Visual Comfort and Energy Efficiency for User Centric Lighting Control

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ABSTRACT

Energy consumption for lighting constitutes a sizable portion of the overall energy consumption of commercial office buildings. Many smart lighting control products are already available in the market, but their penetration has been limited and even installed systems have had limited use. One of the main reasons is that they tend to control lighting based on universal set-points which are agnostic to the individual preferences of the occupants thus hampering their comfort. The paper will present an automated lighting control framework which dynamically learns the lighting preferences of each user, models his visual comfort and controls the light dimming in a truly personalized manner so as to always control the comfort vs. energy efficiency trade-off. This approach effectively removes the single most important complaint of occupants when using such systems, loss of comfort, and paves the way for their wide scale adoption in order to untap the energy reduction potential of commercial lighting.

INTRODUCTION

Lighting constitutes one of the major electricity end-uses in office buildings accounting for over 30% of total electricity usage (US Department of Energy, 2013). Thus, significant cost savings are possible using intelligent lighting control systems. Such systems have been available for a number of years already, albeit with limited success in massively penetrating the commercial building stock. The main barrier has been the acceptance of building occupants. Existing commercially available systems tend to be intrusive and to adjust indoor luminance to pre-defined set-points for "optimal" lighting levels. This fails to take into account the diversity and heterogeneity of visual comfort zones of individual building occupants, hence leading to complaints about the lighting adequacy, manual bypassing of automated controls and ultimately abandonment of automated lighting control systems' operation.

To effectively leverage the untapped potential for reduction of lighting-related energy consumption, the visual comfort of affected occupants should be treated as a main optimization parameter. This paper presents a framework for automated lighting control in commercial buildings. Its application in real-life pilot trials has verified that it is possible to tightly control occupant visual comfort. Even further it demonstrates that combined gains in energy efficiency and visual comfort can be achieved compared to a conventional set-up whereby occupants dim their lights manually using a wall-mounted dimming switch. The framework senses the prevailing ambient conditions and the corrective actions (or lack thereof) of the occupant in a non-intrusive manner to infer a stochastic visual comfort model of each occupant. Combining the model with the ambient lighting conditions sensed in real-time, the framework identifies opportunities for energy reduction that affect visual comfort in a controlled manner. The trade-off between minimum allowable occupant comfort and energy reduction gives rise to alternative control strategies that can steer the automated lighting control.

STATE OF THE ART ANALYSIS

Currently available models and technological solutions in commercial environments fail to adequately capture the underlying relationship between energy efficiency and occupants' comfort, eventually translated into enterprise productivity. The concept of productivity is thoroughly studied in literature providing evidence of how workplace conditions can significantly affect productivity. As far as modern building management practice is concerned there are no modelling tools that sufficiently deal with occupant activities and personal preferences (Robinson, 2006). The most frequently used form of models are diversity profiles (Abushakra et al., 2001), which represent a stochastic estimate of combined behaviour of all occupants. Diversity profiles however have failed to sufficiently capture dependencies of occupancy patterns with overall environmental conditions (Bourgeois, 2005) or temporal variations (Page, 2007), eventually leading to poor assumptions and predictions about average user preferences and behaviours, (Clevenger et al, 2006).

(Shen et al, 2014) provide a comprehensive overview of integrated lighting control techniques that have been proposed and evaluated in the literature in the past years. Personalization in lighting control is synonymous to lighting set-points according to policy recommendations for office/computer work. This highlights the lack of true personalization according to user preferences in the recent literature. Some works have introduced limited occupancy or user profiling to improve on energy efficiency, especially in the domain of Building Management Systems. Both (Singhvi, 2005) and (Wen, 2008) track occupants' location and try to balance occupants' lighting preferences and energy consumption levels. In a similar approach, (Chen, 2009) proposes a building control system that is able to manage real-time location in an office and retrieve personal preferences of lighting, cooling, and heating. In (Dong, 2009), the authors use the total number of building occupants to define the power demand of the building and thus the extraction of building occupancy is a significant variable which increases the model accuracy. Therefore, the incorporation of a user profiling framework is very important in order to clearly define the preferences of users that further set constrains to the automation mechanism.

