Combined Visual Comfort and Energy Efficiency through True Personalization of Automated Lighting Control

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Abstract: Lighting consumes a sizable portion of the energy consumed in office buildings. Smart lighting control products exist in the market, but their penetration is limited and even installed systems see limited use. One of the main reasons is that they control lighting based on universal set-points agnostic to individual human preferences, thus hampering their comfort. This paper presents an automated lighting control framework which dynamically learns user lighting preferences, models human visual comfort and controls light dimming in a truly personalized manner so as to always control the comfort vs. energy efficiency trade-off. It effectively removes the most important complaint when using such systems - loss of comfort - and paves the way for their wider scale adoption in order to untap the energy reduction potential of commercial lighting.

1 INTRODUCTION

Lighting is a major (over 30%) electricity end-use in office buildings (US Department of Energy, 2010) (El-TERTIARY Project, 2008) (US Department of Energy, 2013). Significant cost savings are possible using intelligent lighting control systems. Such systems have long been available, albeit with limited success in massively penetrating the building stock. The main barrier has been their acceptance by occupants. Existing 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 humans, leading to complaints about the lighting adequacy, manual bypassing of automated controls and ultimately abandonment of lighting control systems’ operation.

To leverage the untapped potential for reducing lighting-related energy consumption, the visual comfort of occupants should be treated as a main optimization parameter. This paper presents THOR, a framework for automated lighting control in commercial buildings. Its application in real-life pilot trials has demonstrated tight control of occupant visual comfort and combined gains in energy efficiency and visual comfort compared to a conventional set-up where occupants dim their lights manually using wall-mounted dimming switches.

The THOR framework non-intrusively senses ambient conditions and occupant corrective actions (or lack thereof) to infer a stochastic personalized visual comfort model. Combining the model with real-time sensed lighting conditions, it 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 strategies to steer the automated lighting control.

All currently available building control solutions use predefined universal control strategies that always sacrifice individual comfort. Individual preferences are captured manually requiring lengthy surveys and significant system calibration effort. These systems cannot automatically adapt to changes in workspace occupancy or individual preferences. Moreover, occupant preferences are seldom conscious and feasible to extract. THOR tackles these issues by allowing facility managers to automatically optimize building control strategies that balance global operational goals with real time office-level needs based on individual and group level preferences. Control strategies trading-off energy efficiency and comfort can be established; maximizing comfort (Comfort Mode) with some savings, or maximizing savings (Energy Efficient Mode) with controlled discomfort.

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2 STATE OF THE ART

Currently available models and technological solutions in commercial environments do not adequately capture the relationship between energy efficiency and occupants' comfort. Modern building management practice has no modelling tools that sufficiently deal with occupant activities and personal preferences (Robinson 2006) (Zimmermann, 2003 & 2006).

(Shen et al, 2014) provide a comprehensive overview of integrated lighting control techniques 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 occupant location and balance their lighting preferences with energy consumption. In a similar approach, (Chen, 2009) proposes a building control system that manages real-time location and retrieves personal preferences of lighting, cooling, and heating. (Dong, 2009) uses the number of occupants to define the building power demand and thus the extraction of occupancy is a significant variable to increase model accuracy. Incorporating a user profiling framework is crucial to clearly define user preferences that set constrains to the automation mechanism.

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

3 THE THOR FRAMEWORK

This paper introduces THOR, a holistic framework for personalized lighting control in commercial buildings, based on the premise that proper lighting control should incorporate energy efficiency together with occupant comfort. It delivers accurate, "context aware" occupant visual comfort profiles that are generated and are continuously adapted to low-level ambient sensor, energy consumption and user control data. Occupant visual comfort profiles encapsulate all important personalized and lighting-related preferences of occupants and are used to steer diverse lighting control strategies that provide reduced energy consumption and improved comfort levels.

THOR is an "event-driven" Service Oriented Architecture built around an innovative occupant profiling mechanism continuously analysing ambient information and deriving dynamic models of occupant comfort & preferences. An intelligent infusion engine collectively analyses asynchronous events over different time periods and correlates them into causal relationships, thus detecting event patterns and event relationships that span over longer time periods (from seconds to months). The occupant visual comfort profiles are subsequently used to deliver personalized, occupant-centric, energy efficient lighting control services.

The THOR core profiling engine has inherent support for modelling human-centric visual comfort. Visual (dis)comfort 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. 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 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.

