An identification approach to lighting control

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Abstract—The problem of daylight estimation in a smart lighting system is considered. The smart lighting system consists of multiple luminaires with collocated occupancy and light sensors. Using sensor information, the objective is to attain illumination levels higher than specified values at the workspaces. We consider a training phase wherein light sensors are used at the workspaces to collect preliminary data. Data from the light sensors at the ceiling and workspaces is used to estimate the mapping across the sensors. In the operational phase, the estimated mapping is used at the lighting controller to obtain an estimate of the illuminance value at the workspaces. Under the constraint that the estimated illuminance is higher than a specified target value, the controller optimizes the dimming levels of the luminaires to minimize power consumption. We evaluate the performance of the proposed approach in an open-office lighting model by considering different daylight conditions. Comparisons with alternative approaches and standard practices show the major benefit of the proposed approach both in terms of reduced under-illumination and energy saving. Keywords: Lighting control systems, Daylight estimation, Least squares, Occupancy and daylight adaptation, Optimization.

I. INTRODUCTION

Artificial lighting makes up a major proportion of the electrical energy consumption in commercial office buildings [1]. A majority of energy spent on lighting is wasted because of inefficient management of occupancy and daylight conditions [2], [3]. In order to reduce the energy consumption, control of artificial lighting has been an active topic of research lately, in particular by adapting to occupancy and daylight changes [6]-[17]. Dimmable luminaires are required to implement such lighting control systems. The introduction of light emitting diode (LED) based luminaires has made this feasible since they can be dimmed easily and flexibly.

In this paper, a lighting system with multiple luminaries and collocated occupancy and light sensors along with a central controller is considered. These sensors provide respectively binary occupancy and net illuminance values within their fields-of-view. The local sensor information at each luminaire is used to control the luminaires individually using a control law at the central controller. The main objective is to design a control law that, taking into account the values from the sensors, is able to provide at certain control points at workspaces a total illuminance level that is higher than some specified values. The total illuminance consists of both artificial light and daylight contributions. A key challenge in the design of the control law is the lack of knowledge of the daylight mapping from ceiling (where measurements are made by the light sensors) to the workspaces.

A. Related work

Since the illuminance over workspaces is of interest, a direct approach is to measure the illuminance at certain control points in this plane. The works in [4] and [5] assumed that light distributions at the workspaces were available at the controller, based on which simplex methods were used to control the artificial light output to daylight and occupant locations. In [8], [9], light sensors were placed at workspaces and lighting control for daylight adaptation was performed with the measurements transmitted by wireless means at a controller. In [6], [7], light sensors were carried by users. Such a sensor configuration however has limitations. A commissioning step is used to properly associate light sensor data to control the luminaires appropriately. Furthermore, temporary physical obstructions may occur that impact both the sensor measurements as well as the wireless connectivity between the sensors and the controller.

It is thus common practice to use light sensors at the ceiling [13], [14], [16], [18], [19]. In particular, collocated sensors at the luminaires simplifies the commissioning step. This however means that direct measurements at the control points at workspaces are not available. As such, a simple night time calibration [18] using the artificial lighting is used to establish a relation between illuminance at the ceiling and illuminance at the workspaces.

B. Our approach and contributions of the work

In this work, we consider a training phase wherein light sensors are places at workspaces in addition to those at the ceiling. In this phase, daylight values are collected at both sets of sensors. The data is then used to obtain an estimate of the mapping between the ceiling measurement points and the control points at the workspaces. This procedure is explained further in Section III.

We then formulate an optimization problem for minimizing the power consumption of the lighting system with illuminance constraints defined at the workspaces. The estimated mapping is used herein to obtain an estimate of the achieved illuminance. This optimization framework is described in Section IV.

We then evaluate the performance of our proposed approach using data from an open-office lighting model in Section V. As comparison, we consider a lighting system that is controlled solely on the basis of measurements at the ceiling-based light sensors (no training phase), with illuminance constraints defined at these light sensors. We show that the proposed approach is able to achieve lesser under-illumination, while also obtaining some energy savings.