The main differentiator of the approach presented in this paper is the true personalization of lighting control, even when individual occupants cannot quantitatively express their visual comfort preferences. Instead of working with the assumption of a given set-point for the target luminance (either an average for all occupants or even a set-point per occupant), the proposed framework utilises occupant profiling techniques to infer and quantify the individual occupant preferences. This allows lighting control that is truly personalized to the preferences of each user, while minimizing calibration and commissioning effort and cost since set-up effort is significantly reduced.

A USER CENTRIC LIGHTING MANAGEMENT FRAMEWORK

Visual (dis)comfort of occupants is an obscure concept due to the multiplicity of variables affecting it and the difficulty of reconciling aesthetic and physiological elements. Even the discovery of a "perfect" common model and metrics of visual discomfort would not make modelling and control universally accepted because different occupants perceive light in very different ways. Thus, only a fully adaptive control approach which adapts to individual occupants can provide the necessary flexibility to satisfy their divergent preferences. Our work aims at establishing dynamic user profiles that reflect and more specifically quantify the visual discomfort of occupants based on the analysis of evidence captured exclusively from the observation of users' control actions under specific luminance conditions.

The framework utilizes a multiplicity of sensor configurations to sense ambient conditions. The sensing layer, continuously processes asynchronous events captured in live information streams towards generating dynamic occupant behavioural profiles. These occupant behavioural profiles constitute the point of reference of the control framework, defining and quantifying in real-time the "boundaries" and "cost" of visual comfort. Three types of events are analysed by the framework, namely: a) occupancy events b) luminance events and finally c) control action events triggered by the occupants when acting on the operational status of lighting. The ambient profiling engine appropriately analyses both actions and lack of (re)-actions of occupants under specific environmental conditions, in a completely implicit and transparent way. A high level view on the formalism of the Bayesian Approach as addressed in the framework is presented:

$$Pr(D \mid En)=w*Pr(En \mid D)/[w*Pr(En \mid D)+(1-w)*Pr(En \mid C)] \quad (1)$$

Where:

- w : Weight factor

- Pr(D | En) : Discomfort level given the luminance conditions
- Pr(En | D) : Luminance state probability given the discomfort level as explicitly indicated by the occupant
- Pr(En | C) : Luminance state probability given comfort level as explicitly and implicitly indicated by the occupant

The formula estimates the probability that the occupant is uncomfortable in the current ambient conditions, given the probabilities of environmental conditions where he feels comfort or discomfort. These probabilities can be calculated either on-the-fly upon usage of the system or from historical data. The former corresponds to a real deployment scenario; the latter corresponds to the experimental setup we have used in this paper whereby luminance information is collected from the user premises in order to monitor his actions to adjust lighting levels.

It is important to highlight the distinction between the definitions of explicit and implicit comfort. Explicit (Dis)Comfort refers to the occupant (dis)comfort as it can be extracted from the physical actions he undertakes in order to customize the lighting settings to his liking. When a user intentionally and consciously adapts the ambient luminance, two conclusions can be inferred: he is uncomfortable with the current conditions and the target conditions make him comfortable. Both set-points (current and target) provide valuable information regarding the user preferences and are a trustworthy estimation of his visual comfort. Implicit Comfort, on the other hand, refers to the occupant comfort as it can be inferred through the lack of his actions. If the occupant is present and not reacting to current luminance, we infer important information regarding his comfort levels. This information is valuable because it is used to understand his tolerance to luminance variations, a metric that is hard to capture directly. The weight factor (w) in the previous formula is a dynamically adjusted factor which balances the importance of explicit vs implicit information when quantifying the discomfort probability. Implicit information is generally more difficult to collect and interpret appropriately in the context of each user. So, this factor initially assigns more weight to the discomfort component (which includes only explicit information) and gradually shifts toward the comfort component as time passes and the system better learns the user preferences.

