in order to investigate the impact of sensitivity of individuals on energy savings potential. The objective is formulated as:

$$\min_{SP} f(SP) \quad \text{subject to:}$$

$$u(SP) \geq (1 - \varepsilon \sqrt{2} \sigma) \cdot \max_{SP} u(SP)$$

(4)

The tolerance $\varepsilon$ is selected as 0.1 in this study, representing 10% of the maximum unscaled utility, which equals to 1 based on the Gaussian bell form structure. The glare constraint is still required at every time step.

**Optimization Algorithm**

The integrated lighting and personalized visual satisfaction models, as well as the multi-objective optimization were implemented in Matlab. A fast and efficient simple enumeration method was adopted. The controlled variable SP can be pre-defined with discrete options as a feasible set. To compromise between computation efficiency and accuracy, 11 shade positions are pre-defined with 10% increments $SP \in \{0, 0.1, 0.2...1\}$. In the MOO process, the two objective models run with all possible shade positions at each time step, and objective values are provided through the discretized feasible region. At each time step, SP does not belong to a Pareto solution if there is $SP'$ that dominates it, i.e.:

$$-u(SP') \leq -u(SP) \quad \text{and} \quad f(SP') < f(SP) + \tau$$

where $\tau$ is a positive constant, selected such that points with negligible differences in power consumption, but lower visual satisfaction, would be filtered out as not part of Pareto solutions: 0.1 W/m$^2$ (lighting power per floor area) is sufficient for that purpose. In the SOO process, the optimal at each time step is found from the minimum lighting power consumption among all the feasible points, given the visual satisfaction constraint.
Results

The effectiveness of the developed optimization strategies was studied through annual simulation for both SOO and MOO, using the two personalized satisfaction profiles of Fig. 2. The models were applied to the same private offices used to experimentally derive the inferred satisfaction models. The offices are 3.2 m × 4 m × 3.3 m high and have a south-facing curtain wall facade with 55% window-to-wall ratio with high performance glazing units (normal visible transmittance=70%). They are equipped with motorized roller shades (openness factor=2.1%) and dimmable electric lights (32-W T5 fluorescent lamps). The interior surface reflectivities are 80% (ceiling), 50% (walls) and 30% (floor). Light dimming levels are mapped to work plane illuminance levels on a specified grid at the desk height. The offices are located in West Lafayette, Indiana and TMY3 data for that location were used. A 15-minute time step was used for both lighting and the satisfaction models, as well as for the optimization algorithm, from 8:00 am to 6:00 pm, to consider working hours only. The 15-min time interval is a compromised decision based on two considerations: 1) frequent shading operation would disturb occupants, and 2) a longer time step would not respond to changing weather conditions on time. This time interval was validated as acceptable in sunny and cloudy days respectively through experiments. However, for capturing really fluctuating weather (fast passing clouds), real-time glare-based control could be used (Xiong and Tzempelikos, 2016).

Representative optimization results

Fig. 4 shows the MOO feasible optimal points (dashed line) for a single representative time step (winter sunny day at 5:30 pm) with Profile A. The units of the y-axis are relative: the lower the value on the plot, the higher the satisfaction utility value. The corresponding shading positions (the control variable) are shown next to the feasible points, which form a V-shaped curve. Due to the tolerance added in the power objective and the discretization of SP, the actual Pareto front limits SP between 0.2 and 0.5, marked with solid dots in the graph.

Time-varying Pareto fronts and optimal points

The shape of the feasible region, the objectives’ values, and the number of Pareto front points will vary with time (computed every 15-min). Fig. 5 shows the transition of the feasible region and the optimal points for two representative days, for both profiles. The solid dots are the Pareto front points obtained from MOO, while the X marks are the optimal solutions obtained from the SOO at the same time steps. In both examples, the feasible region becomes narrower from 11:30 am-3:30 pm, and in some cases the Pareto front consists of a unique point –due to the shape of feasible curve and the tolerance in the power objective. The single-objective optimization results are sometimes one of the Pareto front points (e.g., at 9:30 am and 5:30 pm). In other time steps, that is not the case, as the tolerance added in the SOO satisfaction constraint relaxes the satisfaction objective compared to the MOO strategy.

MOO daily and annual results with different visual satisfaction profiles

The impact of weather conditions and different visual preference profiles on the multi-objective optimization results is shown in Fig. 6. The optimal SP range is plotted for four days (8 am - 6 pm) of representative weather types (winter sunny, winter cloudy, summer sunny, summer cloudy) for the climate of West Lafayette, Indiana. During early morning and late afternoon hours, the glare constraint is more evident due to lower sun positions. Also, the optimal shade positions are seldom fully closed (SP=1), indicating the energy savings potential. The resulting optimal lighting power density does not exceed 2 W/m², except when it’s nearly dark outside. The differences between the two visual satisfaction profiles are clear.