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II. MODELING AND PROBLEM FORMULATION

We consider a lighting system with $M$ luminaires each provided with collocated occupancy and light sensors. Consider $N$ control points on the workplace, i.e. zones over the workspace for which a reference illuminance is specified. This scenario is illustrated in the lighting plan shown in Figure 1. Denote by $y(k) \in \mathbb{R}^M$ and $w(k) \in \mathbb{R}^N$ the vectors that contain the illuminance values at the time instant $k$, at the ceiling and at workplace levels, respectively. Typically the illuminance at the workplace level $w(k)$ cannot be directly measured. We also define $d(k) \in \mathbb{R}^M$ and $p(k) \in \mathbb{R}^N$ the daylight contribution to the total illuminance at the ceiling and at the workplace level, respectively. The power output of the luminaries is controlled using pulse width modulation (PWM). Denote the vector containing the duty cycles of the luminaries, representing their dimming values, by the input vector $u(k) \in \mathbb{R}^M$. Due to physical limits on dimming, each element is limited between zero and unity, i.e.

$$0 \leq u(k) \leq 1 \quad (1)$$

where the inequality is to be intended component-wise, and $0 = [0 \cdots 0]^T \in \mathbb{R}^M$ and $1 = [1 \cdots 1]^T \in \mathbb{R}^M$ represent vectors of all zeros and all ones, respectively. For LED luminaries, the energy expenditure is assumed to be proportional to the control input [18]. Therefore the total energy $J(u(k))$ consumed at time instance $k$ is proportional to the sum of the input entries, i.e.

$$J(u(k)) = c \| u(k) \|_1 = c \sum_{i=1}^{M} |u_i(k)| = c \mathbf{1}^T u(k) \quad (2)$$

where $c$ is a positive scalar representing the energy consumption per fraction of dimming value and we used the observation that $|u_i(k)| = u_i(k)$. We also denote by $w_r(k) \in \mathbb{R}^N$ the vector of the reference illuminance values at the workplace level at a certain time instant $k$, which is a function of the presence of a person and possibly his/her personal desired illuminance level.

The measurements $y(k)$ and the workplace illuminance $w(k)$ can be expressed as a linear combination of the artificial illumination power set at the previous time instant $k-1$ and the daylight contribution at current time $k$ [10]. More formally:

$$\begin{align*}
y(k) &= Gu(k-1) + d(k) \\
w(k) &= Hu(k-1) + p(k)
\end{align*} \quad (3)$$

where $G \in \mathbb{R}^{M \times M}$ and $H \in \mathbb{R}^{N \times M}$ represents the illuminance gain matrices for the ceiling and workplace illumination, respectively. More specifically $G_{i,j}$ represents the illuminance measured by the $i$-th sensor when the $j$-th luminaire is turned on to its maximum, i.e. $u_j(k) = 1$ while all the others are off, i.e. $u_h(k) = 0$, $h \neq j$, and there is no external light present, i.e. $d(k) = 0$. Similar consideration holds for the $H_{i,j}$ entry. Note that since luminaries can only provide “positive” light output, the element of these matrices are all non-negative, i.e. $G, H \succeq 0$, where the inequality is to be intended component-wise.

The objective of this work is to minimize the energy expenditure $J$ while satisfying the input constraints and the desired luminance at the ceiling based on the measured luminance at the ceiling. More formally,

$$u^*(k) = \arg \min_{u(k)} c \mathbf{1}^T u(k)$$

subject to

$$\begin{cases}
0 \leq u(k) \leq 1 \\
y(k) = Gu(k-1) + d(k) \\
w(k + 1) = Hu(k) + p(k + 1) \\
w(k + 1) \geq w_r(k + 1).
\end{cases} \quad (4)$$

III. DATA-DRIVEN DAYLIGHT ESTIMATION

The optimization problem described in (4) implicitly assumes that the daylight illumination at the workplace $p(k+1)$ is known. Unfortunately this is not possible since it is inconvenient or too expensive to place additional light sensors at the workspaces. To overcome this difficulty, we propose a method that estimates the daylight illumination $p(k+1)$ at workspaces based on the current value of the daylight illumination at the ceiling $d(k)$ that can be directly measured once the light sensor measurements $y(k)$ and the previous control input $u(k-1)$ are known. More formally, we want to compute an estimator function $f : \mathbb{R}^M \rightarrow \mathbb{R}^N$ such that

$$\hat{p}(k+1) = f(d(k)) = f(y(k) - Gu(k+1)) \quad (5)$$

where $\hat{p}(k+1)$ is an estimate of $p(k+1)$ at time instance $k+1$. This function will be computed via an identification-based (or data-based) statistical analysis [24] based on experimental data. That is, we assume that it is possible to collect not only light sensor measurements at the ceiling $y(k)$, but also the sensor measurements at the workplace level $w(k)$. In the next subsections we describe in detail the proposed approach.