VISUAL COMFORT MODELLING FRAMEWORK

Live data streams were collected, pre-processed, normalized and analysed for a period of 12 months (November 2014 to November 2015) from various types of pilot premises involving different types of spaces (single occupant offices, multiple occupants spaces, meeting rooms, etc.). A day sample of the collected luminance data and the user's manual control actions is illustrated (Fig. 1). Appropriate clustering techniques were applied to robustly identify the boundaries (luminance levels) of user control actions (both preferred and unfavourable luminance states).

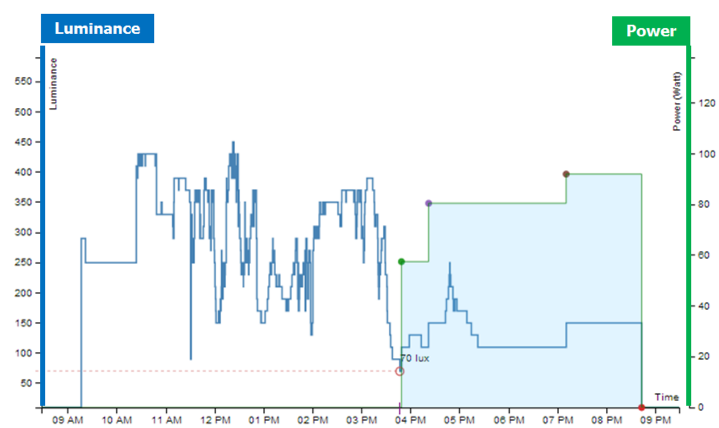

Figure 1 (Indoor Luminance Levels (volatile line) vs Manual Control Actions (step-wise line).

Two core indicators are dynamically inferred by the profiling engine: a) a weighted comfort indicator and b) a weighted discomfort indicator (Fig. 2), reflecting the amount of occupant comfort and discomfort under different luminance levels. As mentioned earlier, subsequent clustering techniques of neighbouring luminance levels, with high and low comfort values, reveal major comfort and discomfort zones, highlighted.

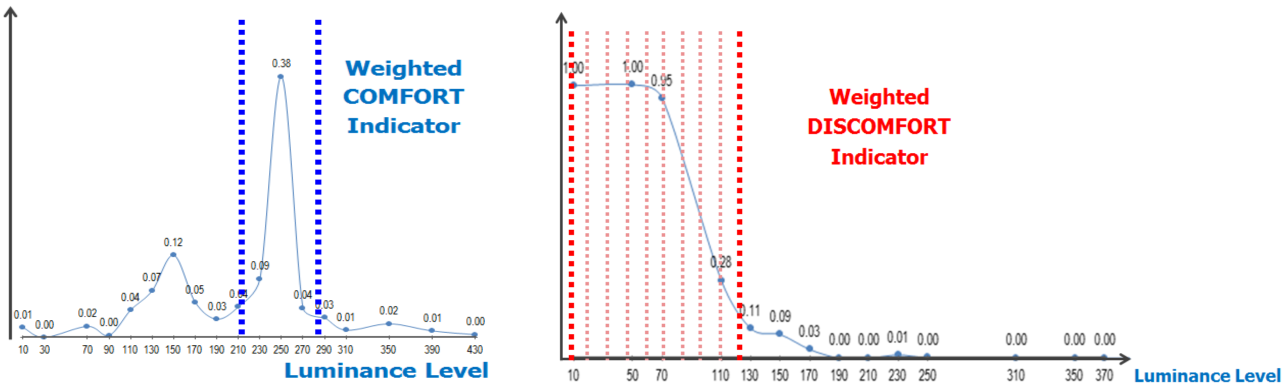

Figure 2 Weighted Comfort & Discomfort Indicator

The comfort and discomfort indicators calculation process is based on a Hidden Semi-Markov Model (HSMM), a doubly stochastic process that can estimate the occupant comfort and discomfort with respect to the time that she stays in the same conditions of luminance. According to the adapted model, a state transition probability depends on the current state duration and the explicitly observed transitions from the current state, due to the occupant reactions. The combination of all the separate probabilities determines the final calculated comfort and discomfort indicator as a function of the luminance level and time.

