An Experimental Survey of Feedback Control Methodologies for Advanced Lighting Systems

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Abstract

Lighting constitutes a significant portion of building energy consumption. Various lighting control strategies exist that reduce the energy consumption by decreasing dimming level of the fixtures and also ensure the color quality of the achieved light. These strategies differ in their input parameters, control objectives, control algorithms, cost of installation, complexity of commissioning, availability of hardware, etc. Each of these control schemes has a unique set of factors that affect their performance in terms of energy savings as well as the achieved light quality. This paper presents an experimental survey of four state-of-the-art lighting control strategies, the formulation of their associated problems as well as their solution approaches, the experimental results obtained from their implementation in a standard testbed, and the factors affecting their performances.

Keywords: Smart Lighting; Feedback Control; Polychromatic LED Sources; Spectral Optimization; Hierarchical Optimization; Daylight Harvesting; Daylong Experiment; Experimental Survey.

Nomenclature

Acronyms

<i>CCT</i>	Correlated Color Temperature
<i>CRI</i>	Color Rendering Index
<i>DIC</i>	Decentralized Integral Control
<i>IBA</i>	Illumination Balancing Algorithm
<i>LDR</i>	Light Dependent Resistor
<i>LED</i>	Light Emitting Diode
<i>LTM</i>	Light Transport Matrix
<i>PWM</i>	Pulse Width Modulation
<i>SCR</i>	Smart Conference Room

Variables

Δ_{uv}	Degree of departure from the black body curve
G	Light Transport Matrix
$T(\mathbf{u})$	CCT of the generated light
T_d	Desired CCT
u	Input intensities of the LED sources
y	Measurement from color sensors
y_d	Desired sensor measurement

1. Introduction

With rapid advancement in the sensing, actuation, and networking technologies, the new generation of advanced lighting systems can accomplish far more than mere illumination. While illumination is a crucial functionality in a building, other factors such as safety, power efficiency, and human comfort are also critical to management of modern commercial buildings.

In 2015, about 404 billion kilowatthours (kWh) of electricity were used for artificial lighting by the residential sector and the commercial sector in the United

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Figure 1: The systems-level structure of the feedback control loop in a smart lighting system.

States; which was about 15% of the total electricity consumed by both of these sectors and about 10% of total U.S. electricity consumption [1]. While LEDs (Light Emitting Diodes) are inherently more efficient than other lighting technologies such as incandescent and fluorescent bulbs, utilization of feedback control allows for even further energy savings as well as better illumination. Two main mechanisms that contribute to the energy savings in closed loop lighting systems are occupancy-based lighting and daylight harvesting. The former is the dimming of the lights in unoccupied areas in the illuminated space, and the latter is the incorporation of the incoming daylight from windows or skylights into space illumination, so that the fixtures can be dimmed where and when daylight is available. Due to the varying nature of the space occupancy and daylight, use of feedback control is an essential requirement for these capabilities. Besides energy efficiency, the objective of achieving comfortable lighting has also been studied in literature. Although lighting comfort depends on different parameters such as illumination, correlated color temperature (CCT), perception of color, and glare, two major criteria that have been studied in literature to ensure comfortable lighting are uniform illumination and color accuracy.

Figure 1 shows different components and the corresponding interconnections in an advanced lighting system. The illuminated space is equipped with LED fixtures, color sensors, and occupancy sensors. The intensity of the light generated by individual LEDs in the fixtures can be controlled by the input signal. The occupancy sensors estimate the number and location of

the occupants, while the color sensors measure the intensity and spectral content of the incident light. The occupancy information is used to determine the desired lighting condition for the ongoing use scenario in the space, while the color data is used to efficiently generate and maintain the desired condition subject to varying daylight levels. The controller takes in the desired values and the sensor measurements, and generates the required input for the fixtures to achieve the control objective. Advanced lighting systems are now being incorporated into the Building Management Systems. Input from the building manager/ occupants thus plays an important role in designing feedback controllers for lighting systems. The building manager can determine the desired lighting condition or specify the optimization goal of the controller. As shown in Figure 1, feedback control of advanced lighting systems no longer focuses on only achieving the desired set point, but also attempts to optimize various performance metrics like power efficiency, color rendering index, spectral matching, spatial uniformity of illumination and so on.

The existing feedback control algorithms in the literature have different control objectives, different solution approaches, and have been implemented in testbeds with various sizes and configurations. An overview of these studies is presented in Section 2. The wide diversity in these algorithms creates the motivation for a comparative study of their performances. A few studies have targeted this goal [2–4], but only power savings have been reported without looking at the spectral content of the generated light. Further, the performance comparison based on the data in these sur-

veys is difficult to interpret since the data is obtained from implementation in significantly different testbeds and conditions. As a first attempt of its kind, this article introduces a comparative study of the feedback control algorithms for advanced lighting systems by experimental evaluation in a unique full-size standard testbed. We selected four recently proposed algorithms that capture the wide diversity of the existing literature, implemented them in a standard testbed, and experimentally validated their performances by evaluating various performance metrics such as power consumption, color quality, etc. The performances of these state-of-the-art algorithms are demonstrated and discussed in Sections 5 - 8. The algorithms were tested under identical natural lighting condition in a controlled environment for several days and the results from these experiments are shown in Section 9. Finally, conclusions are drawn in Section 10.

2. Literature review

A wide variety of lighting control methodologies have been proposed in the literature. Most of the initial studies focused on achieving a sufficient illumination level by controlling single channel light sources. The emergence of color-tunable LED sources and multi-channel sensing created an opportunity to look into other aspects of lighting systems as well. During the last few decades, many studies have been conducted regarding the control of these advanced lighting systems. The modeling methods, control strategies, and actuation and sensing technologies used in these studies are diverse, accomplishing various control objectives under different constraints and assumptions. In the following sections, a broad classification of these existing studies is presented.

2.1. Classification based on control objectives

One of the diverse aspects of the existing studies on control of lighting systems is the control objective, i.e., the predefined set of goals that the implementation of the controller aims to achieve. A simple example is achievement and maintenance of an illuminance level in the illuminated space subject to various levels of incoming daylight from windows and/or skylight [5–21]. In these studies, it is assumed that the comfort level of the user solely depends on the illuminance level of the work surface. In other studies, more complex representations of the human factors are considered to either guarantee or maximize the occupant comfort level [15, 22–28]. For example, in [27], Pan et al. proposed

a control algorithm to achieve user satisfaction with different activity profiles using a wireless sensor network. Two models were used to describe occupant satisfaction, a binary satisfaction model and a continuous satisfaction model. For binary satisfaction model, it was assumed that the user would be completely satisfied if the generated illuminance fell within the desired interval for the particular time period, and completely unsatisfied otherwise. In the continuous satisfaction model, the satisfaction level for occupants was assumed to be a continuous function of the generated illuminance compared to the desired interval. In [23], Kurian et al. presented a framework to optimize power consumption, visual comfort, and thermal comfort based on fuzzy logic and using control of light fixtures and blinds. In this study, the user comfort was achieved by reducing the effect of glare and ensuring uniform lighting. Uniformity of the illuminance pattern on the work surface is another control objective that has previously been studied [15, 21]. Another common control objective is minimization of the electrical power consumed by the lights [14–16, 23, 24, 27–31]. Occupancy-based lighting has also been studied as a method to improve power efficiency [9, 13, 19, 20, 22, 32–35].

