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A Data-Driven Daylight Estimation Approach to Lighting Control

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ABSTRACT We consider the problem of controlling a smart lighting system of multiple luminaires with collocated occupancy and light sensors. The objective is to attain illumination levels higher than specified values (possibly changing over time) at the workplace by adapting dimming levels using sensor information, while minimizing energy consumption. We propose to estimate the daylight illuminance levels at the workplace based on the daylight illuminance measurements at the ceiling. More specifically, this daylight estimator is based on a model built from data collected by light sensors placed at workplace reference points and at the luminaires in a training phase. Three estimation methods are considered: regularized least squares, locally weighted regularized least squares, and cluster-based regularized least squares. This model is then used in the operational phase by the lighting controller to compute dimming levels by solving a linear programming problem, in which power consumption is minimized under the constraint that the estimated illuminance is higher than a specified target value. The performance of the proposed approach with the three estimation methods is evaluated using an open-office lighting model with different daylight conditions. We show that the proposed approach offers reduced under-illumination and energy consumption in comparison to existing alternative approaches.

INDEX TERMS Lighting control systems, daylight estimation, occupancy and daylight adaptation, least squares, linear programming.

I. INTRODUCTION

A major proportion of the electrical energy consumption in commercial office buildings is due to artificial lighting [1]. Portions of lighting energy are often misspent due to inefficient management of ambient conditions [2], [3]. To reduce lighting energy consumption, control of artificial lighting has been an active topic of recent research, in particular by adapting to occupancy and daylight changes [6]- [19]. Such lighting control systems require dimming ability in luminaires, which can be achieved flexibly with light emitting diodes (LEDs) [20].

In this paper, a smart lighting system consisting of multiple luminaries, with collocated occupancy and light sensors, and a central controller is considered. These sensors provide binary occupancy and net illuminance values within their fields-of-view respectively. 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 a total illuminance level that is higher than specified values at certain control points at workplaces. The total illuminance is an aggregation of both artificial light and daylight. 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 workplaces.

A. RELATED WORK

Since the illuminance over workplaces is of interest, a direct approach is to measure the illuminance at certain control points in this plane. The works in [4] and [5] considered optimization techniques for lighting control assuming knowledge of light distributions at the workplaces as well as occupant locations. In [8]–[10] light sensors were placed at workplaces. Lighting control for daylight adaptation was performed using sensor measurement feedback transmitted to a controller by wireless communication [8], [9]. In [6] and [7], light sensors were carried by occupants. Such sensor configurations however have limitations. A commissioning step is needed to properly associate light sensor data to control the luminaires. Moreover, temporary physical obstructions may occur that impact the quality of the sensor measurements as well as the wireless connectivity between the sensors and the controller.

It is thus common practice in lighting control systems to deploy light sensors at the ceiling [12], [16], [17], [18], [21], [22]. In particular, collocated sensors at the luminaires simplifies the commissioning step and have been considered for lighting controls [11], [18], [21]. This however means that direct measurements at the control points at workplaces are not available. As such, a simple night time calibration [21] using the artificial lighting is used to establish a relation between illuminance at the ceiling and illuminance at the workplaces.

The contribution of daylight at the workplace and at the ceiling can vary with time, depending on the incidence of daylight (influenced by time of day, weather conditions, etc.) in the indoor space. To the best of our knowledge, this important insight was first reported in [22] and [23], to show that maintaining a constant output at a ceiling based light sensor does not result in constant illumination at the workplace. In these works, an offset was proposed to be included in a closed-loop proportional control algorithm for a single light sensor driven lighting system. This offset related to the ceiling sensor to workplace daylight ratio was determined using a one-time daylight calibration. An assumption made here was that the ceiling sensor to workplace daylight ratio during calibration is a good fit to the overall set of possible ratios. Extensions of such an approach to a distributed lighting system with multiple light sensors were studied in [11]. In [17], we showed that a constrained optimization approach results in a lower energy consumption compared to [11], while still achieving the light sensor set-points. All the aforementioned methods cannot effectively deal with the daylight mismatch problem since light sensor measurements are done at ceiling locations.

B. CONTRIBUTIONS AND OUTLINE OF THE PAPER

In this work, we propose a data-driven daylight estimation approach to lighting control. We consider a training phase wherein light sensors are placed at workplaces 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 workplaces. Three methods are investigated to obtain the estimate: regularized least squares, locally weighted regularized least squares, and cluster-based regularized least squares. These methods are described further in Section III.

We then formulate an optimization problem for minimizing the power consumption of the lighting system under the constraints that the achieved illuminance at certain control points at the workplaces is higher than specified values and the dimming levels are within physical limits. The estimated mapping is used in the first constraint to obtain an estimate of the achieved illuminance value. This optimization framework is described in Section IV.

Finally we 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 reduced under-illumination, while also obtaining substantial energy savings.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a smart lighting system in an open office with N workplaces. The smart lighting system has M LED luminaires with collocated occupancy and light sensors that provide binary occupancy information and illuminance levels, respectively. At each workplace, a control point is defined where a minimum illuminance level is desired. This scenario is illustrated in the lighting models shown in Figure 1 and 2.

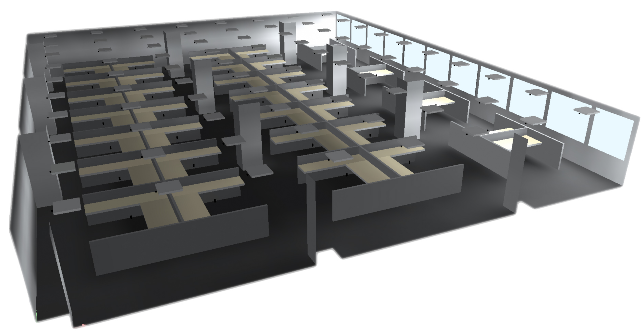

FIGURE 1. Open-office lighting system model with multiple luminaires and collocated sensors.

Let $y(k) \in \mathbb{R}^M$ and $w(k) \in \mathbb{R}^N$ be the vectors that contain the illuminance levels at time instant k at the light sensors at the ceiling and at the control points at the workplace plane, respectively. We also define $d(k) \in \mathbb{R}^M$ and $p(k) \in \mathbb{R}^N$ as the daylight contribution to the light sensors at the ceiling and at the control points at the workplace plane, respectively.