A. Data collection modeling

We assume that it is possible to collect some illuminance data at both the ceiling light sensors and the workplace level control points during a preliminary training phase. This data can be collected during periods of unoccupancy, e.g. over weekends. The light sensors at the workplace level do not need to be permanently installed, but only over a time period necessary to collect the data. Another option is to obtain the data set via realistic simulated light propagation models. Although not necessary, we also assume that this data is collected when luminaries are all turned off, i.e. $u(k) = 0$, $\forall k$ during the identification phase. We assume that $r$ samples are available and collected in the data set $\mathcal{D}$, i.e.

$$\mathcal{D} = \{(p_i, d_i)\}_{i=1}^r \quad (6)$$

where each pair $(p_i, d_i)$ represents the measurements collected at some time instant $t_i$, i.e. $p_i = p(t_i), d_i = p(t_i)$. In our approach we will not take into account the specific time of the day and the month when samples where collected, but we will look for a simple static function that is able to predict the current value of the daylight contribution at the workplace based on the measurement vector at the ceiling.
As so, the specific order of the pairs \((p_i, d_i)\) is irrelevant and the sampling time \(t_s\) is not used as part of the information set. The data set is further divided in two disjoint subsets: a training set \(\mathcal{T}\) used to compute the estimator, and a validation set \(\mathcal{V}\) used to evaluate the prediction performance. More formally:

\[
\mathcal{D} = \mathcal{T} \cup \mathcal{V}, \quad \mathcal{T} = \{(d_i, p_i)\}_{i=1}^q, \quad \mathcal{V} = \{(d_i, p_i)\}_{i=q+1}^r.
\]

Typically the size of the training data set is around 80 – 90% of the global data set, i.e. if \(q\) is the number of element in the training set, then \(\frac{q}{r} \approx 0.8 \text{ – } 0.9\). In the next subsections we propose an approach based on least-squares model identification.

### B. Least Squares (LS) daylight predictor

In this section we want to identify the best static predictive linear mapping \(C \in \mathbb{R}^{N \times M}\) between the daylight measured at the ceiling and the daylight measured at the workplane level, i.e.

\[
\hat{p} = f(d) = Cd.
\]  

(7)

The least-squares (LS) approach to this problem identifies \(C\) as the solution of a quadratic optimization problem that minimizes the sum of the square of the residual between the measured illumination vector at the workplane level \(p_i\) and the model prediction \(\hat{p}_i = Cd_i\), i.e. more formally

\[
C_{LS} := \text{arg min}_C \sum_{i=1}^q \|p_i - Cd_i\|^2 = PD^T (DD^T)^{-1} \quad \text{(8)}
\]

where \(P = [p_1 \, p_2 \ldots p_q] \in \mathbb{R}^{N \times q}\) and \(D = [d_1 \, d_2 \ldots d_q] \in \mathbb{R}^{M \times q}\) are typically “fat” matrices, i.e. \(q \gg M, q \gg N\) obtained by the data available in the training set \(\mathcal{T}\).

### C. Model validation and performance metrics

The performance of the predictor is evaluated based on the root average mean square error (RAMSE) computed with respect to the validation data set \(\mathcal{V}\) defined as follows:

\[
\text{RAMSE} := \sqrt{\frac{\sum_{i=q+1}^r \|p_i - \hat{p}_i\|^2}{N(r-q)}} \quad \text{(9)}
\]

where \(\hat{p}_i = C_{LS}d_i\). In other words the quantity RAMSE represents the averaged error that one would expect on illuminance across the workplane level.

Another interesting performance characterization is given by the empirical error cumulative distribution function (CDF) for a given zone, defined as

\[
\text{CDF}(e) := \frac{1}{N(r-q)} \sum_{i=1}^N \sum_{n=1}^{r-q} \mathbb{1}(e - [e_i]_n), \quad e_i := p_i - \hat{p}_i
\]

where \(e_i \in \mathbb{R}^N\) represents the prediction error vector at the workplane level, \([e_i]_n \in \mathbb{R}\) indicates its \(n\)-th entry, and \(\mathbb{1}(x)\) indicates the indicator function which is equal to zero for \(x < 0\) and equal to one for \(x > 0\).