2.2. Classification based on actuation and sensing techniques

Another important aspect of the existing studies on control of lighting systems is the type of actuation and sensing technologies that the algorithms have been designed for and verified with. Various lighting technologies such as incandescent [21, 26, 28], fluorescent [5–9, 17, 18, 27, 29], and LEDs [14–16, 30, 31] have been used to implement and verify the proposed algorithms. While the typical actuation systems are light sources, a few studies have focused on control of other lighting-related actuators such as automatic blinds [10, 23, 24], light pipes [9], and electro-chromatic windows [25]. Different sensing technologies used in the existing literature include photosensors [5–8, 10], wireless network of ambient light sensors [17, 18, 22, 26, 29], network of infrared motion and occupancy sensors [9, 13, 20, 22, 32–35], network of RGB color sensors [14–16, 30, 31], Light Dependent Resistors [21], and cameras [19].

2.3. Classification based on control architecture

Control architecture is another important aspect of the existing studies on feedback control of the lights. Control architecture describes the set of system architectures, algorithms, and design techniques that have been proposed to achieve the above control objectives.

From the closed loop system architecture perspective, the proposed algorithms can be classified into the centralized, decentralized, and distributed categories. In a centralized closed loop lighting system, the sensory data from all the sensors are sent to a single main controller, where the input for all the light fixtures is calculated and transmitted to the fixtures [5–8, 15–18, 20, 26, 29–31, 33, 36, 37]. In a decentralized closed loop lighting system, each light fixture has its own light source, sensing module, and controller, and the input to the light source is determined solely based on the fixture’s own sensor measurement [13, 14, 21]. A distributed lighting system is similar to a decentralized system, with the difference that the fixtures can use local communication to transmit data to and receive data from the nearby fixtures [13, 21, 28, 35].

2.4. Classification based on control methodology

From a mathematical perspective, the proposed control methodologies can be classified into three categories of logic-based controllers, regulation-based controllers, and optimization-based controllers. In logic-based methods, various decision-making techniques are used to infer the correct action for the lighting system in different situations based on the measured values from the sensors [9, 10, 22–24, 29]. Regulation-Based control algorithms are those that aim to achieve closed loop stability while guarantee that the generated illumination tracks a pre-determined reference value [5–8, 13, 14, 21]. Optimization-based algorithms are an alternative approach to controller design for closed loop lighting systems where the control problem is posed as an optimization problem and solved using optimization techniques [15–18, 20, 26, 28, 30, 31, 33, 35]. While the proposed algorithms in most of the existing literature are based on a mathematical model that describes the generation and distribution of the light in the space, in some studies the control rule is independent of the plant model [9, 10, 21, 22, 29].

2.5. Recent surveys on lighting control systems

The diversity in the existing literature creates the motivation for a comparative study among the performances of different algorithms. In an attempt towards that goal, in 2012, Williams et al. published a meta-analysis of the existing literature on power savings in lighting by including 240 power savings values from 88 papers and case studies [2]. The gathered data were categorized into 4 strategy classes including occupancy (28 percent of the data), daylighting (32 percent of the data), personal tuning (8 percent of the data), and institutional

tuning (7 percent of the data). The remaining 25 percent were reported to be on daylighting together with occupancy (8 percent), occupancy together with personal tuning (7 percent), and other strategies (10 percent). Another review was presented by Asif ul Huq et al.[3], in which the control strategies were divided into two broader categories: daylight linked and occupancy based systems. Various methods of occupancy detection and daylight harvesting along with their respective power savings were presented. Recently, Pandharipande et al.[4] presented a comparative survey of luminaire-based sensing strategies (where sensors are co-located with the light sources) in office lighting applications. The spectral content of the generated light was not taken into account in these comparative studies and the addressed control methodologies were implemented and evaluated in testbeds of various sizes and configurations, which creates a challenge for comparative performance evaluation.

To overcome this challenge, here we survey four recently proposed algorithms, chosen to broadly represent the different existing design methodologies. The Illumination Balancing Algorithm [21] approach uses a regulation-based solution approach to a tracking problem that deals with single-color lighting. The daylight and occupancy adaptive lighting control [20] approach is an iterative optimization technique for single-color lighting systems. The energy efficient control of polychromatic lighting systems [30] approach uses a one-shot optimization technique for color-tunable lighting systems. Finally, the control of non-square lighting systems [31] approach deals with a constrained optimization problem with multi-channel sources and sensors and proposes an iterative technique to solve the problem. These state-of-the-art strategies were implemented in a room-scale standard testbed (described in the next section) and their performance evaluations are presented in the subsequent sections. Day long experiments were also carried out for all of these algorithms under identical natural lighting condition. The results from these experiments are presented in Section 9.

3. Testbed description and system modeling

3.1. An experimental testbed for benchmarking

A variety of different testbeds with various sizes and configurations have been used in existing literature to implement and validate the proposed feedback control algorithms. A standard testbed for experimental comparison between these algorithms should be equipped with dimmable and spectrally tunable fixtures as well

as occupancy and color sensors. This enables the generation of a wide range of lighting conditions as well as measurement of light levels and occupancy state necessary for evaluating different algorithms. The standard testbed should also have windows or skylights for natural light in order to evaluate the effect of ambient lighting on the performance of the algorithms. The actuators (lighting fixtures), sensors, and the controller should be connected through a fast reliable network to ensure a robust controlled environment. Ideally, the testbed should be a full-scale space that is used by real occupants on a consistent basis to enable testing of various use cases.

An example of such a standard experimental testbed is the Smart Conference Room (SCR), a full-size conference room [38] equipped with color-tunable LED fixtures, RGBC (Red-Green-Blue-Clear channels) color sensors, and Time-Of-Flight occupancy sensors, located in Rensselaer Polytechnic Institute campus in Troy, New York. This room is used for meetings and conferences, and also serves as one of the testbeds within the Center for Lighting Enabled Systems and Applications (LESA), where experiments on feedback control of lighting systems, human factors, and occupancy-based lighting are conducted. The room is equipped with ten LED light fixtures retrofitted in $2' \times 2'$ cases, each containing five different LED colors (i.e., input channels). The five LED channels are red, green, blue, amber, and phosphor-converted white. Also, fifty three RGBC color sensors are installed on the ceiling to measure the light field in the room, one per each ceiling tile. These sensors consist of a TCS34725 RGBC sensor, an optical lens, and a ceiling mount. Additionally, eighteen multi-pixel Time-Of-Flight sensors are installed on the ceiling, from which occupancy information is extracted. The room has windows on the eastern and northern walls, allowing for natural daylight to serve as ambient external light. Figures 2 and 3 demonstrate the SCR, the different components used in it, and the layout of the different components.

The LED fixtures are connected to a main computer via local Ethernet connections, supported by TCP/IP protocol. Further, all the sensors transmit their measured data to a single main Raspberry Pi computer via I^2C bus. The main Raspberry Pi is programmed to act as a multiplexer, acquiring the data from all the sensors and sending it to the main server using local Ethernet connection. In view of the above definition given for a standard testbed, the SCR possesses the qualifications for a comprehensive study. Hence, the selected four algorithms were implemented in this space to experimentally validate their performances on a standard baseline.

Figure 2: (a) The ceiling of the Smart Conference Room, (b) the 5-channel light fixture, (c) the RGBC color sensor, (d) the multi-pixel Time-Of-Flight sensor.

Figure 3: A top-view schematic diagram of the different components in the Smart Conference Room.