3.1 Integrated Learning Model of User Preferences

THOR continuously and collectively processes various asynchronous events captured in live information streams and analysed by an intelligent infusion engine to generate dynamic occupant behavioural profiles. Occupant profiles are:

- *"context-aware"*: they relate occupant actions or lack of actions representing his comfort under the specific environmental conditions,
- *"dynamic"*: they continuously adapt to sensor information capturing seasonal patterns.

Occupant behavioural profiles constitute the point of reference, defining and quantifying in real-time the “boundaries” and “cost” of visual comfort. Three types of events are analysed: **a) occupancy events**: presence information, **b) luminance events**: w.r.t variations in the room luminance and, **c) control action events**: triggered by occupants acting on the operational status of lighting.

The profiling engine analyses actions and lack of (re)-actions under given ambient conditions using a Bayesian Engine to correlate events and generate personalized (dis)comfort indicators to build occupant dynamic profiles. The formalism can be generalised as follows:

$$Pr(Disc \mid Envir) = \frac{w * Pr(Envir \mid Disc)}{w * Pr(Envir \mid Disc) + (1 - w) * Pr(Envir \mid Comf)}$$

w: weight factor

$Pr(Disc \mid Envir)$: Discomfort level given the luminance conditions

$Pr(Envir \mid Disc)$: Luminance state probability given the discomfort level as explicitly indicated by the occupant

$Pr(Envir \mid Comf)$: Luminance state probability given the 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 (dis)comfort. These probabilities are calculated either on-the-fly upon system usage or from historical data. The former corresponds to a real deployment scenario; the latter to the experimental setup of this paper where luminance information is collected from user premises to monitor his light adjustment actions.

We should highlight the distinction between the definitions of explicit and implicit comfort. ***Explicit (Dis)Comfort*** refers to occupant (dis)comfort as it can be extracted from physical actions he undertakes to customize the lighting settings to his liking. When a user intentionally and consciously adapts the ambient luminance, two conclusions are inferred: he is uncomfortable with the current setting and the target conditions make him comfortable. Both set-points provide valuable information regarding 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 by a lack of action. If he is present and not reacting to current luminance, we infer information about his comfort. 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 (w) in the formula is dynamically adjusted, it balances the importance of explicit vs implicit information in quantifying the discomfort probability. Implicit information is generally more difficult to collect and interpret. So, this factor initially assigns more weight to the discomfort component (explicit information) and gradually shifts toward the comfort component as time passes and the system better learns the user preferences.

3.2 Occupant Visual Comfort Modelling

Live data streams were collected, pre-processed, normalized and analysed for 12 months (Nov. 2013 to Nov. 2014) from various types of pilot premises (commercial offices, university campuses, university clinics) involving different types of spaces (single occupant offices, multiple occupants spaces, waiting rooms, coffee places, meeting rooms, etc.). A day sample of collected luminance data and the user’s manual control actions is illustrated in Fig. 2. Clustering techniques were used to robustly identify the boundaries (luminance levels) of user control actions (both preferred and unfavourable states).

Two core indicators are dynamically inferred by the THOR profiling engine: a) a weighted comfort indicator (Fig. 1) and b) a similar weighted discomfort indicator, reflecting the amount of occupant comfort and discomfort under different luminance levels. Subsequent clustering techniques of neighbouring luminance levels, with high and low comfort values, reveal major comfort and discomfort zones, highlighted in Fig. 1.

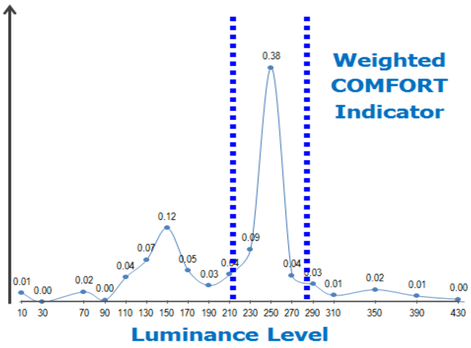

Figure 1: Weighted Comfort Indicator.

Both indicators contain a temporal attribute, allowing us to model and/or predict how (dis)comfort varies over time when remaining under certain luminance conditions. This proves to be a decisive factor when evaluating and eventually deploying alternative energy efficiency strategies, which consist of the

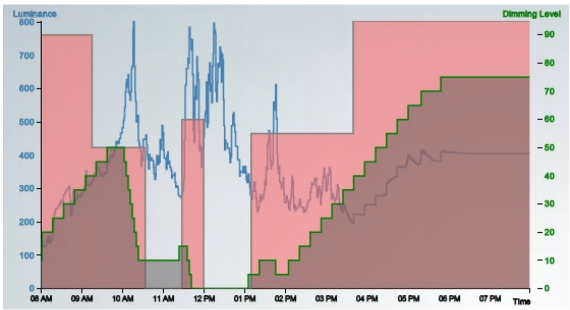

Figure 2: The "Wise" strategy applied in the "South" office on a cloudy day. (Volatile line - luminance; Upper/coarse step-wise line – manual; Lower/fine step wise line – automated actions).

optimal coordination of multiple local control actions with varying durations. This way, appropriate combinations of demand shaping strategies can be designed, executed and re-adjusted based on the cumulative discomfort caused at each point in time.