We consider that the output power of the luminaries is controlled using pulse width modulation (PWM). Denote by $u(k) \in \mathbb{R}^M$ the vector containing the PWM duty cycles of the luminaires, representing their dimming values. Due to physical limits on dimming, each element of $u(k)$ takes a value between zero and unity, i.e.

$$\mathbf{0} \le u(k) \le \mathbf{1}, \tag{1}$$

where the inequality should be interpreted component-wise, and $\mathbf{0} = [0\,0 \cdots 0]^T \in \mathbb{R}^M$ and $\mathbf{1} = [1\,1 \cdots 1]^T \in \mathbb{R}^M$ represent vectors of all zeros and all ones, respectively. Under PWM dimming, lighting energy is proportional to the control input [21]. Therefore, $J(u(k))$, the total energy consumed at time instant k is proportional to the sum of the dimming

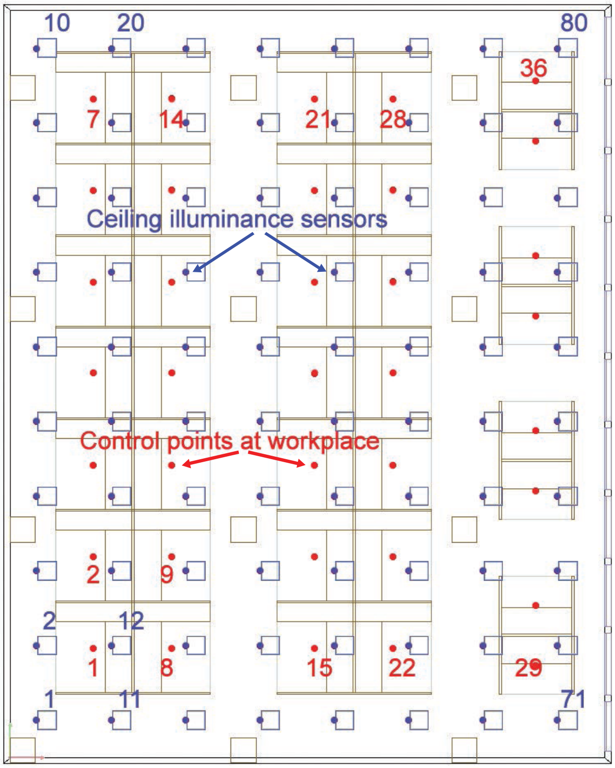

FIGURE 2. Top view of the simulated office model in Figure 1 showing location and numbering of the 80 luminaries and collocated ceiling sensors (depicted by blue boxes and red dots respectively) and of the 36 light sensors at the workplaces (red dots). Windows span the right side of the office.

values, i.e.

$$J(u(k)) = \mathrm{E}_{\max} \sum_{m=1}^{M} u_m(k) = \mathrm{E}_{\max}\, \mathbf{1}^T u(k), \tag{2}$$

where $\mathrm{E}_{\max}$ is the maximum energy consumption of each LED luminaire and $u(k) = [u_1(k) \cdots u_M(k)]^T$.

The illuminance levels at time instant k at the ceiling and workplace plane ($y(k)$ and $w(k)$, respectively) can be written as a linear combination of the artificial illumination due to the lighting system and daylight contribution [11],

$$\begin{cases} y(k) = Gu(k-1) + d(k), \\ w(k) = Hu(k-1) + p(k), \end{cases} \tag{3}$$

where

$$\begin{aligned} y(k) &= [y_1(k) \cdots y_M(k)]^T, \\ d(k) &= [d_1(k) \cdots d_M(k)]^T, \\ w(k) &= [w_1(k) \cdots w_N(k)]^T \text{ and} \\ p(k) &= [p_1(k) \cdots p_N(k)]^T. \end{aligned}$$

Matrices $G \in \mathbb{R}^{M\times M}$ and $H \in \mathbb{R}^{N\times M}$ are the illuminance gain matrices for the ceiling and workplace illumination, respectively. More specifically, $G_{i,j} \geq 0$ represents the illuminance measured by the i-th light 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 under the absence of daylight, i.e. $d(k) = 0$. A similar consideration holds for $H_{i,j} \geq 0$.

The illuminance levels at the control points at the workplace plane, $w(k)$, can only be measured by placing light sensors at each control point. However, in practice, this might not be possible or desirable due to reliability issues, e.g. the user may unintentionally block the light sensor. Note that using (3) we can estimate the illuminance level at time instant k for each control point at the workplace plane, $w(k)$, if we have knowledge of: (i) illuminance gain matrix, H, (ii) dimming vector, $u(k-1)$, and (iii) daylight contribution term, $p(k)$. The illuminance gain matrix H can be measured during a calibration phase and the dimming vector is known at the lighting control. Thus, the only remaining unknown is the daylight contribution term $p(k)$.

The objective of this work is to propose a method to obtain an estimate of the daylight contribution at each control point at the workplace plane at each time instant k, $\widehat{p}(k)$, based on daylight contribution measurements at light sensors at the ceiling, $d(k)$. Using the estimate $\widehat{p}(k)$, we propose a lighting control method that minimizes the energy consumption of the lighting system while providing the desired illuminance levels at each control point at the workplace plane, i.e.

$$u^*(k) = \arg\min_{u} \; \mathrm{E}_{\max}\, \mathbf{1}^T u \quad s.t. \begin{cases} \mathbf{0} \leq u \leq \mathbf{1} \\ w(k) = Hu + \widehat{p}(k) \\ w(k) \geq w_r(k), \end{cases} \tag{4}$$

where $u = [u_1 \cdots u_M]^T$. Here, $w_r(k) \in \mathbb{R}^N$ is the vector of reference illuminance values at the workplace plane at time instant k, which is a function of the presence of a person and possibly his/her personal desired illuminance level.