3.2. Light transport modeling and identification

In a typical lighting system, the input to the system is the set of individual intensity signals to different fixtures, and the output is the measurement from the sensors. The light field at a point in space is characterized by the plenoptic function, $\phi(r, \theta, \lambda)$, which is the spectral irradiance (in $W/m^2 \cdot nm$) along the ray given by the location of the point, $r \in \mathbb{R}^3$, and solid angle of the incoming light direction, $\theta \in S^2$, for the wavelength, $\lambda \in \Lambda$, where Λ is the visible light range [390, 750]nm [39]. Consider a space with n light fixtures, each of which contains p adjustable intensity channels (e.g., different color LEDs). Assume that the input to each fixture is

Figure 4: Control architecture and system modeling based on Light Transport Matrix (LTM) for feedback control of advanced lighting systems. In this article, we are mainly focused on the feedback control algorithm, marked with red.

represented as a vector, $u^i \in \mathbb{R}^p$, $i = 1, \dots, n$, and each entry in u^i is normalized to the range $[0, 1]$. Each light fixture generates a light field throughout the space. Let the unit plenoptic light field generated by fixture i be $S^i(r, \theta, \lambda) \in \mathbb{R}^p$, with the spectral dependence for each channel given by the spectral characteristics of the corresponding light source. Denote the ambient light field as $\psi(r, \theta, \lambda)$. Then the total light field is the linear combination of the generated and ambient light,

$$\phi(r, \theta, \lambda) = \sum_{i=1}^n S^i(r, \theta, \lambda)^T u^i + \psi(r, \theta, \lambda). \quad (1)$$

Assume there are m locations of interest for the overall light field in the space, and there is a sensor with q channels of spectral sensing at each location. The overall output vector is therefore a vector with qm elements, consisting of the different $y^j \in \mathbb{R}^q$, $j = 1, \dots, m$. Let the responsivity function for each sensor be $C^j(r, \theta, \lambda) \in \mathbb{R}^q$. The output at each location is thus given by

$$y^j = \langle C^j, \phi \rangle + v^j \quad (2)$$

where $\langle \cdot, \cdot \rangle$ denotes integration over the spatial, angular, and spectral ranges of the color sensor, and v^j is the measurement noise. Without loss of generality, we will assume $y^j \in \mathbb{R}^4$ represents the RGBC sensor measurements at the locations corresponding to $j = 1, \dots, m$. The overall output vector is therefore a vector with $4m$ elements.

Substituting the light field in Equation (1) into Equation (2), we obtain

$$y = Gu + w + v \quad (3)$$

where $y = [y^1, y^2, \dots, y^m]^T \in \mathbb{R}^{4m}$ is the output light measurement vector, $u = [u^1, u^2, \dots, u^n]^T \in \mathbb{R}^{pn}$ is the input light intensity vector, $G \in \mathbb{R}^{4m \times pn}$ is the Light Transport Matrix (LTM) [40], $w \in \mathbb{R}^{4m}$ is the ambient light, and $v \in \mathbb{R}^{4m}$ is the measurement noise. The LTM is used to characterize the input-output relationship for the lighting system [36]. An example of using linear light transport model in dual photography can be found in [41]. A schematic diagram illustrating the closed loop controller and the different variables is shown in Figure 4.

Different methods can be used to identify the light transport matrix for an illuminated space. A typical approach is posing of the model identification problem as a least squares problem. Let $U = [u_1, u_2, \dots, u_N]$ be a set of N input vectors to the system, and $Y = [y_1, y_2, \dots, y_N]$ be the corresponding sensor measurements from the space. Then the least square estimate of the LTM is simply $\hat{G} = YU^+$, where U^+ is the Moore-Penrose pseudo-inverse of U . Note that U has to be full row rank and well conditioned in order for this estimate to be accurate. This is usually ensured by using randomly generated u_i .

We introduced the wide variety of the existing algorithms for closed loop control of advanced lighting systems in Section 2. In the following sections, we will

take a closer look at four of the recently proposed algorithms, chosen to represent the different existing design methodologies. We will start with a brief description of the proportional-integral control of lighting systems in Section 4, which is the most basic controller for a lighting system. Then Sections 5 to 8 will present the problem formulation, controller design methodology, and performance evaluation for the selected algorithms.

4. Decentralized Integral Control

The simplest control methodology beyond on-off control of lights with guarantee of zero steady state error is pure integral control, described as

$$u(k) = \alpha \sum_{j=0}^{k-1} e(j) \quad (4)$$

where $e(j) = y_d(j) - y(j)$.

here α is the controller gain, and $e(j)$ represents the error between the desired (y_d) and measured (y) sensor measurements at j -th time-step. Note that, the integral controller considers the history of the error, i.e., how far the measured light level y has been from the desired value y_d over time. By considering this error history, the integral controller eliminates the steady state error.

For decentralized implementation of the integral controller, putting the value of $u(k-1)$ into $u(k)$, the control law for i -th location can be stated as:

$$u_i(k) = u_i(k-1) + \alpha e_i(k-1) \quad (5)$$

where $e_i(k-1) = y_d(k-1) - y_i(k-1)$.

here α is a parameter to adjust the speed of convergence, and $y_d(k-1)$ and $y_i(k-1)$ are respectively the desired and measured light levels at i -th location at the $(k-1)$ -th time-step. This control law will be termed as Decentralized Integral Controller (DIC) for the rest of this article. We implemented this algorithm in the SCR to compare its performance with the Illumination Balancing Algorithm from [21]. The results of this comparison are discussed in Section 5.3.

5. Illumination Balancing Algorithm [21]

For lighting systems with collocated light sources and sensors, the cross-illumination effect between the different fixtures is a major obstacle in achievement of uniform illumination. In [21], Koroglu and Passino addressed this issue by proposing a distributed control algorithm that uses the illumination levels of the neighboring fixtures to generate the control input for each fixture. While the basic DIC fails to achieve the uniformity

objective under cross-illumination effects, the proposed algorithm balances the illumination level by taking the local sensor measurements of the neighbor fixtures into account. This algorithm is termed as the Illumination Balancing Algorithm, or shortly IBA.

5.1. Problem statement

The control objective of IBA was defined in [21] as tracking a desired light level while ensuring uniform illumination across all the zones of the work surface, with communication among the light fixtures being restricted within a small neighborhood. The work surface was divided into some pre-defined zones, where each zone consisted of a mono-chromatic (i.e., white channel only) light source and a Light Dependent Resistor (LDR), used as sensors.

5.2. Solution approach

The proposed solution begins with picking an arbitrary 'leader' zone l , which is the only zone that has access to the desired illumination level. Both the integral control and illumination balancing are applied in this zone, described in Equation (6). All the other zones can only balance their illumination level within the pre-defined neighborhood (described in Equation (7)) and eventually follow the 'leader' zone l and track the desired illumination level without explicitly knowing its value.

$$u_l(k) = u_l(k-1) + \alpha e_l(k-1) - \sum_{j \in N(l)} \gamma (y_l(k-1) - y_j(k-1)). \quad (6)$$

$$u_i(k) = u_i(k-1) - \sum_{j \in N(i)} \gamma (y_i(k-1) - y_j(k-1)) \quad i \neq l. \quad (7)$$

Here, $N(i)$ represents the set of neighboring zones adjacent to the i -th zone. The illumination balancing term in the proposed algorithm takes into account the illumination difference between the neighboring zones. If zone i has higher illumination than its neighbors at a particular time-step, this term compensates for the existing difference by decreasing the input intensity of the light fixture in the i -th zone proportionally. Here, γ is a parameter that adjusts the stability margin and convergence speed for illumination balancing, and α denotes the convergence speed of the integral controller. According to [21], the speed of illumination balancing should be higher than the speed of integral controller, i.e., $\gamma > \alpha$, in order to achieve uniform illumination

Figure 5: Zone configuration and neighborhood topology for the implementation of IBA. Zones 1, 4, 5, and 8 have two neighbors each, while zones 2, 3, 6, and 7 have three neighbors.

equal to the desired value across the work surface. In the case of zero cross-talk among the fixtures, the closed loop stability condition for γ is proved in [21] to be $\gamma \leq \frac{1}{N_I+1}$, where N_I denotes the maximum number of neighbors for an individual zone. In the SCR, $N_I = 3$.