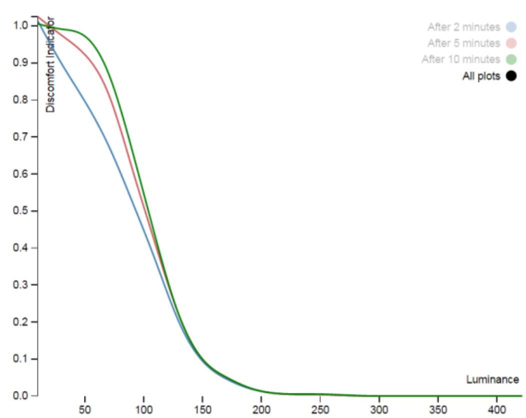

Figure 3 Temporal weighted discomfort indicator (the three lines represent occupant discomfort after 2, 5, 10 minutes at the given luminance).

Figure 3 indicates an example of how discomfort changes while the occupant is under a given luminance state. The discomfort indicator increases with time as she stays under the same unpleasant conditions.

In real building installations, cases exist where a set of light fixtures can be commonly controlled by more than one light dimmer. All the collected explicit and implicit data are always correlated with the occupant(s) using the specific light dimmer. When two or more occupants can control common fixtures, the framework performs a real-time negotiation by extracting the intersection of occupant profiles Zone using a Sweep Line algorithm in order to find the common ground that satisfies the preferences of all occupants to the maximum possible extent.

AUTOMATED PERSONALIZED CONTROL STRATEGIES FOR OFFICES & HOMES

The key strength of the proposed framework is that it leverages the coarse granularity of typical lighting control actions of humans, who are unlikely to fine-tune the light dimming to an accurate level that exactly matches their comfort zone. The framework analyses real-time events and ambient information while it utilizes user/occupant profiles to deliver personalized, human centric management services. The user profile models continuously adapt to real-time events and are utilized within different automated lighting control strategies aiming at maximum comfort, energy efficiency or compromises of the two. The framework delivers timely, non-intrusive, multi-modal and personalized ambient services that discretely follow building occupants, learn and subsequently safeguard their preferences under different control scenarios. Occupant profiling is implicit and performed in an entirely discrete and transparent manner. Different views, from simple and quick real-time hints to detailed historical analytics and data mining are provided. These views have proven effective in improving building energy efficiency strategies, while also increasing occupant awareness by triggering sustainable behaviours.