III. DATA-DRIVEN DAYLIGHT ESTIMATION

In this Section, we propose a method to estimate at each time instant k the daylight contribution term $p(k)$ based on the current value of daylight contribution at the ceiling $d(k)$. Note that $d(k)$ can be estimated from the light sensor measurements $y(k)$ and the previous control input $u(k-1)$ as $d(k) = y(k) - Gu(k-1)$. More formally, we want to compute an estimator function $f : \mathbb{R}^M \rightarrow \mathbb{R}^N$ such that

$$\widehat{p}(k) = f(d(k)), \tag{5}$$

where $\widehat{p}(k)$ is an estimate of $p(k)$ at time instant k.

This function will be computed via an identification-based approach [30] based on experimental data collected during a training phase. During the training phase, we assume that it is possible to collect not only daylight measurements at the ceiling $d(k)$, but also daylight measurements at the workplace plane $p(k)$. In the next subsections we describe in detail the proposed approach. In section V-B the performance of the estimation techniques will be evaluated and compared.

A. DATA COLLECTION

During the training phase, illuminance data is collected at both the ceiling light sensors and the control points at the workplace plane. This data can be collected during periods of unoccupancy, e.g. over weekends. The light sensors at the workplaces do not need to be installed permanently; they only need to be in place over a time period necessary for data collection. Another option is to obtain the data set via realistic simulated light propagation models. For simplicity, we also assume that this data is collected when all luminaries are turned off, i.e. $u(k) = \mathbf{0}, \forall k$ during the training phase. Let $\mathcal{D}$ be the data set containing all the collected data. We assume that r samples were collected during the training phase, i.e.

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

where each pair (p_i, d_i) represents the measurements collected at some time instant t_i, i.e. $p_i = p(t_i)$, $d_i = d(t_i)$. In our approach we will not take into account the specific time of the day and the month when samples were collected, but we will look for a function that is able to estimate the current value of the daylight contribution at the workplace based on the measurement vector at the ceiling. As such, the specific order of the pairs (p_i, d_i) is irrelevant and the sampling time t_i is not used as part of the data 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 estimator performance. More formally:

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

Typically the size of the training data set is larger than the size of the validation set. In the next subsections, we propose several approaches to perform the estimation in (5).

B. REGULARIZED LEAST SQUARES (RLS) DAYLIGHT ESTIMATOR

We now consider estimation of a *static* linear mapping $C \in \mathbb{R}^{N\times M}$ between the daylight measured at the ceiling and the daylight measured at the workplace plane for any time instant k, i.e.

$$\widehat{p}(k) = f(d(k)) = Cd(k). \tag{7}$$

Using a least-squares (LS) approach [24], C in (7) is given as the solution of a quadratic optimization problem that minimizes the sum of the square of the residual between the measured illuminance vector at the workplace plane p_i and the model estimation $\widehat{p}_i = Cd_i$, i.e.

$$C_{LS} = \underset{C}{\operatorname{argmin}} \sum_{i=1}^{q} ||p_i - Cd_i||^2 \tag{8}$$

where $||\cdot||$ is the ℓ_2 norm. If the inverse of DD^T exists, then the closed-form solution to (8) is given by

$$C_{LS} = PD^T(DD^T)^{-1},$$

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

Matrix DD^T may be ill-conditioned if the data elements d_i are strongly correlated, i.e. very similar to each other (overfitting problem), or the size of the training set $\mathcal{T}$ is small. A good practice in these scenarios is to add a regularization term $\epsilon > 0$. The regularized least square problem is formally defined as follows:

$$C_{RLS}(\epsilon) = \underset{C}{\operatorname{argmin}} \sum_{i=1}^{q} ||p_i - Cd_i||^2 + \epsilon\|C\|_F^2 \tag{9}$$

$$= PD^T(DD^T + \epsilon I)^{-1}. \tag{10}$$

where we made explicit the dependence of C_{RLS} on ϵ and $||\cdot||_F$ is the Frobenius norm. Parameter ϵ is often chosen by finding the best performance on the validation set $\mathcal{V}$ [25], i.e.

$$\epsilon^* = \underset{\epsilon\geq 0}{\operatorname{argmin}} \sum_{i=q+1}^{r} ||p_i - C_{RLS}(\epsilon)d_i||^2. \tag{11}$$

Note that the LS solution in (8) is a special case of (9) where the regularization parameter ϵ is set to zero.

C. LOCALLY WEIGHED REGULARIZED LEAST SQUARES (LWRLS) DAYLIGHT ESTIMATOR

The LS problem can be extended by possibly weighing each residual $\|p_i - \widehat{p}_i\|^2$ differently. To do so, a Locally Weighted Least Squares (LWLS) approach is performed. The problem formulation is the following

$$C_{LWLS}(d,\lambda) = \underset{C}{\operatorname{argmin}} \sum_{i=1}^{q} \gamma_i(\mathcal{T}, d, \lambda)||p_i - C\cdot d_i||^2$$

$$= P\Gamma(\mathcal{T}, d, \lambda)D^T(D\Gamma(\mathcal{T}, d, \lambda)D^T)^{-1}, \tag{12}$$

where P and D are defined as above, $\gamma_i(\mathcal{T}, d, \lambda) \geq 0, \forall i$ and $\Gamma(\mathcal{T}, d, \lambda) = \operatorname{diag}(\gamma_1(\mathcal{T}, d, \lambda), \ldots, \gamma_q(\mathcal{T}, d, \lambda)) \in \mathbb{R}^{q\times q}$ is referred as a diagonal weight matrix where the weight are computed as follows:

$$\gamma_i(\mathcal{T}, d, \lambda) = g\left(\frac{\|d - d_i\|}{h(\mathcal{T}, d, \lambda)}\right), \tag{13}$$

where $g : \mathbb{R}^+ \rightarrow \mathbb{R}^+$ is a weight function,

$$h(\mathcal{T}, d, \lambda) = \max_{i\in\mathcal{N}(\mathcal{T},d,\lambda)} \|d - d_i\|, \tag{14}$$

and $\mathcal{N}(\mathcal{T}, d, \lambda)$ is a subset of $\mathcal{T}$ containing the $\hat{q}$ closest neighbors to d such that $\frac{\hat{q}}{q} = \lambda$.