Similar to the setup described in [21], we chose a subset of eight light fixtures and eight sensors in the SCR to implement this algorithm ($n = m = 8$). The zone configuration and the neighborhood topology that we used in our implementation is shown in Figure 5. Since this algorithm was proposed for single-color lighting systems ($p = q = 1$), the white channels of the fixtures were selected as the source and the clear channels of the color sensors were assumed to be the illuminance sensors. Note that in the SCR, the light sensors are co-located with the fixtures. However, in [21], the LDRs used as illumination sensors were placed on the work surface directly under the lights. To compensate for this difference, an additional calibration step was taken to map the illumination values on the work surface to the illumination values measured by the sensors on the ceiling. This calibration procedure normalizes both the input intensities u_i and the sensor measurements y_i in the absence of cross-illumination effects to the range $[0, 1]$. Note that, in the presence of cross-illumination effects, the sensor measurements can be larger than 1. A similar calibration procedure was described in [21].

5.3. Results

First, the DIC algorithm described in Equation (5) was implemented in each of the individual zones in SCR depicted in Figure 5. Note that in this implementation, it was assumed that there was no communication between the light fixtures in different zones. The cross-illumination effect between the zones prevented achievement of uniform illumination across the work surface. As shown in Figure 6, zone 3 stayed over-illuminated.

Next, the IBA was implemented in the SCR with

$\alpha = 0.1$, $\gamma = 0.2$, and l arbitrarily chosen as 7. For all the zones except zone 7, the tracking was achieved without the knowledge of the desired light level, and simply by balancing their light input with the input intensity of their respective neighboring fixtures. Figure 6 shows that using IBA, zone 3 could track the desired light level without explicitly knowing this value in the presence of cross-illumination effects.

Figure 6: Sensor measurements at zone 3 during the implementation of the DIC and IBA. IBA can achieve uniform illumination in the presence of cross-illumination. But it can not withstand significant amount of cross-illumination (i.e., the case with all ten fixtures).

Figure 7: Zone configuration and neighborhood topology for the case of maximum cross illumination. Zones 1, 4, 7, and 10 have two neighbors each, zones 2, 3, 8, and 9 have three neighbors each and zones 5 and 6 have four neighbors.

To examine the robustness of the IBA to high cross-illumination, we implemented it with a set of ten lights and ten sensors. The topology and sensor configuration are shown in Figure 7. In the new configuration with ten lights, IBA could not achieve uniform illumination across the work surface due to the excessive cross-illumination among the lights. Figure 6 shows that, zone 3 could not track the desired light level with this new zonal configuration.

6. Daylight and Occupancy Adaptive Lighting [34]

Unlike the distributed approach taken in IBA, Caicedo et al [34] adopted a centralized approach to optimize power efficiency subject to daylight harvesting and occupancy adaptation. The objective was to minimize the total power consumption of the system while maintaining a variable minimum level of illuminance at each sensor and keeping the input intensities of the neighboring fixtures close for light field uniformity purposes. The desired minimum illuminance level depended on the occupancy state of the zones.

6.1. Problem formulation

The light fixtures in SCR use pulse width modulation (PWM) dimming, for which the power consumption by each light channel is proportional to its input intensity. We therefore chose to represent the total power consumption of the system with the summation of the input intensities of the lights $\sum_{i=1}^n u_i$, where $n = 10$. The overall optimization problem can be formulated as

$$\begin{aligned} \Delta \mathbf{u}(\mathbf{k}) &= \underset{\Delta \mathbf{u}}{\operatorname{argmin}} \sum_{i=1}^n \Delta u_i(k) \\ \text{subject to :} \\ \mathbf{G}\Delta \mathbf{u}(\mathbf{k}) &\geq \mathbf{y}_d^x(k) - \mathbf{y}(k-1), \\ -\Delta \mathbf{u}(k-1) &\leq \Delta \mathbf{u}(k) \leq \mathbf{1} - \Delta \mathbf{u}(k-1), \\ |\Delta u_i(k) - \Delta u_j(k)| &\leq \delta u - \Delta u_i(k-1) + \Delta u_j(k-1), \\ \text{where } i &= 1, \dots, n \text{ and } \forall j \in N(i). \end{aligned} \quad (8)$$

where $\Delta \mathbf{u}(\mathbf{k}) = [\Delta u_1(k), \dots, \Delta u_n(k)]^T$ is the incremental step vector for the input intensity, $\mathbf{y}(k-1)$ is the sensor measurement at $(k-1)$ -th time step, $\mathbf{y}_d^x(k)$ is the desired illuminance based on the occupancy state, x represents the occupancy state (0 and 1, for unoccupied and occupied respectively) at k -th time step, δu is the threshold for the input intensity differences within the neighborhood fixtures, $N(i)$ defines the set of neighbor fixtures of the i -th fixture, and $\mathbf{G} \in \mathbb{R}^{qm \times pn}$ is the LTM described in Section 3.2.

The objective of this optimization problem is to minimize the power consumption of the lighting system while satisfying the following constraints: (i) the illuminance level $y(k)$ at each sensor is above a desired set point $y_d^x(k)$ depending on the occupancy state x , (ii) the input intensities take values within the physical constraints, and (iii) the difference in input intensities of luminaries within the neighborhood defined by $N(i)$ is less than δu .

6.2. Solution approach

The optimization problem with the linear objective function and linear constraints shown in Equation (8) was solved using the interior point method in an iterative approach [34]. The update equation for the input intensity level at iteration k is

$$\mathbf{u}(k) = \mathbf{u}(k-1) + \alpha \Delta \mathbf{u}(k). \quad (9)$$

At each iteration k , the centralized controller solves the linear optimization problem in Equation (8) to obtain the incremental step vector for the input intensity $\Delta \mathbf{u}(k)$, and uses Equation (9) to update the complete input intensity vector $\mathbf{u}(k)$ for the next time-step.

The advantage of using such an iterative approach over a direct solution is to eliminate the requirement of explicit knowledge of the daylight contribution, $\mathbf{y}_{dark}$, at the sensor nodes at each time instant k . The first constraint in Equation (8) is actually simplified from $\mathbf{G}(\mathbf{u}(k-1) + \Delta \mathbf{u}(k)) \geq \mathbf{y}_d^x(k) - \mathbf{y}_{dark}(k)$, which ensures that the achieved illumination at time step k is higher than the desired illumination level. This simplification utilizes the sensor measurements at time instant $(k-1)$, $\mathbf{y}(k-1) = \mathbf{G}\mathbf{u}(k-1) + \mathbf{y}_{dark}(k-1)$. Here it is assumed that the daylight contribution between time instant k and $(k-1)$ changes slowly, i.e., $\mathbf{y}_{dark}(k) \approx \mathbf{y}_{dark}(k-1)$.

This algorithm assumed co-located light fixtures and sensors and an occupancy sensor for each zone. For the implementation of this algorithm in SCR, we selected ten zones of interest directly under the ten light fixtures ($n = m = 10$). The zone configuration and the neighborhood topology used in this implementation is shown in Figure 7. Since this algorithm was proposed for single-color lighting systems, the white channels ($p = 1$) of the fixtures were selected as the source and the clear channels ($q = 1$) of the color sensors were assumed to be the illuminance sensors. For simplicity, the occupancy state for each zone was assumed to be known.