Figure 4. A representative Pareto front with optimal points (satisfaction profile A, single time step).

Figure 5. Transition of MOO feasible region (dashed lines) and Pareto front points (solid dots), as well as single-objective optimal points (marked with X) during representative winter days for satisfaction profile A (top) and B (bottom). Different optimal points correspond to different shading positions and interior lighting conditions.
The range of annual lighting energy use based on the MOO results is shown in Table 1, with two set points. For reference, the annual lighting energy use for the same office without lighting control is 31.6 kWh/m².

### Table 1: Annual lighting energy use with MOO

<table>
<thead>
<tr>
<th>Visual satisfaction profile</th>
<th>Work plane illuminance set point</th>
<th>Range of annual lighting energy use (from minimum energy – maximum satisfaction) kWh/m²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>500 lux</td>
<td>1 - 9.3 0.3 - 2.4</td>
</tr>
<tr>
<td></td>
<td>300 lux</td>
<td>1 - 8.9 0.3 - 2.3</td>
</tr>
</tbody>
</table>

The impact of weather conditions and visual preference profiles on the single-objective optimization results is shown in Fig. 7. The same daily weather profiles are used as before, and the optimal MOO daily variations are plotted along with optimal lighting power. The graphical results are clearer compared to MOO since there are single optimal points in this case. Optimal SP is clearly determined by the different personalized satisfaction profiles under the same sky conditions. As a result, the optimal lighting power is different between the two profiles, and allowing a 10% relative tolerance in satisfaction utility can save a noticeable amount of energy during daytime, especially for profile A. The optimal annual lighting energy use is shown in Table 2.

### Table 2: Annual lighting energy use with SOO

<table>
<thead>
<tr>
<th>Visual satisfaction profile</th>
<th>Annual lighting energy use (kWh/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Work plane illuminance set point</td>
</tr>
<tr>
<td></td>
<td>500 lux</td>
</tr>
<tr>
<td>A</td>
<td>3.65</td>
</tr>
<tr>
<td>B</td>
<td>1.34</td>
</tr>
</tbody>
</table>

### Effects of occupant’s sensitivity (σ)

The personalized satisfaction utility functions include the parameter, which represents how sensitive each individual is to the utility function. An example of the effect of σ is shown in Fig. 8. The representative satisfaction utility (profile A) is plotted as a function of shading position, for a typical winter sunny day at 5:30 pm. A virtual utility representing an occupant who has the same satisfaction profile but is less sensitive to the utility – with doubled σ – is plotted in the same graph. That results in a broader range of feasible shading positions. The optimal SP for that time (corresponding to the minimum lighting power), changes from 0.8 to 0.7. Therefore, more daylight is admitted and further lighting energy savings are realized for occupants who are less sensitive to the utility function. The dashed line shows the corresponding lighting power consumption (right y-axis) as a function of SP for this specific time step.

### Application of Multi-Objective Optimization

- Occupants balancing between their personalized preferences and lighting use

The MOO scheme is designed for application in perimeter offices with personalized shading and lighting controls.
As the optimization usually provides a set of Pareto solutions, there are no standard rules for selecting a single “optimal” point for the control system from the solution set. Selecting one of the Pareto front points is equivalent to transforming the problem into a single-objective optimization with assigned weights for the objectives. This approach was in previous studies; however, any ad-hoc weighting of objectives is questionable when considering the trade-off between energy and comfort. Especially for personalized control, fixing arbitrary weights for individuals is meaningless. To overcome this problem and implement personalized preferences in optimal controls, we propose a solution that introduces variable weights determined by occupants. The optimal points found by MOO at every time step provide a pool of options to the users, who become the final decision makers in the real-time balancing between their personalized visual satisfaction limits and energy use.

Absolute energy and satisfac
tion numbers have no practical meaning to the occupants; therefore, the set of non-dominated points should be transformed into a set of sorted options ranging from “most satisfied” (corresponding to maximum satisfaction utility) to “highest energy-savings” (corresponding to minimum lighting energy use). These sorted points need to be provided as possible control options to the occupants using a simple, intuitive user interface.

A slider (Fig. 9) can serve that purpose well: different points on the slider can be mapped to each optimal solution; in addition, the two ends of the slider will be mapped to the two extreme values of the Pareto front points (maximum satisfaction and minimum energy), and other intermediate points can be evenly sorted accordingly between the two ends. In that way, override actions would fit into the optimal conditions range. Communication between the web interface and the building management and control system is of course required for this application. Sliders “work best when the specific value does not matter to the user” – the trade-off between personalized satisfaction and energy objectives influence the user decision, while the actual values do not. Therefore, the actual values on the bar are hidden to users; by sliding in any direction, they will reflect the balance between objectives intuitively, without being overwhelmed with extra information.