Note that the diagonal matrix $\Gamma(\mathcal{T}, d, \lambda)$ selects a fraction λ of measurements from the set $\mathcal{T}$ that are closer to input vector d; these measurements are assigned a weight defined by function $g(\cdot)$. The intuition behind this choice is that the estimated workplace luminance $\widehat{p}$ will be close to the observed workplace luminance $\widehat{p}_i$ whose corresponding ceiling measurement d_i is close to the current measured value d. In particular, if the n-th diagonal entry in matrix $\Gamma(\cdot)$ is close to 1, then the n-th measurement in set $\mathcal{T}$ will have a higher importance during the estimation of matrix $\boldsymbol{C}_{\text{LWRLS}}$.

The weight function $g(\cdot)$ can be any function that satisfies the properties as discussed in [31]. A standard choice of g for locally weighted regression problems is the tri-cube weight function [31]:

$$g(x) = \begin{cases} \left(1 - |x|^3\right)^3 & |x| \leq 1 \\ 0 & |x| > 1. \end{cases}$$

The parameter $\lambda \geq 0$ is chosen by computing the best performance on the validation set

$$\lambda^* = \underset{\lambda \geq 0}{\text{argmin}} \sum_{i=q+1}^{r} ||p_i - C_{LWLS}(d_i, \lambda) d_i||^2. \quad (15)$$

Similarly to the LS problem, it is convenient to regularize the problem to obtain a Locally Weighted Regularized Least Square problem (LWRLS):

$$C_{LWRLS}(d, \epsilon, \lambda) = P\Gamma(\mathcal{T}, d, \lambda) D^T (D\Gamma(\mathcal{T}, d, \lambda) D^T + \epsilon I)^{-1}. \quad (16)$$

In this case ϵ and λ need to be chosen by computing the best performance on the validation set:

$$(\epsilon^*, \lambda^*) = \underset{\lambda \geq 0, \epsilon \geq 0}{\text{argmin}} \sum_{i=q+1}^{r} ||p_i - C_{LWRLS}(d_i, \epsilon, \lambda) d_i||^2. \quad (17)$$

D. CLUSTER-BASED REGULARIZED LEAST SQUARES (CRLS) DAYLIGHT ESTIMATOR

The LWRLS has the potential to provide better performance than standard RLS. The main disadvantage is that at any time instant k, when a new measurement d is available, a new matrix C should be calculated using (16). This can be computationally expensive if the training data set $\mathcal{T}$ is large. A possible solution is to compute off-line a set of different estimated transfer matrices C which are constant within a certain domain of the ceiling measurement space d. To do this, during the preliminary training phase, a clustering of the measurements at the ceiling $\{d_i\}_{i=1}^q$ is performed. We define L clusters and for the ℓ-th cluster a RLS estimation matrix $C_{CRLS}^{[\ell]}$ based only on the data belonging to the ℓ-th cluster is obtained. A convenient metric, used for the clustering, is the Euclidean distance.

When a new measurement data d becomes available, we find the closest cluster centroid to this measurement and then the corresponding RLS estimation $\widehat{p}$ is obtained using the matrix $C_{CRLS}^{[\ell]}$. More specifically, we divide the data set $\mathcal{T}$ into L subsets $\mathcal{T}_\ell$ with possibly non-uniform sizes r_ℓ, i.e.

$$\mathcal{T} = \cup_{\ell=1}^{L} \mathcal{T}_\ell, \quad |\mathcal{T}_\ell| = r_i, \quad \sum_{\ell=1}^{L} r_\ell = q.$$

This can be obtained by applying the *k-mean++* algorithm [32] using the measurements at the ceiling $\{d_i\}_{i=1}^q$. Let the centroid of the ℓ-th cluster be given by

$$\overline{d}^{[\ell]} = \frac{1}{q_\ell} \sum_{(d_i, p_i) \in \mathcal{T}_\ell} d_i.$$

For the ℓ-th cluster the corresponding regularized regression matrix $C_{CRLS}^{[\ell]}$ is calculated as follows

$$C_{CRLS}^{[\ell]}(\epsilon_\ell) = \underset{C}{\text{argmin}} \sum_{(d_i, p_i) \in \mathcal{T}_\ell} ||p_i - C d_i||^2 + \epsilon_\ell \|C\|_F^2,$$

where ϵ_ℓ is optimized using the data in the validation set, i.e.

$$\epsilon_\ell^* = \underset{\epsilon \geq 0}{\text{argmin}} \sum_{(d_i, p_i) \in \mathcal{V}_\ell} ||p_i - C_{CRLS}^{[\ell]}(\epsilon) d_i||^2$$

and

$$\mathcal{V}_\ell = \{(d_i, p_i) : \|d_i - \overline{d}^{[\ell]}\| < \|d_i - \overline{d}^{[j]}\|, \ \forall j \neq \ell\}.$$

When a new measurement vector at the light sensors at the ceiling d is available, the corresponding estimation at the workplace $\widehat{p}$ is calculated as

$$\widehat{p} = C_{RLS}^{[\ell^*(d)]} d,$$

where

$$\ell^*(d) = \underset{\ell}{\text{argmin}} \{\|d - \overline{d}^{[\ell]}\|\}_{\ell=1}^{L}$$

is the cluster with the lowest Euclidean distance between its centroid and d.

This approach is computationally more efficient than the LWRLS since the computation of the clusters and the matrices $C_{CRLS}^{[\ell]}$ along with the optimal regularization parameters is performed off-line. Only the computation of the closest cluster $\ell^*(d)$ and the RLS estimation step $\widehat{p} = C_{CRLS}^{[\ell^*(d)]} d$ are computed on-line.

Note that the number of clusters needs to be chosen depending on the size of the training data set. We consider only the Cluster-based regularized Least Squares because of the overfitting problem: the size of the data set used to compute $C_{CRLS}^{[\ell]}$ is smaller than all the previous approaches.

IV. LIGHTING CONTROL

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

A. CEILING-BASED CONTROL

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

- daylight contributions at each light sensor at the ceiling, $d(k)$;
- illuminance gain matrices for the ceiling, G; and
- desired illuminance levels at each light sensor at the ceiling, $y_r(k)$.