The design parameter α determines the speed of adaptation, and can be adjusted to achieve smoother transition of the intensity levels. To solve this iterative optimization problem, the central controller does not require the knowledge of daylight contribution at each time-step as long as the variation in daylight contribution is negligible between two consecutive iterations.

6.3. Results

To demonstrate the effect of the desired illumination level y_d , the experiment was repeated with the value of y_d varied from 75 lux to 400 lux with a 25 lux increment. The uniformity threshold was fixed at 0.2 throughout the

Figure 8: Results obtained from the implementation of daylight and occupancy adaptive lighting algorithm, as desired illumination varies from 75 to 400 lux with uniformity threshold kept constant at 0.2, (a) maximum non-uniformity among the input intensities, (b) average error between desired and achieved illumination level.

experiments. The results are shown in Figure 8. Figures 8(a) and (b) show the maximum non-uniformity among the steady state input intensities and the error in achieved illumination level.

7. Spectral optimization for polychromatic lighting [30]

Both the control strategies discussed in the previous sections were designed for monochromatic lighting systems. Aldrich et al. [30] studied the problem of controlling color-tunable LED fixtures. These fixtures are polychromatic, i.e., they can generate a wide range of colors. The authors posed the control problem as a constrained optimization problem, similar to [34]. The objective was to either minimize the energy consumption or maximize the color rendering index (CRI) for a given color temperature (T_d), determined by the user.

7.1. Problem formulation

As shown in Equation (10), the piece-wise cost function for the optimization problem includes three different terms. These terms are the norm of the difference between the desired and measured color temperatures (T_d and T respectively), a nonlinear term ($\Delta uv(T)$) that

quantifies the distance between the generated color and the black body curve in the chromaticity space, and an additional term that may be chosen as either the normalized power consumption (shown as J_1 in Equation (10)) or the normalized CRI of the generated light (shown as J_2 in Equation (10)). Notice that the black body curve or planckian locus characterizes the set of all color points of the light radiated from a black body in different temperatures. The overall control design problem was formulated as the following optimization problem

$$\begin{aligned} \min_{\mathbf{u}} \quad & J_i(\mathbf{u}) \quad i = 1, 2 \quad \text{subject to} \\ & y_d - y_{dark} \leq \mathbf{G}\mathbf{u} \leq (1 + \beta)(y_d - y_{dark}), \\ & \text{and} \quad \mathbf{0} \leq \mathbf{u} \leq \mathbf{1} \end{aligned}$$

where

$$\begin{aligned} J_1(\mathbf{u}) &= \left(\frac{T_d - T(\mathbf{u})}{T_d} \right)^2 + \alpha_1 \Delta uv(T(\mathbf{u}))^2 + \alpha_2 \left(\frac{\Gamma_E \mathbf{u}}{P_t} \right)^2, \\ J_2(\mathbf{u}) &= \left(\frac{T_d - T(\mathbf{u})}{T_d} \right)^2 + \alpha_1 \Delta uv(T(\mathbf{u}))^2 - \alpha_2 \left(\frac{R_e(\mathbf{u})}{100} \right)^2. \end{aligned} \quad (10)$$

Here, $\mathbf{u} = [u_1, \dots, u_p]^T$ is the input intensity vector for the LED channels (total of p channels), Γ_E is a row vector consisting of the power consumption of each LED channel in the full-on state, $P_t = \sum_{i=1}^p \Gamma_E$ is the maximum power consumption for an individual light fixture, α_1 and α_2 are two weighting parameters, y_d and y_{dark} are respectively the desired minimum illumination and the ambient illumination measured at the sensor node position, and $\mathbf{G} \in \mathbb{R}^{qm \times pn}$ is the LTM described in Section 3.2. The linear constraints ensure that the achieved illumination level on the work surface falls within a neighborhood (defined by the parameter β) of the desired minimum illumination level, y_d . It also ensures that the achieved input intensities fall within the fixture saturation range.

Note that the first term in Equation (10) ensures that the CCT of the generated light ($T(\mathbf{u})$) is close to the desired CCT, T_d . However, this does not guarantee that the generated color point lies on the black body curve. The distance from the black body curve (i.e., degree of departure from the black body) is traditionally indicated in units of Δuv . Putting a penalty on $\Delta uv(T(\mathbf{u}))$ in the cost function (Equation (10)) ensures that the generated color is close to that of a black body radiator with the same CCT.

7.2. Solution approach

The standard non-linear solver in MATLAB was used to obtain the optimum input intensity

$$\mathbf{u} = \argmin_{\mathbf{u}} J(\mathbf{u}). \quad (11)$$

satisfying all the constraints specified in Equation (10).

Note that this algorithm does not take the spatial variation of the light field into account and is designed for a system with a single light source and a single sensor placed at a predefined position. Therefore, for implementation of this algorithm in SCR, the inputs to all ten light fixtures were assumed to be identical, essentially merging them into a single large color-tunable light source with 5 channels (red, green, blue, amber and phosphor-converted white). Also, the algorithm only requires measurement of the illumination level from a single sensor. In our experiments, we used the clear channel measurement of the color sensor located in zone 5 of Figure 7. The choice of the particular sensor on the ceiling was arbitrary. Unlike the testbed used by Aldrich et al., all the sensors in SCR are located on the ceiling. To estimate the illumination level on the work surface from the measurement of the sensor on the ceiling, a mapping between these two values was obtained during the calibration stage. It was also assumed that the user had the option to change the desired minimum illumination level, y_d , and the desired CCT, T_d , at any time.

7.3. Results

In order to study the effect of different desired CCTs (T_d) on this algorithm, a number of experiments were conducted. The algorithm was implemented for 20 different desired CCTs from 2800 K to 6600 K with steps of 200 K. The desired minimum illumination level was chosen as 400 lux on the work surface. For each desired CCT, two experiments were carried out, one minimizing power consumption and one maximizing CRI. Next, different performance parameters were measured for the achieved light field in the illuminated space. The results are shown in Figure 9. Figure 9(a) shows that for lower desired CCT values, the CRI optimization achieved higher illumination level with a higher level of power consumption compared to the higher desired CCTs. This effect of CCT on power consumption and illumination was more subtle for the power optimization case. The largest achieved power saving for the two optimization cases was 50 W for the desired CCT of 4200 K using the power optimization algorithm.

Figure 9(b) shows that for the CCT range [3600K, 4600K], both power and CRI optimization achieved CRI of more than 95. For the other desired CCTs, a significant difference between the achieved CRIs existed for the two algorithms. In case of power optimization, the achieved CRI went down to 85 for the desired CCT of 6600 K, while maximum value of 96 was achieved at 4000 K. On the other hand, the CRI optimization guaranteed high CRI throughout

Figure 9: Results obtained from the implementation of power and CRI optimization techniques for spectral optimization algorithm, as desired CCT varies from 2800 K to 6600 K with minimum desired illumination kept constant at 400 lux, (a) total power consumption and (b) achieved CRI.

the entire desired CCT range with the maximum of 98 for 5800K. Figures 10(a) and (b) demonstrate the individual LED channel intensities for the optimal input vectors in the case of CRI and power optimization respectively. The reason for the difference in achieved CRI levels for the two optimization algorithms can be observed in these two plots. For power optimization, the controller turned off all the channels except blue and white for the high desired CCTs in order to achieve power savings, which resulted in low CRI level. However, the CRI optimization kept a higher number of LED channels on, which resulted in high CRI throughout the range of the desired CCTs with the cost of higher power consumption.