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. The 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.

3.3 Automated Personalized Control Strategies for Offices & Homes

THOR’s key strength is that it leverages the coarse granularity of manual dimming actions, who are unlikely to fine-tune dimming to a level that exactly matches their comfort zone. This can partly be attributed to the difficulty to internalize visual comfort as a concept. Most office occupants will have a wide range of luminance levels where they feel comfortable enough for professional activities. When manually dimming lights, however, they will seldom look for the lowest possible dimming level which lies within the comfort zone so as to simultaneously optimize comfort and energy efficiency.

To automate this process we have developed an "event-driven” service oriented framework (SOA 2.0) for adaptive and personalized lighting control, evolving around an innovative consumer profiling mechanism. The framework analyses real-time events and ambient information while it utilizes user/occupant profiles to deliver personalized, human centric demand side management services. The user profile models continuously adapt to real-time events and are used by different automated lighting control strategies aiming at maximum comfort, energy efficiency or compromises of the two.

THOR delivers **timely**, **non-intrusive**, **multi-modal** and **personalized ambient services** that discretely learn occupants and safeguard their preferences under different control scenarios. Occupant profiling is implicit. Different views, from simple real-time hints to detailed historical analytics and data mining, are provided (Fig. 2). These views are effective in improving building energy efficiency strategies and increasing occupant awareness by triggering sustainable behaviours. Engagement is improved by revealing intrinsic user profiles related to unconscious behavioural preferences. Information is ***timely*** (the right information at the right time), ***context-sensitive*** (taking into account real-time conditions) and ***ambient*** (exploiting sensing means). Finally, the **visual analytics** allow facility managers to thoroughly evaluate the effect and cost of different strategies, leading to human centric strategies that balance different and **often conflicting performance factors** like ***energy efficiency*** and ***comfort***.

THOR is designed to facilitate three different modes of operation: (i) comfort, (ii) wise and (iii) energy efficient. The three modes differ on the weight of user comfort and achievable energy reduction during the dimming optimization. In the *comfort* operational mode, the system seeks ways to reduce total energy consumption, while ensuring maximum user comfort. In the *wise* operational mode it 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, but it is achieved with more precise and less generous dimming actions. Finally, the *energy efficient* operational mode aims to minimize 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.

4 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 FP7 research projects. The following experiment illustrates its performance after training with the data set mentioned in Section 4.2. Automated control was simulated on two single-occupant offices; one facing south and one north. Real luminance data was collected for two days, a sunny and a cloudy day. The office windows have a different orientation so the acquired luminance profiles for the same day (sunny or cloudy) are not identical. Lighting was monitored between 08.00 and 20.00 on working days to represent typical office hours. Table 1 depicts the results of simulating (on the collected data) three control strategies.

The preferences of the two occupants are quite different. The South office occupant prefers roughly 450 lux and the North office occupant about 400 lux. Moreover, the observed dead-band, i.e. the range where the user is unlikely to react and correct the light conditions, is about 550 lux to 390 lux for the South occupant and 490 lux and 350 lux for the North occupant. The North occupant prefers less light, but is more sensitive to light changes in his environment.

The "manual" entry in Table 1 indicates the results collected from the real-user manual actions. Occupants were asked to control lights manually to provide a baseline for comparing the performance of the lighting control engine and its strategies. Ambient conditions were meticulously recorded during the experiment. Automated control strategies' results were obtained by simulating the strategies for two distinct days (cloudy & sunny).

The average needed time for the learning algorithm to converge to an accurate (dis)comfort indicator ranges from *one to two weeks* according to the data available. This assumes that ambient luminance varies sufficiently so that the occupant performs enough explicit actions to let the system learn. After this period the learning model can be over 90% accurate on the estimation of user comfort. Accuracy further improves with time; after two months average accuracy is about 96%. The likely seasonality of user profiles is taken into account during the learning process by attaching greater weight to most recent luminance and control events of the last 2 months. So, the learning mechanism is more versatile in both the seasonal light level changes and a possible change of the occupant in the office.