In [17], the ceiling-based control was formulated as an optimization problem given by

$$u^*(k) = \arg\min_u \mathbf{1}^T u \quad s.t. \begin{cases} y(k) \geq y_r(k) \\ y(k) = Gu + d(k) \\ 0 \leq u \leq 1. \end{cases} \tag{18}$$

The ceiling-based control given by (18) is hereafter referred to as *REF_CONTROL*. In [17], this approach was shown to result in a lower energy consumption compared to [11], while still achieving the light sensor set-points. Hence we use this as a reference method for performance comparison.

The ceiling sensor references, $y_r(k)$, are determined in a preliminary night time calibration phase as explained in [11] and [21]. In the absence of daylight, the luminaries are turned to maximum intensity and both the average workplace plane illuminance value and the ceiling sensor measurements are saved. The ceiling sensor references are then obtained by suitable scaling to result in the specified reference average illuminance at the workplace plane. It is assumed that the reference values are feasible, i.e. $G\mathbf{1} \geq y_r(k)$ which implies that there is a set of dimming values $u(k)$ (in the most extreme scenario $u(k) = \mathbf{1}$), that ensures that the illuminance on the ceiling is no smaller than the reference illuminance.

B. WORKPLACE-BASED CONTROL

In workplace-based control, at each time instant k, the lighting system is adapted based on:

- daylight contributions at each control point at the workplace plane, $p(k)$ (or estimates $\widehat{p}(k)$);
- illuminance gain matrices for the workplace, H; and
- desired illuminance levels at each control point at the workplace plane, $w_r(k)$.

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

$$u^*(k) = \arg\min_u \mathbf{1}^T u \quad s.t. \begin{cases} w(k) \geq w_r(k) \\ w(k) = Hu + \widehat{p}(k) \\ 0 \leq u \leq 1, \end{cases} \tag{19}$$

where $\widehat{p}(k)$ is the estimate of daylight contribution at the workplace plane obtained using the estimation approaches described in Section III. It is assumed that the references are feasible, i.e. $H\mathbf{1} \geq w_r(k)$. The workplace-based control given by (19) is hereafter referred to as *WP_CONTROL*, regardless of the estimation method used.

The optimization problems given by (18) and (19) are linear programming problems. These can be solved, for example, with the simplex method, interior-point algorithms or variants [33]. In this paper, we focus our attention on the steady-state behavior and do not consider the entire control behavior. As such, with knowledge of the daylight contribution estimate $\widehat{p}(k)$ and illuminations gains, H, at the workplace, the optimization problem (19) can be solved to obtain the optimal dimming level $u^*(k)$ and applied to the LEDs to achieve the desired value W_r. To ensure smooth changes in dimming levels such that the user is not disturbed by dimming control, methods considered in [34] may be used.

We now consider a way for the controller to deal with errors in daylight estimation. In particular, we consider over-estimation errors since our main concern is the under-illuminated workplaces. The optimization problem (19) may be modified as follows:

$$u^*(k) = \arg\min_u \mathbf{1}^T u \quad s.t. \begin{cases} w(k) \geq \min\{w_{\max}, w_r(k) + \xi\} \\ w(k) = Hu + \widehat{p}(k) \\ 0 \leq u \leq 1, \end{cases} \tag{20}$$

where $w_{\max}$ is a vector with the maximum achievable illuminance level at each control point due to artificial light and ξ is a offset vector to be determined. The purpose of adding this offset vector is to provide some robustness against errors in daylight estimation. In section V-B, we will explain how ξ is computed. The improved control given by (20) is hereafter referred to as *WP_CONTROL with Offset*, regardless of the estimation method used.

We do not consider adding an offset to the target level for the REF_CONTROL because in practice we do not know the offset vector to be added to the target levels at the light sensors at the ceiling such that the target illumination at the workspace is achieved.

V. SIMULATIONS RESULTS

A. LIGHTING DATA SET

The open-plan office lighting model considered in [11] was used, with the lighting plan depicted in Figure 2. The office has length 24 m, width 19 m and height of the ceiling is 2.6 m. There are $M = 80$ luminaires with collocated sensors in a grid of 10 by 8, and $N = 36$ workplaces with a collocated light sensor. The additional light sensors at control points at the workplaces were used for data acquisition as explained in Section III-A. The windows are located on the right side of the office next to luminaires 71-80; hence the biggest contribution of the daylight is observed in this area. All the artificial light and daylight distributions were obtained from the office model implemented in lighting software DIALux [38]. The lighting control system was implemented in Matlab.

Data from days in different months (January, March, June, August, September and December) and with different sky conditions (clear sky, overcast sky and mixed sky) was collected at a 15 minute interval. The daylight distributions in the office were simulated from 7:00 AM to 7:45 PM for a total of 18 days spread across all four seasons and with the three different sky conditions. The data from these 18 days was divided into 12 days for the training set $\mathcal{T}$ and 6 days for the validation set $\mathcal{V}$.

B. MODEL VALIDATION AND PERFORMANCE METRICS

We consider the following metrics for evaluating the performance of each estimator described in Section III with respect to the validation data set $\mathcal{V}$:

- root mean squared error (RMSE) for each control point n,

$$\text{RMSE}_n = \sqrt{\frac{1}{(r-q)} \sum_{i \in \mathcal{V}} [e_i]_n^2}, \tag{21}$$

  where $e_i = p_i - \widehat{p}_i$ is the vector containing the error in daylight estimation at the control points at the workplace plane;
- root average mean squared error (RAMSE) over all control points,

$$\text{RAMSE} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (\text{RMSE}_n)^2}; \tag{22}$$

- cumulative distribution function (CDF) of the error in daylight estimation for each control point n,

$$\text{CDF}_n(e) = \frac{1}{r-q} \sum_{i \in \mathcal{V}} \mathbb{1}(e - [e_i]_n), \tag{23}$$

  where $\mathbb{1}(x)$ is the unit step function which is equal to zero for $x < 0$ and equal to one for $x > 0$; and
- CDF of the error in daylight estimation over all control points,

$$\text{CDF}(e) = \frac{1}{N} \sum_{n=1}^{N} \text{CDF}_n(e). \tag{24}$$

Using (23), we choose the bias term in (20) as

$$[\xi]_n = \max\{0, -\alpha_n\}, \quad n = 1, \dots, N \tag{25}$$

where $\text{CDF}_n(\alpha_n) = 1 - \Xi$ and $0 \le \Xi \le 1$ is a parameter that indicates the proportion of samples to be compensated during offset control in (20). We choose $\Xi = 0.99$.