A final useful parameter is the empirical Root Mean Squared Error for zone \(n\), defined as follows

\[
\text{RMSE}_n := \sqrt{\frac{1}{(r-q)} \sum_{i=1}^{r-q} (p_{in} - \hat{p}_{in})^2} \quad \text{(11)}
\]

### IV. CONTROL DESIGN

In this section we consider two different type of controllers: (A) ceiling-based control and (B) workspace-based control.

#### A. Ceiling-based control (Reference approach)

In a ceiling-based control, the lighting system is adapted at each time instant \(k\) based on:

- daylight contributions at each light sensor at the ceiling, \(d(k)\), and
- illuminance gain matrices for the ceiling, \(G\).

In [14] the ceiling-based control was formulated as an optimization problem given by

\[
u^*(k) = \arg\min_{u(k)} 1^T u(k)
\]

s.t.

\[
\begin{align*}
y(k + 1) & = Gu(k) + d(k + 1) \geq y_r(k + 1) \\
0 & \leq u(k) \leq 1 \\
d(k + 1) & = d(k) = y(k) - Gu(k - 1).
\end{align*}
\]

(12)

The ceiling-based control given by (12) is hereafter referred to as “Reference approach”.

It is necessary to define the ceiling sensor references: \(y_r(k+1)\). This is accomplished in a preliminary night time calibration phase as explained in [10], [18]. In the absence of daylight, the luminaries are turned to maximum intensity, both the average workplane level illuminance value and the ceiling sensor measurements are saved. Given a specific reference average illuminance at the workplane level, the ceiling sensor references are then obtained by suitable linear scaling. It is assumed that the references are feasible, i.e.

\[G1 \geq y_r(k)\]

which implies that there is a set of dimming values \(u(k)\) (in the most extreme scenario \(u(k) = 1\)), that ensures that the illuminance on the ceiling is equal or greater than the reference illuminance.

#### B. Workspace-based control

In a workspace-based control, the lighting system is adapted at each time instant \(k\) based on:

- daylight contributions at each light sensor at the workspace, \(p(k)\) (or estimates \(\hat{p}(k)\)), and
- illuminance gain matrices for the workspace, \(H\).

In this paper, we propose the following optimization problem for workspace-based control:

\[
u^*(k) = \arg\min_{u(k)} 1^T u(k)
\]

s.t.

\[
\begin{align*}
w_r(k + 1) & \leq Hu(k) + \hat{p}(k + 1) \\
\hat{p}(k + 1) & = \hat{p}(k) = f(d(k)) = f(y(k) - Hu(k - 1)) \\
0 & \leq u(k) \leq 1
\end{align*}
\]

(13)
where $\hat{p}(k) = C_{LS}d(k)$ is the least-squares predictor. It is assumed that the references are feasible, i.e. $H1 \geq w_r(k)$. This implies that there is a set of dimming values $u(k)$ (in the most extreme scenario $u(k) = 1$), that ensures that the achieved illuminance on the workplane level is greater than or equal to the reference illuminance. The workspace-based control given by (13) is hereafter referred to as “Identification approach”.

The problems given by (12) and (13) are linear programming (LP) problems. These can be solved, for example, with the simplex method, interior-point algorithms or variants [25].

V. SIMULATIONS RESULTS

A. Data set extraction

The open-plan office lighting model considered in [10] is used. As depicted in Figure 1, some additional light sensors at control points at the workplane level were used to perform the data acquisition explained in III-A. The office has length $24$ m and width $19$ m with height of the ceiling of $2.6$ m. There are $M = 80$ luminaires and sensors organized in a grid of $10$ by $8$. $N = 36$ zones are included with one illuminance sensor for each zone. The windows are located on the right side of the wall next to luminaires 71-80, hence the biggest contribution of the daylight is observed in this area. All the light distributions were obtained from the model implemented in lighting software DIALux [26]. The lighting control system was implemented in Matlab.