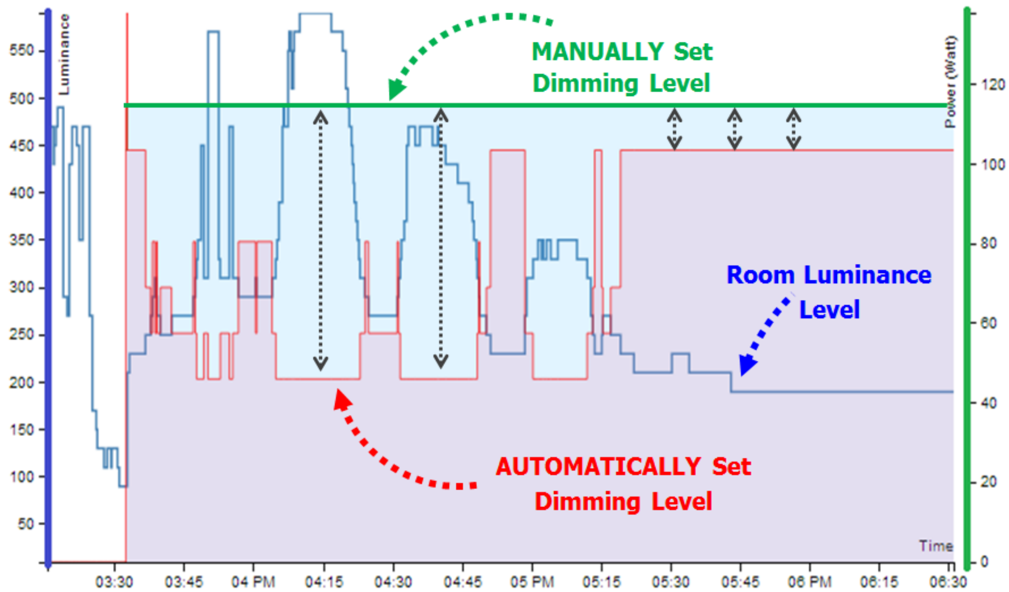

Figure 4 Time - series Analytics View

The system is designed to facilitate three different modes of operation: (i) comfort, (ii) wise and (iii) energy efficient. The three modes differ on the weight they give on the user comfort and the achievable energy reduction during the dimming optimization. More specifically, during the comfort operational mode, the system seeks for ways to reduce the total energy consumption, while ensuring maximum user comfort. During the wise operational mode the system operates in a similar mode, but is more sensitive to the noticed luminance changes to which it reacts more quickly and more accurately. Occupant comfort is again the highest priority in this mode, but it is achieved with more precise and less generous dimming actions. Finally, the energy efficient operational mode aims to minimize the energy consumption allowing to the system to sacrifice user comfort, albeit in a controlled manner. During energy efficient operational mode, the system may jeopardize the user's comfort for small time periods if energy gains are significant, but never to the point where the user will experience discomfort.

LIGHTING MANAGEMENT FRAMEWORK EVALUATION AND PRELIMINARY RESULTS

The proposed framework has been trained, successfully validated and thoroughly evaluated on various tertiary premises (commercial offices and academic institutions) and different application scenarios within the context of EU co-funded research project. The experiment reported in this paper illustrates the performance of the lighting control engine after it has been trained using the data set mentioned in previous Section. The automated control actions were simulated on a selected test-bed of two single-occupant offices, the one facing south and the second north, from which actual luminance data was collected and for two days, a sunny and a cloudy day. Due to the fact that the office windows have a different orientation the acquired luminance profiles for the same day (sunny or cloudy) are different, albeit with a lot of similarities. Each of the two occupants has his own visual comfort preferences. Lighting was monitored for the time period between 08.00 and 20.00 on working days to represent the time when office occupants would typically be active. Tables 1&2 depict the results of simulating several control strategies on the data collected during these two days.

Table 1. Occupant 1 ("South" office)

	Cloudy day - luminance profile				Sunny day - luminance profile			
	Average Occupant Comfort	Energy Savings	Average Luminance	Average Dimming Level	Average Occupant Comfort	Energy Savings	Average Luminance	Average Dimming Level
Comfort	91.35%	15.7%	419 Lux	45.7%	92.95%	11.5%	557.09 Lux	29.1 %
Wise	82.56%	29.2%	369 Lux	35.5%	85.85%	22.1%	529.65 Lux	23.8 %
Energy Efficient	74.16%	44.4%	342 Lux	28.5%	77.64%	36.5%	504.32 Lux	18.4 %
Manual	88.78%	-	517 Lux	63.4%	94.19%	-	588.83 Lux	35.3 %

Table 2. Occupant 2 ("North" office)

	Cloudy day - luminance profile				Sunny day - luminance profile			
	Average Occupant Comfort	Energy Savings	Average Luminance	Average Dimming Level	Average Occupant Comfort	Energy Savings	Average Luminance	Average Dimming Level
Comfort	92.9%	17.4%	388 Lux	39.3%	94.08%	12.2 %	500.09 Lux	25.5 %
Wise	84.7%	29.1%	344 Lux	30.9%	86.49%	23.4 %	473.41 Lux	20.3 %
Energy Efficient	75.9%	44.4%	307 Lux	23.2%	77.6%	40.6 %	450.23 Lux	15.4 %
Manual	89.07%	-	452 Lux	51.0%	94.59%	-	526.84 Lux	30.6 %

The characteristics of these profiles are summarized in Table 3 to provide a benchmark for comparison of the results. It is also interesting to note the differences between the lighting preferences of the two office occupants.