Figure 3 shows the CDF for the proposed daylight estimation methods (RLS, LWRLS and CRLS) over all control points as given by (24). We can see that the estimation errors for the three proposed approaches are concentrated within an error bound of ±20 lux. The error is rather small (less than 5%) as compared to the desired illuminance at the workplace plane which is around 500 lux. Figure 4 gives a more detailed insight on how these errors (using (21)) are distributed across the $N = 36$ different workplaces (control points). It clearly shows that the larger errors are on those workplaces near the windows (29 - 36). This is expected since those are the workplaces over which daylight exhibits the largest variation (up to several thousands lux as seen in Figure 5). The workplaces that are further away from the windows (1 - 28) receive small amounts of daylight even on a bright day as seen in Figure 5.

For our data set, all approaches (RLS, LWRLS and CRLS) achieve similar performance for estimating daylight contribution at control points over the workplace plane. The RAMSE as given by (22) is about 3.732 for RLS, 3.004 for LWRLS and 3.229 for CRLS.

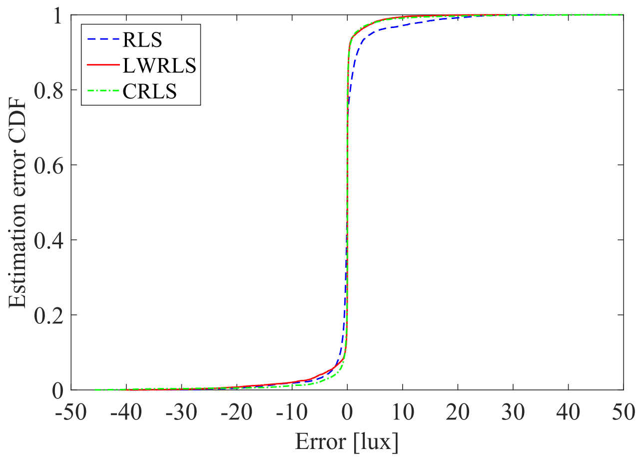

FIGURE 3. CDF of the daylight estimation error on workplaces for the considered estimators.

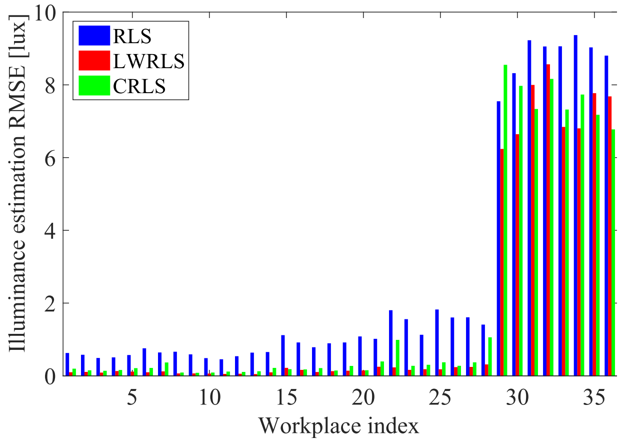

FIGURE 4. RMSE of the daylight estimation error for each workplace as given by (21). LS, LWRLS and CRLS are considered.

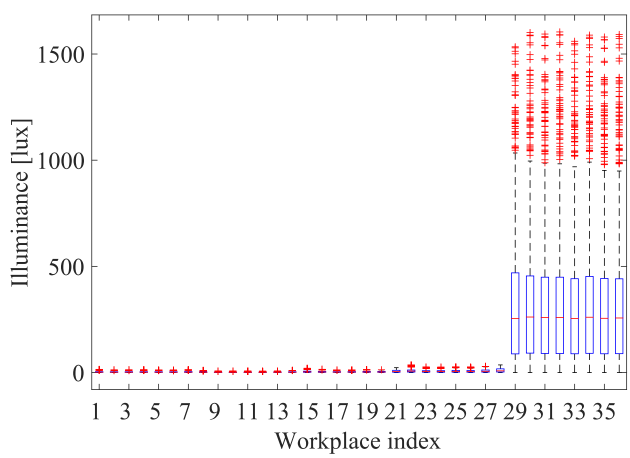

FIGURE 5. Boxplot showing the daylight value at workplace level for our data set.

C. SATURATION OF LIGHT SENSORS

For most lighting control applications, if the illuminance level due to daylight is larger than several hundred lux, then it would result in the luminaire dimming down to minimum intensity. Hence, in practice, light sensors are designed to measure a limited range of illuminance levels [39], [40]. An illuminance level larger than the maximum range of a light sensor would result in saturation, i.e. the measurement is capped to the maximum valid value.

In this section, we compare the performance of the estimators under saturation of the light sensors. We consider a saturation level for the light sensors of 1000 lux.

The percentage of the samples that are affected by saturation is zero for the data originating from the light sensors at the ceiling. The percentage of the samples affected by saturation from the workplace plane is around 2%; if we consider just the workplaces next to the windows the percentage is about 8%. In Figure 5, we plot the daylight values at each control point at the workplace plane without saturation. We can see that those control points in the proximity of the windows (29 to 36) have the largest daylight contribution and thus they are more likely to be affected by saturation. Hence, we focus our comparison on only those control points.