Data from days in different months (Jan., Mar., Jun, Aug., Sep., Dec.) and with different sky conditions (clear sky, overcast sky, mixed sky) was collected every 15 minutes. The daylight distributions in the office were simulated from 7:00 AM to 6:45 PM for a total of 12 days spread across all four seasons and with the three different sky conditions. The data from these 18 days was divided into 12 days which was used to construct the training $\mathcal{T}$ and 6 days used to construct the validation set $\mathcal{V}$ for evaluating the performance.

B. Daylight predictor performance

In this section we evaluate the prediction performance of the LS predictor proposed in Section III-B using the metrics defined in Section III-C.

Figure 2 shows the CDF of the estimation error on the LS predictor on the zones as given by (10). This curve clearly indicates that the prediction error are concentrated within an error bound of 10 lux and they are evenly distributed around zero, thus indicating that the predictor is presumably unbiased and symmetric. This error is rather small as compared to the desired illuminance at the workplane level which is around 500 lux. Figure 3 gives a more detailed insight on how these errors are distributed across the 36 different zones. It clearly shows that the larger errors are on the zones closer to the windows which is to be expected since those are the zones for which the illuminance due to the daylight exhibits largest range variation from zero to several thousands lux, while the zones that are further away receive very small amounts of daylight even on a bright day.

C. Controller performance

In this section we evaluate the performance of the different controllers described in Section IV using the validation set $\mathcal{V}$. The simulations are done with all the zones being occupied which require an illuminance at workplane level of $W = 500$ lux in all the zones, i.e. $w_r(k) = W1, \forall k$.

For comparison, we also include a lighting system that under the absence of daylight provides on average an illuminance at the workplane level of about $W = 500$ lux, hereafter referred to as “No control”. Under "No control", all the luminaires are set to a constant value of 0.85 throughout the day, i.e. $u(k) = 0.85 \times 1$ and $\frac{1}{N} \sum_{n=1}^{N}[w(k)]_n \approx W$ when $d(k) = 0$.

Figure 4 shows the CDF of the controller error on the zones with respect to the nominal value of $W = 500$ lux for three different strategies: No control, the Reference approach described in Section IV-A, and the proposed Identification approach described in Section IV-B. More specifically it
computes:
\[
\text{CDF}_w(e) := \frac{1}{NK} \sum_{n=1}^{N} \sum_{k=1}^{K} \mathbb{I}(e - [e_w(k)]_n), \tag{14}
\]
\[
e_w(k) := w(k) - w_r(k).
\]

In Figure 4, we can see that the lighting system under No control exhibits poor performance. This approach still presents several zones that are under-illuminated. The Reference approach provides worse performance regarding the illumination provided. The Reference approach adapts the dimming level of the luminaries based on the measured illuminance at the ceiling at any time step \( k \), however it still fails to illuminate some zones by up to 40 lux at some times. The new proposed approach shows some under-illumination too, but the error is smaller that 10 lux for more than 99% of the times in all zones. Note that large positive errors, i.e. \([w(k)]_n - [w_r(k)]_n > 0\) for many zones \( n \) and time instances \( k \), is observed since over-illumination due to daylight in zones near the windows is expected.

Figure 5 shows the energy consumption averaged over several days of the years and weather conditions for different control strategies. The energy consumption is normalized with respect to the energy consumption of the lighting system under No control. The energy benefits can be substantial for both control strategies as compared to the lighting system under No control, but the strategy proposed in this work (Identification approach) exhibits more energy saving with respect to the Reference approach.

Finally, in Figure 6 we summarize both the average energy consumption and the under-illumination level on the same graph. This figure clearly shows that the proposed control strategy (Identification approach) substantially outperforms both the lighting system with no control and the Reference approach on both metrics.

VI. CONCLUSIONS AND DISCUSSION

We considered an approach to lighting control using daylight mapping estimation in a training phase. The daylight mapping is used to obtain an estimate of the achieved illuminance at the workspaces. This knowledge is used in deriving a control law to obtain the dimming levels of the luminaires and adapt the artificial light output to changing daylight conditions. We show that in comparison to a reference approach, our proposed solution achieves illuminance...
values closer to the desired values and also saves energy.

In this work, we considered a least-squares approach for estimation. In ongoing work, we are investigating clustering-based methods to efficiently cluster the training data and reduce the computational complexity involved in training.

REFERENCES