8. Hierarchical optimization for spectrally tunable LEDs [31]

In [31], Afshari and Mishra proposed an optimization-based framework for control of LED lighting systems with higher number of source channels than sensor channels. The authors presented several control algorithms for performance optimization in these systems, exploiting the inherent redundancy due to the color metamerism that results from the high

Figure 10: Achieved CRI and individual LED channel intensities for the case of (a) CRI optimization and (b) power optimization, as desired CCT varies from 2800 K to 6600 K at fixed minimum desired illumination level of 400 lux.

number of LED channels. The overall optimization problem was posed as choosing the appropriate light input to minimize the weighted sum of two metrics, μ_Q and μ_F , representing the light quality and a user-defined performance metric respectively.

8.1. Problem formulation

Given the LTM, $\mathbf{G} \in \mathbb{R}^{qm \times pn}$, as described in Section 3.2, and a vector $\mathbf{y}_d \in \mathbb{R}^{qm}$ consisting of the desired RGB values for each of the sensors, the light quality metric was formulated as the Euclidean norm of the difference between the desired and measured sensor values ($\mathbf{y}_d$ and $\mathbf{y}$). On the other hand, the performance metric was formulated as a function of the input intensities ($\mathbf{u}$) to optimize a particular aspect of system performance such as power efficiency, CRI, etc, depending on the application.

The overall control design problem was formulated as

$$\begin{aligned} \min_{\mathbf{u}} \quad & \|\mathbf{y}_d - \mathbf{y}_k\|_2^2 + \alpha_f f(\mathbf{u}_k) \\ \text{subject to} \quad & \mathbf{0} \leq \mathbf{u} \leq \mathbf{1}. \end{aligned} \quad (12)$$

where $\mathbf{u} = [u_1, u_2, \dots, u_{pn}]^T$ is the input intensities of the light fixtures, $f(\mathbf{u})$ denotes a user-defined performance metric, and α_f is a weighting coefficient. $\mathbf{u}_k$ and $\mathbf{y}_k$ denote the input intensity vector and RGB sensor measurement vector at k -th time-step respectively.

8.2. Solution approach

To achieve precise color matching between the desired and measured light fields, the optimization problem in Equation (12) was solved in a two-step hierarchical approach. In the first step, a candidate solution ($\bar{\mathbf{u}}_k$) to drive the output of the system toward the desired light field is calculated using a gradient based method. This step is demonstrated with the red arrows in Figure 11. The update equation for this step is defined as

$$\bar{\mathbf{u}}_k = \mathbf{u}_k + \epsilon(\mathbf{G}^T(\mathbf{G}\mathbf{G}^T)^{-1}(\mathbf{y}_d - \mathbf{y}_k)). \quad (13)$$

where ϵ is the step size. Note that the system has more number of source channels than sensor channels. This redundancy in the generation of color results in existence of an infinite number of candidate solutions, all resulting in the same sensor measurements. Each of these solutions may successfully achieve the desired color set-point, as long as achievement of $\mathbf{y}_d$ is feasible. This creates the opportunity of further optimization of the system performance within the set of all the candidate solutions.

Figure 11: The schematic demonstration of hierarchical optimization. Red and green arrows represent the first step and second step of the algorithm (shown in Equations (13) and (15) respectively)

In the next step, another optimization problem is solved to find the input intensity vector from the set of all candidate solutions that optimize the user-defined performance metric. This optimal solution, $\mathbf{u}$, is obtained using the following equation

$$\mathbf{u}_{k+1} = \bar{\mathbf{u}}_k - \mathbf{G}_N \mathbf{w}. \quad (14)$$

where $\mathbf{G}_N$ is an orthogonal matrix with columns spanning the null space of $\mathbf{G}$, and $\mathbf{w}$ is obtained from solving the following optimization problem

$$\begin{aligned} & \min_{\mathbf{w}} f(\mathbf{u} - \mathbf{G}_N \mathbf{w}) \\ \text{subject to} \quad & \mathbf{0} \leq (\mathbf{u} - \mathbf{G}_N \mathbf{w})(i) \leq 1, \quad i = 1, \dots, pn. \end{aligned} \quad (15)$$

The second step is demonstrated with the green arrow in Figure 11. As an example of the user-defined performance metric $f(\mathbf{u})$, we chose to optimize the total power consumption of the system. As discussed in Section 6, the LED light fixtures in SCR use PWM dimming. Therefore, the power consumption of individual LED channels of the fixtures can be approximated as a linear function of the channel's input intensity. Hence, we can model the performance metric $f(\mathbf{u})$ as $\Gamma_E \mathbf{u}$. The row vector Γ_E represents the power consumption by the individual LED channels when they are in full-on state. Using this formulation, the hierarchical approach results in convergence to the most power efficient solution that obtains $\mathbf{y}_d$ at the sensor locations. Note that this approach ensures zero steady state error as well as power minimization, as opposed to trading off light quality with power savings in a single step.

In order to implement this algorithm in SCR, we selected ten zones directly under the ten light fixtures ($n = m = 10$). The zone distribution was identical to Figure 7. However, unlike the previous three algorithms, this algorithm is designed for lighting systems with multi-channel light sources and sensors, hence all the five channels ($p = 5$) of the fixtures and three channels ($q = 3$) of the RGB sensors were considered for this implementation. The five LED channels were red, green, blue, amber and phosphor-converted white, while each sensor had red, green, and blue channels to measure the spectral content of the incident light.

8.3. Results

A number of experiments were conducted to study the effect of variation in $\mathbf{y}_d$ on the performance of this algorithm. In these experiments, a desired input set-point was generated at first, and the corresponding sensor measurements were recorded ($\mathbf{y}_d$). Next, closed loop control operation was started from an arbitrary initial point. The algorithm was implemented for 20 different sets of $\mathbf{y}_d$ that corresponded to the desired CCT from 2800 K to 6600 K with steps of 200 K. Various performance parameters were measured for the desired and achieved steady state light fields on the work surface in zone 5. This zone was arbitrarily chosen to represent the system performance throughout the testbed.

Figure 12: Results obtained from the implementation of hierarchical optimization, as desired CCT varies from 2800 K to 6600 K with desired illumination kept constant at 400 lux, (a) total power consumption and (b) achieved CRI.

The results are shown in Figure 12. Figure 12(a) shows that for lower desired CCT values, the controller achieved smaller power consumption than that for higher desired CCT values. For lower CCTs, the controller had the option of choosing between all the available LED channels including red and amber, as shown in Figure 13. However, at the higher CCT range, the controller had no option but choosing the blue channel to ensure color accuracy. Note that the hierarchical controller does not take into account the spectral information of the fixtures. Therefore, as shown in Figure 12(b), the achieved CRI levels in these experiments were smaller than the values achieved by the CRI optimization technique described in Section 7. Figure 13 shows the input intensity levels for the individual LED channels of light fixture 5. The low CRI is a result of eliminating the amber channel from the solution by the controller for most of the desired CCT values for power saving purpose. If CRI had been chosen as the user-defined performance metric instead of power consumption (provided that the spectral information of the LED channels are available to the controller), we would have found a different combination of channel intensities to achieve the same $\mathbf{y}_d$ with a higher CRI level.

Figure 13: Achieved CRI and individual LED channel intensities for hierarchical optimization as desired CCT varies from 2800K to 6600K.