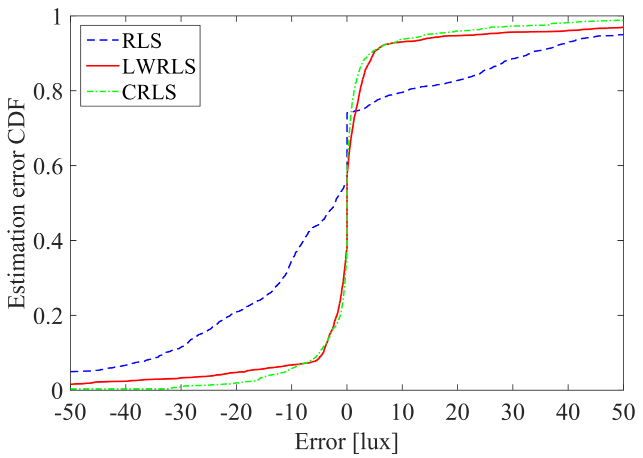

FIGURE 6. CDF of the daylight estimation error on the workplaces 29 to 36 for the considered estimators. All sensors are saturated at 1000 lux.

In Figure 6, we show the CDF of the daylight estimation error for all approaches under saturation of light sensors. Note that the saturation of light sensors introduces a non-linearity in the relationship between daylight levels at the ceiling and at the workplace plane. We can see that the performance of the RLS approach is degraded due to this non-linearity. In comparison, the LWRLS and CRLS approaches provide a good estimate of daylight under saturation of light sensors.

D. SMALL TRAINING SET

In Section III, we discussed that adding a regularization parameter could be effective if the training data set is small. In fact, adding the regularization term when we use the entire training set has little effect on the estimation performance. Using a small training set, we compare the performance of the LWRLS and RLS approach. For comparison, we also consider the performance of a LS approach, i.e. RLS with $\epsilon = 0$. Note that the cluster-based approach would further divides the training set into smaller sets and thus it is not recommended when the training set is small.

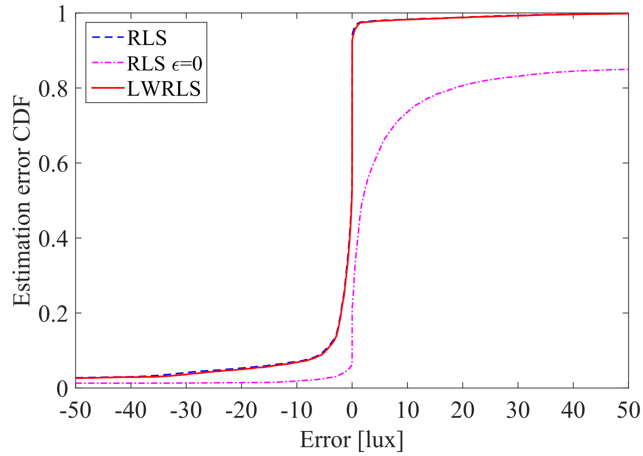

FIGURE 7. CDF of the daylight estimation error on all workplaces using only two training days: overcast day in September and December. No saturation.

In Figure 7, we show the CDF of the daylight estimation error when the training set is small. We consider a training set with only two days with small variations in daylight conditions: Overcast Sky days in September and December. We can see that all approaches overestimate the daylight contribution at control points at the workplace plane. In particular, the RLS approach with $\epsilon = 0$ overestimates more often (around 15% of the samples are overestimated by more than 50 lux) than the other two approaches (less than 10% of the samples are overestimated by more than 50 lux).

Additionally, we show in Figure 8 the CDF of the daylight estimation error when the training set includes two days with large variations in daylight conditions: a single day in September with clear sky and another single day in December with overcast sky. We can see that the RLS and LWRLS

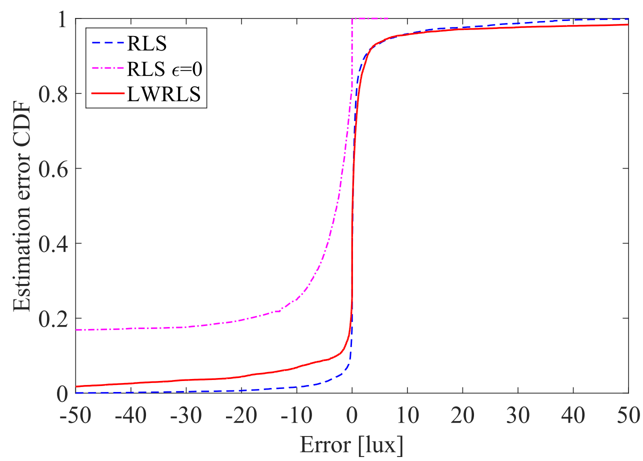

FIGURE 8. CDF of the daylight estimation error on all workplaces using only two training days: clear day in September and overcast day in December. No saturation.

approaches provide good estimates of the daylight contribution while the RLS approach with $\epsilon = 0$ underestimates the daylight contribution (around 20% of the samples are underestimated by more than 50 lux).

E. CONTROLLER PERFORMANCE

In this section we evaluate the performance of the different controllers described in Section IV using the validation set $\mathcal{V}$. For the *WP_CONTROL* and *WP_CONTROL with Offset* we consider the LWRLS approach for daylight estimation due to its good performance under large and small training set, and saturation of light sensors. For comparison, we consider the *WP_CONTROL* when the daylight contribution terms $p(k)$ are perfectly known, hereafter referred to as *ORACLE_CONTROL*, and the *REF_CONTROL* introduced in (18).

The simulations were done by having all workplaces in occupied state, which requires an illuminance level at workplace plane of $W = 500$ lux in all the workplaces, i.e. $w_r(k) = W\mathbf{1}, \forall k$.

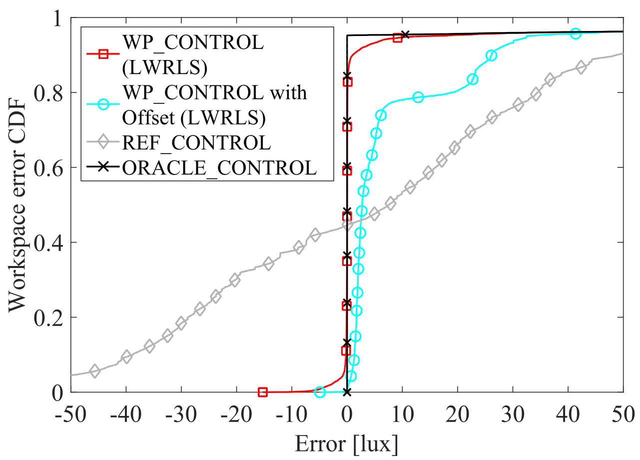

FIGURE 9. CDF of the controller error on the workplaces for different approaches with respect to the nominal value of 500 lux as given by Eqn. (26).