The "comfort" strategy (Table 1) maximizes the time when the occupant is in his *high comfort zone*, i.e. above 90%. The "wise" and "energy efficient" strategies achieve smaller high comfort time periods. As indicated by the results, occupant comfort is slightly sacrificed for energy savings. Nevertheless, occupant comfort is always preserved above 70%.

The results of applying the three control strategies are shown in Table 1. Several conclusions can be deducted. In sunny days occupants are more comfortable due to the abundance of natural light and they use artificial lights less, hence potential energy gains are lower. This is also reflected by the lower average dimming throughout the day compared to cloudy days. Daylight limits the need for artificial

Table 1: Comparison of achieved energy efficiency and occupant comfort for a two offices/occupants different control strategies in two different days.

	Ocupant 1 ("South" office)									
	Cloudy day - luminance profile					Sunny day - luminance profile				
	Average Occupant Comfort	Time in High Comfort Zone	Energy Savings	Average Luminance	Average Dimming Level	Average Occupant Comfort	Time in High Comfort Zone	Energy Savings	Average Luminance	Average Dimming Level
Comfort	91.35 %	446 min	15.7 %	419.77 Lux	45.7 %	92.95 %	363 min	11.5 %	557.09 Lux	29.1 %
Wise	82.56 %	275 min	29.2 %	369.25 Lux	35.5 %	85.85 %	184 min	22.1 %	529.65 Lux	23.8 %
Energy Efficient	74.16 %	99 min	44.4 %	342.27 Lux	28.5 %	77.64 %	67 min	36.5 %	504.32 Lux	18.4 %
Manual	88.78 %	308 min	-	517.09 Lux	63.4 %	94.19 %	357 min	-	588.83 Lux	35.3 %

	Occupant 2 ("North" office)									
	Cloudy day - luminance profile					Sunny day - luminance profile				
	Average Occupant Comfort	Time in High Comfort Zone	Energy Savings	Average Luminance	Average Dimming Level	Average Occupant Comfort	Time in High Comfort Zone	Energy Savings	Average Luminance	Average Dimming Level
Comfort	92.9 %	483 min	17.4 %	388.6 Lux	39.3 %	94.08 %	355 min	12.2 %	500.09 Lux	25.5 %
Wise	84.7 %	343 min	29.1 %	344.62 Lux	30.9 %	86.49 %	191 min	23.4 %	473.41 Lux	20.3 %
Energy Efficient	75.9 %	111 min	44.4 %	307.8 Lux	23.2 %	77.6 %	60 min	40.6 %	450.23 Lux	15.4 %
Manual	89.07 %	368 min	-	452.32 Lux	51.0 %	94.59 %	337 min	-	526.84 Lux	30.6 %

lighting and the slack for energy optimization, so automated lighting control can produce lower (absolute and relative) efficiency gains compared to "darker" days when artificial light is used more.

Results indicate that subject occupants, when manually adjusting dimming levels, consistently keep the lights at higher luminance levels compared to their comfort zone boundary. This slack is used by the automated control to produce energy savings. This is a natural human reaction and has been consistently observed in all collected measurements so far.

A related side-effect is that the "comfort" automated strategy performs consistently better than the manual control. Users are likely to tolerate some discomfort to avoid the inconvenience of going to the lighting switch to dim the lights (Figure 2). The area between the two step-wise lines is a proxy of the possible energy savings by automated control. As shown in Table 1, 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%).

Also, it is possible and practical to implement several control strategies which span the entire energy efficiency vs. occupancy comfort continuum. Tight comfort control removes the main entry barrier for the widespread uptake of automated lighting control solutions. Controlling user (dis)comfort allows the facility manager to gain energy efficiency from day one without hampering occupant comfort – and potentially progressively further enhancing energy efficiency by trading off some comfort.

THOR allows automated lighting control systems to consistently improve occupant visual comfort and reduce energy consumption compared to manual control. The two key enablers are: i) the learning algorithm that unambiguously quantifies personal visual comfort preferences and improving 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.

5 RESIDENTIAL LIGHTING CONTROL APP

A residential version of THOR has been developed for mobile devices. It uses available gateways to dim the lights and uses sensors (cameras, luminance sensors, movement sensors) existing on devices to offer enhanced functionality for personalized (comfort based) light control. A free version, called Hue Mate, offering automated personalized light control of Philips Hue lights is available in Google Play and App Store.

6 CONCLUSIONS AND FUTURE WORK

This paper introduces THOR, an innovative framework for automated, personalized lighting control in commercial buildings. It is based on 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% energy savings retaining comfort levels above 90%** or more than **35% savings retaining comfort levels above 75%**.

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