9. Effect of ambient light : Daylong experiments

One of the major drives for feedback control of lighting systems is daylight harvesting for energy efficiency. By sensing the available ambient light, the feedback control systems can dim down the input intensities while ensuring achievement of minimum desired illumination and color quality. To examine the effect of ambient light on the performances and energy savings of the discussed algorithms, 12 hour-long daylight harvesting experiments were carried out for ten different days, with varying ambient lighting conditions (five sunny days and five cloudy days). The daylight was allowed to enter in the SCR through two windows from 6 am to 6 pm. The desired illumination level was set to five preset values for different periods of the day. The ambient illumination was measured every 10 minutes. Due to the slow varying nature of the ambient daylight, it was assumed to be constant during the 10 minute period. The four algorithms were alternatively implemented in a multiplexed fashion during each 10 minute period to ensure identical natural daylight condition, and the steady state results were recorded. In these experiments, the clear channel measurements of different color sensors were used as illumination levels for different zones. Figure 14 shows the ambient, measured and desired illumination in zone 5 (zonal map is shown in Figure 7) for the four algorithms during a cloudy day. The choice of showing the illumination levels of this particular zone is arbitrary. Figure 15 and 16 show the total power consumption and absolute CCT error for the four algorithms respectively during the same day (i.e., under identical daylight conditions).

While IBA shows significant overshoot during the transition periods, the other algorithms track the desired illumination under varying ambient lighting conditions successfully. For this particular day (shown in Figure 14), there was little ambient daylight available so there were significant power consumption for all four cases.

Figures 17 - 19 present meta data analysis from these daylong experiments. Figure 17 shows that the occupancy adaptive lighting control makes the best use of the available ambient daylight, with least average power consumption. The IBA shows least peak power consumption for both sunny and cloudy days. Notice that, the first two algorithms, not taking achieved color quality into account, consume less energy compared to the other two. The hierarchical optimization consumes more power compared to the spectral optimization since it has a constraint on exact color matching between the desired and achieved lighting conditions. Figure 18 shows the peak achieved CRI during a sunny and a cloudy day as well as the average achieved CRI over the ten days period. The hierarchical optimization achieves high CRI with both bright and dim ambient daylight. For spectral optimization, the achieved CRI level falls down significantly during cloudy days. Figure 19 shows the absolute peak CCT error during a sunny and a cloudy day as well as the average CCT error over the ten days period. The desired CCT was kept at 4300K throughout the ten days. The exact color matching property inherent in the hierarchical optimization ensures an average CCT error of less than 100K, with higher peak CCT error (300K) during a cloudy day than a sunny day (60K). On the other hand, spectral optimization results in high peak CCT error during a cloudy day (400K), which results in a higher average CCT error of 200K. So the effect of ambient daylight is more subtle on the achieved CCT values for hierarchical optimization than the spectral optimization technique. This is due to the fact that the spectral optimization only takes the illumination of the daylight into consideration, while the hierarchical optimization also incorporates the color information of the daylight via the color sensor measurements. Further, the CCT matching term appears as a soft constraint in the problem formulation of the spectral optimization (Equation (10)), while the first step in hierarchical optimization algorithm (Equation (13)) treats the color matching as a hard constraint.

In summary, hierarchical optimization demonstrates more robust performance under varying daylight conditions than the spectral optimization, but at the expense of higher average power consumption. Also note that the achieved CRI and absolute CCT error for the first two algorithms were constant (around 65 and 350K re-

Figure 14: Measured and desired illuminations for the four algorithms along with the ambient daylight in zone 5, from 12 hour long daylight harvesting experiments during a cloudy day. The algorithms can track the desired illumination throughout the day successfully.

Figure 15: Total power consumption for the four algorithms from 12 hour long daylight harvesting experiments during a cloudy day. There was little ambient daylight available so there were significant power consumption for all four cases.

spectively) for all ten days, as the controllers modify intensities of only the white channels with different ambient illuminations.

10. Summary and conclusion

In this article we presented a review of state-of-the-art control methodologies for advanced lighting systems followed by experimental performance validation of four recently proposed control algorithms. We also showcased the effect of ambient daylight on the perfor-

Figure 16: Absolute error in achieved CCT for the four algorithms from 12 hour long daylight harvesting experiments during a cloudy day.

Figure 17: Peak power consumption for a bright sunny day and a cloudy day, along with average total power consumption over ten days for the four algorithms.

Figure 19: Peak error in achieved CCT for a bright sunny and a cloudy day, along with average error in achieved CCT over ten days for the four algorithms. The desired CCT was kept constant at 4300k for all experiments.

Figure 18: Achieved peak CRI for a bright sunny and a cloudy day, along with average CRI achieved over ten days for the four algorithms.

mance of these algorithms by running them simultaneously during 12-hour daylight cycles for ten different days. Each algorithm responded differently to varying ambient lighting conditions.

Each of these algorithms has its own merits and drawbacks depending upon the specific control objectives, constraints, and technical capabilities. There is no single control strategy which can be termed as the best solution for all possible scenarios. The choice among these lighting control strategies should be based on the particular control problem and application. A decision tree is presented in Figure 20 showing some sample scenarios and the corresponding preferred feedback control algorithm. With the rapid progress in computation, sensing, and communication technologies, it is not even

Figure 20: A decision tree showing some sample scenarios and the corresponding preferred feedback control algorithm among the four selected algorithms discussed in the article.

necessary to stick to a single control architecture for the new generation of lighting systems. These systems may be flexibly adapted and reconfigured to specific requirements by switching between various methodologies.

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References

- [1] U. EIA, Annual energy outlook 2016, US Energy Information Administration, Washington, DC.
- [2] A. Williams, B. Atkinson, K. Garbesi, E. Page, F. Rubinstein, Lighting controls in commercial buildings, LEUKOS 8 (3) (2012) 161–180.
- [3] M. A. ul Haq, M. Y. Hassan, H. Abdullah, H. A. Rahman, M. P. Abdullah, F. Hussin, D. M. Said, A review on lighting control technologies in commercial buildings, their performance and affecting factors., Renewable and Sustainable Energy Reviews 33 (2014) 268 – 279.
- [4] A. Pandharipande, D. Caicedo, Smart indoor lighting systems with luminaire-based sensing: A review of lighting control approaches, Energy and Buildings 104 (2015) 369 – 377.
- [5] F. Rubinstein, Photoelectric control of equi-illumination lighting systems, Energy and Buildings 6 (2) (1984) 141–150.
- [6] F. Rubinstein, G. Ward, R. Verderber, Improving the performance of photo-electrically controlled lighting systems, J. Illuminating Eng. Soc. 18 (1) (1989) 70–94.
- [7] F. Rubinstein, M. Karayel, The measured energy savings from two lighting control strategies, IEEE Trans. Ind. Appl. IA-20 (5) (1984) 1189–1197.
- [8] F. Rubinstein, M. Siminovitch, R. Verderber, Fifty percent energy savings with automatic lighting controls, IEEE Trans. Ind. Appl. 29 (4) (1993) 768–773.
- [9] S. Gorgulu, N. Ekren, Energy saving in lighting system with fuzzy logic controller which uses light-pipe and dimmable ballast, Energy and Buildings 61 (2013) 172 – 176. doi:http://dx.doi.org/10.1016/j.enbuild.2013.02.037.
- [10] S. Matta, S. Mahmud, An intelligent light control system for power saving, in: Proc. 36th Annu. Conf. IEEE Ind. Electron. Soc., 2010, pp. 3316–3321. doi:10.1109/IECON.2010.5675331.
- [11] A. Choi, R. Mistrick, Analysis of daylight responsive dimming system performance, Building and Environment 34 (3) (1998) 231 – 243.
- [12] A. Choi, M. Sung, Development of a daylight responsive dimming system and preliminary evaluation of system performance, Building and Environment 35 (7) (2000) 663 – 676. doi:http://