Table 3. Ambient lighting conditions in the experiment offices (all values are in Lux)

	"South" office		"North" office	
	Average	**Std.Dev.**	**Average**	**Std.Dev.**
Sunny Day	419	332	377	201
Cloudy Day	200	290	195	188

The preferred luminance levels of the South office occupant is about 450 lux and for the North office occupant about 400 lux. Moreover, the observed deadband, i.e. the luminance range where the user is unlikely to react and correct the light conditions, is about 550 lux to 390 lux for the South office occupant and 490 lux and 350 lux for the North office occupant. As it can be noticed, the North office occupant prefers lower luminance levels, but is more sensitive in the luminance changes happening in his environment. The "manual" entry in Tables 1&2 indicates the results that were collected in the absence of an automated lighting control system, therefore from the real users' reactions. The occupants were asked to control their lights manually in order to provide a baseline for comparing the performance of the lighting control engine and its strategies. The ambient conditions were meticulously recorded during the experiment. The automated control strategies' results were obtained by simulating the strategies for two distinct days (cloudy & sunny). The ambient lighting conditions for the two offices and the two distinct days are depicted in Table 3.

The average needed time for the learning algorithm to converge to accurate (dis)comfort indicator for the occupant ranges from one to two weeks according to the amount of data available. This assumes that the ambient luminance varies sufficiently so that the occupant performs enough explicit actions to adapt it according to this preferences. By the end of this time period the developed learning model can be over 90% accurate on the estimation of the correct comfort luminance level. Accuracy further increases as time passes; after two months average accuracy is about 96%. Furthermore, the likely seasonality of the generated user profiles is taken into account during the learning process by attaching greater weight to the most recent luminance and control events of the last 2 months. In this way, the learning mechanism is more versatile in both the seasonal light level changes and a possible change of the occupant in the office-room.

The comfort strategies of Table 1&2 were developed to maximize the time when the occupant's luminance experience lies in the high comfort zone, i.e. the range of luminance levels for which the occupant's weighted comfort indicators is above 90%. The "wise" and even further the "energy efficient" strategy achieve smaller high comfort time periods. As indicated by the results, occupant comfort is slightly compromised in order to achieve energy savings. However, occupant comfort is always preserved above 70%, which is considered the boundary between comfortable and uncomfortable conditions. The results of applying the three control strategies (energy efficient, wise and comfort) are outlined in Table. Several conclusions can be deducted. In sunny days occupants are more likely to be comfortable due to the abundance of natural light and they use artificial lights much less, hence the potential energy efficiency gains are lower. Daylight limits the need for artificial lighting and the slack for energy optimization, so automated lighting control is bound to produce lower (absolute and relative) efficiency gains compared to "darker" days when artificial light is more heavily used.

The results indicate that the subject occupants, when manually adjusting the dimming levels, were consistently keeping the lights at higher luminance levels compared to the boundary of their comfort zone. This slack between the manual setting and the minimum setting for the given comfort level is exploited by the automated control to produce energy efficiency gains. This is a natural human reaction and has been consistently observed in all collected measurements so far. A side-effect of this observation is that the "comfort" automated strategy performs consistently better than the manual user control, because it continuously tracks the ambient conditions and can rapidly respond based on the inferred user's preferences.