In Figure 9, we show the CDF of the error in achieved illumination at the control points at the workplace plane with respect to the nominal value of $W = 500$ lux for each control strategy. More specifically, we show for each control strategy:

$$\mathrm{CDF}_w(e) = \frac{1}{NK} \sum_{n=1}^{N} \sum_{k=1}^{K} \mathbb{1}(e - [e_w(k)]_n),$$
$$e_w(k) = w(k) - w_r(k). \tag{26}$$

In Figure 9, we can see that the proposed controllers using the daylight estimation approach provides sufficient illumination at the control points at the workplace plane (the under-illumination is less than 10 lux). In comparison, the *REF_CONTROL* has a larger variation in the error in achieved illumination at the control points at the workplace plane (half of the time the control points are under-illuminated and the other half they are over-illuminated). The *WP_CONTROL with Offset* provides most of the time sufficient illumination at the control points at the workplace plane. Note that the *ORACLE_CONTROL* always provides sufficient illumination.

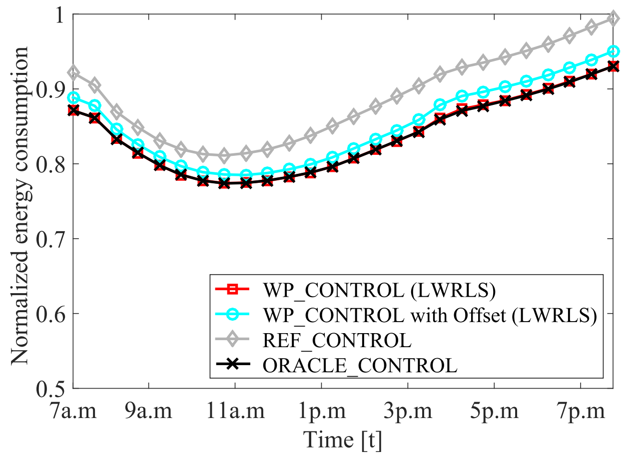

FIGURE 10. Normalized energy consumption averaged over several days of the years and weather conditions for different control strategies.

Figure 10 shows the normalized energy consumption averaged over several days of the years and daylight conditions for each control strategies. The energy consumption is normalized with respect to a lighting system that, under the absence of daylight, provides an average illumination at the workplace plane of about $W = 500$ lux, i.e. all luminaires are set to a constant value of 0.85 throughout the day: $u(k) = 0.85 \times \mathbf{1}$ and $\frac{1}{N}\sum_{n=1}^{N}[w(k)]_n = W$ when $d(k) = 0$. We can see that our proposed control strategies have reduced and similar normalized energy consumption levels with respect to *REF_CONTROL* and *ORACLE_CONTROL*, respectively.

TABLE 1. Normalized energy consumption and percentage of workplaces that are under-illuminated by more than 1 lux, under different control strategies.

	Normalized energy consumption	Percentage of under-illumination
WP_CONTROL (LWRLS)	0.84	4%
WP_CONTROL with Offset (LWRLS)	0.85	0.1%
REF_CONTROL	0.88	44%
ORACLE_CONTROL	0.84	0%

In Table 1, we summarize both the average normalized lighting energy consumption and the level of under-illumination. Here, we can see that our proposed control strategies are close in performance to the *ORACLE_CONTROL*.

Finally, we simulate the effect of different occupancy distributions. We consider a scenario wherein probability of a workplace being occupied is equal to 0.5. In Fig. 11, we can see that the proposed controllers outperform the *REF_CONTROL* with respect to providing sufficient illumination at the workplaces under different occupancy distributions. Note that the proportion of under-illuminated zones

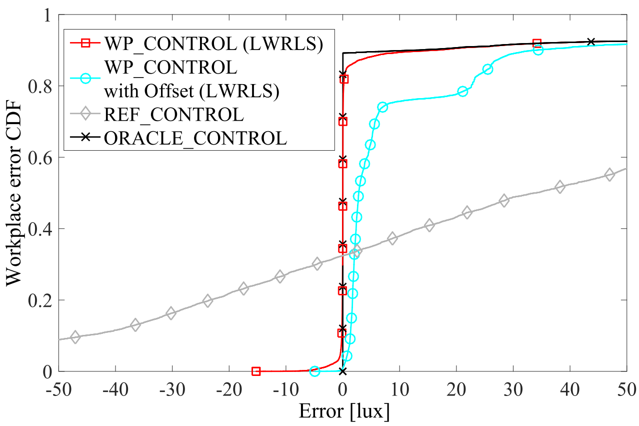

FIGURE 11. CDF of the controller error on the workplaces for different approaches under different occupancy distributions as given by Eqn. (26).

under REF_CONTROL is smaller when compared to all zones occupied (Figure 9). This is due to a lower illumination requirement (300 lx) in unoccupied zones. Similarly, we can see that a larger proportion of zones are over-illuminated under all methods.

VI. CONCLUSIONS

We considered three methods for daylight mapping estimation in a training phase for use in lighting control. The daylight mapping is used to obtain an estimate of the achieved illuminance at the workplaces. This knowledge is used in the 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 the REF_CONTROL approach, the proposed solution achieves illuminance values closer to the desired values and also saves energy. In practice, the least squares method for daylight estimation has worse performance among the considered methods. In particular, the performance is poor when (i) the training set is small, and/or (ii) when non-linearities, for example in the form of saturated light sensor measurements, exist. The former issue can be solved by considering a regularization term. The latter issue can only be handled by the locally weighted regularized least squares and cluster-based regularized least squares methods. Note that both these methods assume linearity within a (neighboring) subset of the measurements.

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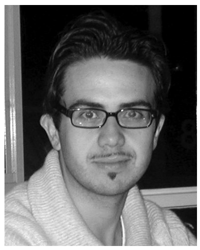

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