- //dx.doi.org/10.1016/S0360-1323(99)00055-4.
- [13] N. van de Meughevel, A. Pandharipande, D. Caicedo, P. van den Hof, Distributed lighting control with daylight and occupancy adaptation, *Energy and Buildings* 75 (2014) 321 – 329. doi:http://dx.doi.org/10.1016/j.enbuild.2014.02.016.
 - [14] S. Afshari, S. Mishra, Decentralized feedback control of smart lighting systems, in: *Proc. ASME Dynamic Syst. and Control Conf.*, 2013, p. V001T13A006.
 - [15] S. Afshari, S. Mishra, A. Julius, F. Lizarralde, J. Wason, J. Wen, Modeling and control of color tunable lighting systems, *Energy and Buildings* 68 (2014) 242 – 253. doi:http://dx.doi.org/10.1016/j.enbuild.2013.08.036.
 - [16] S. Afshari, L. Jia, R. Radke, S. Mishra, Light field estimation and control using a graphical rendering engine, in: *Proc. ASME Dynamic Syst. and Control Conf.*, 2014, p. V001T07A004.
 - [17] Y. Wen, A. Agogino, Wireless networked lighting systems for optimizing energy savings and user satisfaction, in: *Proc. Wireless Hive Networks Conf.*, 2008, pp. 1–7. doi:10.1109/WHNC.2008.4629493.
 - [18] Y. Wen, A. Agogino, Control of wireless-networked lighting in open-plan offices, *Lighting Res. and Technol.* 43 (2) (2010) 235–248. doi:10.1177/1477153510382954.
 - [19] A. Sarkar, M. Fairchild, C. Salvaggio, Integrated daylight harvesting and occupancy detection using digital imaging, in: *Proc. Electron. Imaging Conf.*, 2008, pp. 68160F–68160F. doi:10.1117/12.765961.
 - [20] D. Caicedo, A. Pandharipande, Daylight and occupancy adaptive lighting control system: An iterative optimization approach, unpublished.
 - [21] M. Koroglu, K. Passino, Illumination balancing algorithm for smart lights, *IEEE Trans. Control Syst. Technol.* 22 (2) (2014) 557–567. doi:10.1109/TCST.2013.2258399.
 - [22] J. Sandhu, A. Agogino, A. Agogino, Wireless sensor networks for commercial lighting control: decision making with multi-agent systems, in: *Proc. AAAI Workshop on Sensor Networks*, Vol. 10, 2004, pp. 131–140.
 - [23] C. Kurian, R. Aithal, J. Bhat, V. George, Robust control and optimisation of energy consumption in daylight-artificial light integrated schemes, *Lighting Res. and Technol.* 40 (1) (2008) 7–24. doi:10.1177/1477153507079511.
 - [24] S. Colaco, C. Kurian, V. George, A. Colaco, Integrated design and real-time implementation of an adaptive, predictive light controller, *Lighting Res. and Technol.* 44 (4) (2012) 459–476. doi:10.1177/1477153512445713.
 - [25] J. Lu, D. Birru, K. Whitehouse, Using simple light sensors to achieve smart daylight harvesting, in: *Proc. 2nd ACM Workshop on Embedded Sensing Syst. for Energy-Efficiency in Building*, 2010, pp. 73–78. doi:10.1145/1878431.1878448.
 - [26] V. Singhvi, A. Krause, C. Guestrin, J. Garrett Jr., H. Matthews, Intelligent light control using sensor networks, in: *Proc. 3rd Int. Conf. Embedded Networked Sensor Syst.*, 2005, pp. 218–229.
 - [27] M. Pan, L. Yeh, Y. Chen, Y. Lin, Y. Tseng, A wsn-based intelligent light control system considering user activities and profiles, *IEEE Sensors J.* 8 (10) (2008) 1710–1721. doi:10.1109/JSEN.2008.2004294.
 - [28] T. Pavlic, Physical stigmergy for decentralized constrained optimization: An intelligent lighting example, in: *Proc. 4th ACM/IEEE Int. Conf. Cyber-Physical Syst.*, 2013, pp. 258–258. doi:10.1145/2502524.2502577.
 - [29] Y. Wen, J. Granderson, A. Agogino, Towards embedded wireless-networked intelligent daylighting systems for commercial buildings, in: *Proc. Int. Conf. Sensor Networks, Ubiquitous, and Trustworthy Computing*, Vol. 1, 2006, pp. 326–331. doi:http://doi.ieeecomputersociety.org/10.1109/SUTC.2006.136.
 - [30] M. Aldrich, N. Zhao, J. Paradiso, Energy efficient control of polychromatic solid state lighting using a sensor network, in: *Proc. SPIE Opt. Eng. + Appl. Conf.*, 2010, p. 778408.
 - [31] S. Afshari, S. Mishra, An optimization framework for control of non-square smart lighting systems with saturation constraints, in: *Proc. Amer. Control Conf.*, 2015, pp. 1665–1670.
 - [32] M. Aldrich, A. Badshah, B. Mayton, N. Zhao, J. Paradiso, Random walk and lighting control, in: *Proc. IEEE Sensors Conf.*, 2013, pp. 1–4. doi:10.1109/ICSENS.2013.6688590.
 - [33] A. Pandharipande, D. Caicedo, Daylight integrated illumination control of LED systems based on enhanced presence sensing, *Energy and Buildings* 43 (4) (2011) 944 – 950. doi:http://dx.doi.org/10.1016/j.enbuild.2010.12.018.
 - [34] D. Caicedo, A. Pandharipande, G. Leus, Occupancy-based illumination control of LED lighting systems, *Lighting Res. and Technol.* 43 (2) (2010) 217–234.
 - [35] D. Caicedo, A. Pandharipande, Distributed illumination control with local sensing and actuation in networked lighting systems, *IEEE Sensors J.* 13 (3) (2013) 1092–1104. doi:10.1109/JSEN.2012.2228850.
 - [36] S. Afshari, S. Mishra, J. A., F. Lizarralde, J. Wen, Modeling and feedback control of color-tunable LED lighting systems, in: *Proc. Amer. Control Conf.*, 2012, pp. 3663–3668.
 - [37] L. Jia, S. Afshari, S. Mishra, R. Radke, Simulation for pre-visualizing and tuning lighting controller behavior, *Energy and Building* 70 (2014) 287–302.
 - [38] S. Afshari, T.-K. Woodstock, M. Imam, S. Mishra, A. C. Sander-son, R. J. Radke, Short paper:: The smart conference room: An integrated system testbed for efficient, occupancy-aware lighting control, in: *Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments*, ACM, 2015, pp. 245–248.
 - [39] C. Starr, C. Evers, L. Starr, *Biology: Concepts and Applications*, 8th Edition, Cengage Learning, Independence, KY, USA, 2010.
 - [40] J. Foley, A. van Dam, S. Feiner, J. Hughes, *Computer Graphics: Principles and Practice in C*, 2nd Edition, Addison-Wesley Professional, Boston, MA, USA, 1995.
 - [41] P. Sen, B. Chen, G. Garg, S. R. Marschner, M. Horowitz, M. Levoy, H. Lensch, Dual photography, in: *ACM Transactions on Graphics (TOG)*, Vol. 24, ACM, 2005, pp. 745–755.