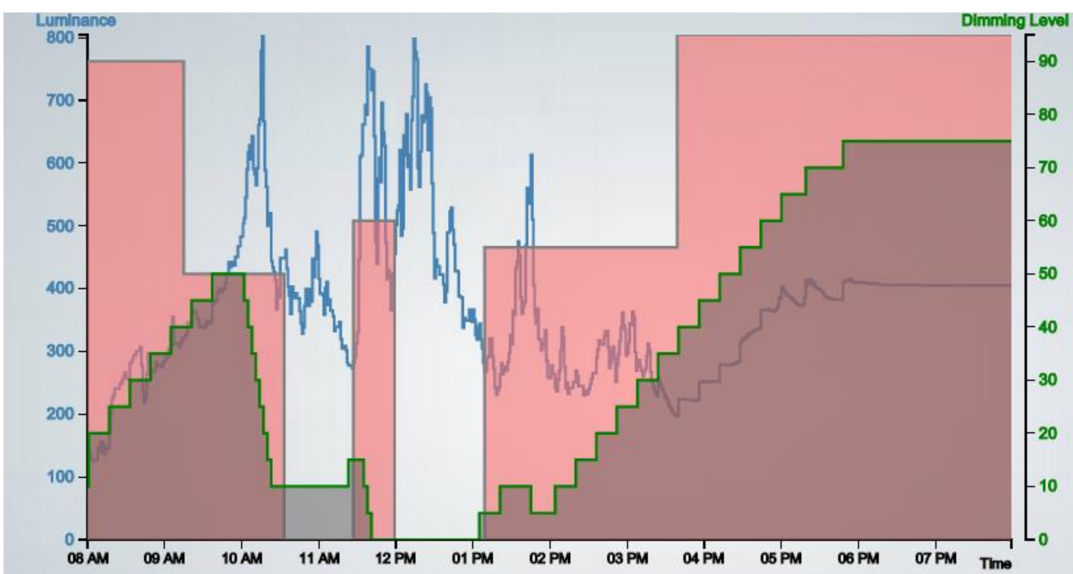

Figure 5 The "Wise" strategy applied in the "South" office on a cloudy day

The user himself is likely to tolerate some discomfort to avoid the inconvenience of going to the lighting switch to dim the lights (Fig. 5). The volatile line depicts the ambient luminance, the upper step-wise line represents the target dimming levels of the manual actions and the lower step-wise line represents the dimming levels set by the automated control. The area between the two step-wise lines is a proxy of the energy savings that can be reaped through automated control. As shown in results presentation, in this experiment 29.2% less energy is used by the "Wise" strategy for a 6.22% sacrifice in comfort of the occupant (from 88.78% to 82.56%).

Furthermore, it is possible and practical to implement several control strategies which span the entire energy efficiency vs. occupancy comfort continuum. This enables the application of centralized lighting control strategies to improve building-level lighting energy efficiency with no or controlled sacrifice in user comfort. The latter has been the main entry barrier for the widespread uptake of automated lighting control solutions. Controlling user (dis)comfort allows the facility manager to gain some energy efficiency from day one without hampering occupant comfort – and potentially progressively further enhancing energy efficiency by trading off some comfort. The proposed framework allows automated lighting control systems to consistently improve occupant visual comfort and reduce lighting energy consumption compared to conventional lighting approaches whereby occupants manually control their lights. The two key enablers are: i) the learning algorithm that unambiguously quantifies personal visual comfort preferences thus improving the acceptance levels for automated lighting control strategies and, ii) the continuous monitoring of ambient conditions that provide the necessary stimuli to the automated lighting control.

CONCLUSIONS

This paper introduces an innovative framework for automated, personalized lighting control in commercial buildings based on an "event-driven" oriented architecture. The framework is structured around a dynamic occupant profiling mechanism constantly adapting to real-time events and ambient information. The core behavioural profiling engine is transparent and entirely implicit, requiring no direct occupant feedback. Integrated but flexible control strategies can reach high levels of savings and comfort.

Pilot assessment indicated more than **10% savings** retaining **comfort levels above 90%** or more than **35% savings** retaining **comfort levels above 75%.** The thorough evaluation of the dynamic seasonal aspects of the proposed occupant profile models is still in progress. Our future research topics include the extension of scope of the profiling models, towards addressing other major commercial and residential loads (other than lighting), along with appropriate integrated building control strategies.

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