![Energy savings vs Satisfaction](image)

Fig. 9. Example of a slider with hidden mapped optimal points within energy and satisfaction ends.

The number of options on the slider (possible control options) is variable –changes at every time step. There could even be only one option when there is a single global optimal from the MOO results. Therefore:

- the application needs to be updated in real-time, so that new optimal points are calculated;
- in each time-step, the new Pareto front points need to be sorted, mapped and evenly distributed on the slider;
- dynamic snapping features should be enabled on the slider to select the Pareto optimal closest to the current bar position every time, always hidden to the users.

An example is shown in Fig. 10 (profile A, winter sunny day). Suppose that we have run the MOO through this day and obtained the Pareto fronts for several time steps (two times shown here for ease of illustration). The Pareto points correspond to different shading positions (also marked on the graph), which are “mapped” on the slider at each time step. This information is hidden to the user. At 11:30 am, optimal results can be obtained with two shading positions: 90% and 100%. In this case, the two ends of the bar automatically correspond to these two positions, mapped to the Pareto points corresponding to maximum savings and maximum satisfaction respectively. If the user moves the slider anywhere towards the satisfaction end, the shades will move to fully closed (SP=1); otherwise, they will move to 90% position to minimize energy use. At 5:30 pm, optimal results can be obtained with four shading positions, from 20% - 50% closed. In this case, the bar will have 4 hidden points mapped to these conditions, evenly distributed on the slider, ranging from minimum energy to maximum satisfaction points. When the user moves the slider, the shades will move to the position closest to the mapped corresponding optimal on the bar, using a snapping feature. If the user does not change the position of the slider, the shades will automatically move at each time step to achieve optimal conditions (since these change with outside conditions). In this example, if the user selects to keep the position of the slider as shown from 11:30 am to 5:30 pm, the shades would automatically move to 100% at 11:30am and 40% at 5:30 pm.

![User-enabled application of MOO in personalized shading and lighting control. Example of mapped optimal conditions on the user interface for two different times, with the slider bar ends corresponding to maximum energy savings and maximum satisfaction respectively, at each time step.](image)

**Figure 10.** User-enabled application of MOO in personalized shading and lighting control. Example of mapped optimal conditions on the user interface for two different times, with the slider bar ends corresponding to maximum energy savings and maximum satisfaction respectively, at each time step.

**Conclusion**

In this study, a personalized shading control framework is presented to maximize occupant satisfaction while...
minimizing lighting energy use in offices with automated shading systems. We present a method to incorporate personalized visual preferences in real-time optimal daylighting control, with energy use considerations, without using generic behavior models or discomfort-based assumptions. Personalized visual preference profiles were used with predicted lighting energy use to form an optimization framework using two approaches. In the multi-objective optimization scheme, the satisfaction utility and predicted lighting energy use are used as parallel objectives to provide a set of Pareto solutions at each time step. The satisfaction utility is converted into constraint with tolerance when minimizing lighting energy use in the single-objective optimization scheme. Representative Pareto fronts of MOO were presented, which prove the effectiveness of the method and the ability to evaluate the dynamic trade-off between the objectives. Daily and annual simulation results of Pareto solutions and optimal points show different patterns with different satisfaction profiles, which verify that the MOO strategy can learn and maintain personalization. Simulation results of SOO, on the other hand, show the effectiveness in energy savings without sacrificing perceptible satisfaction, by using a relative constraint.

A new application framework of the MOO is introduced. Instead of assigning arbitrary weights to objectives, complete Pareto solutions are provided as a pool of sorted options to the users. In this way, occupants are the final decision makers in real-time balancing between their personalized visual satisfaction and energy use considerations, within dynamic hidden optimal bounds. A slider is presented as a potential user interface where different points on the slider can be mapped to each optimal solution; in addition, the ends of the slider are mapped to the two extreme values of the Pareto solutions (maximum satisfaction and minimum energy). Since the optimization is dynamic and the number of optimal solutions varies with time, the application needs to be updated real-time, so that new optimal points are calculated, sorted, and evenly mapped on the interface.

The developed method serves as a prototype study on adaptive control strategies with learned personalized preference profiles and parallel energy use considerations. It is a first step towards optimized, preference-based integrated building control. Implementation of the proposed control framework itself could be challenging: the real-time learning and actual control intervals should be coordinated. Therefore, adaptive and online learning methods should be applied for updating the personalized models with occupant feedback during the optimization implementation—this is the next phase of this work. In addition, more generic temporal and spatial comfort/preference metrics (Atzeri et al., 2016) can be used for overall evaluation of the controls.

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