Inverse Modeling using a Wireless Sensor Network (WSN) for Personalized Daylight Harvesting

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Abstract: Smart lighting systems in low energy commercial buildings can be expensive to implement and commission. Studies have also shown that only 50% of these systems are used after installation, and those used are not operated at full capacity due to inadequate commissioning and lack of personalization. Wireless sensor networks (WSN) have great potential to enable personalized smart lighting systems for real-time model predictive control of integrated smart building systems. In this paper we present a framework for using a WSN to develop a real-time indoor lighting inverse model as a piecewise linear function of window and artificial light levels, discretized by sub-hourly sun angles. Applied on two days of daylight and ten days of artificial light data, this model was able to predict the light level at seven monitored workstations with accuracy sufficient for daylight harvesting and lighting control around fixed work surfaces. The reduced order model was also designed to be used for long term evaluation of energy and comfort performance of the predictive control algorithms. This paper describes a WSN experiment from an implementation at the Sustainability Base at NASA Ames, a living laboratory that offers opportunities to test and validate information-centric smart building control systems.

1 INTRODUCTION

According to the U.S. DOE's Energy yearbook in 2010, the maximum electricity consumption in commercial buildings (13.6%) is attributed to lighting (Department of Energy, 2010). Intelligent daylight and occupancy-based lighting control is becoming increasingly important for future net zero energy buildings, for lighting as well as heating and cooling energy savings. Fortunately, there have been significant improvements in lighting controls and associated hardware (Philips, 2011), in addition to interoperability with building energy management systems (Walton et al., 2007) and advances in daylight harvesting systems such as smart windows (Lee and Tavil, 2007); (Lu and Whitehouse, 2012).

Our prior work has demonstrated 50% savings from individually dimmable and user preference-based luminaire control in absence of daylight. An additional 20% energy savings could be achieved with daylight harvesting according to our simulation results (Wen and Agogino, 2011a; 2011b); (Wen et al., 2011); (Wen, 2008).

In spite of the growing impetus in lighting control research and some successful pilot projects (Lee and Tavil, 2007), the actual adoption of intelligent lighting control systems in commercial buildings has been very limited. Singhvi, Krause, Guestrin, Garrett, and Matthews (2005) developed a centralized lighting system to increase user comfort and reduce energy costs by using a WSN. Suet Fei Li (2006) developed wireless sensing and actuation networks (WSAN) for lighting control in the home environment. Lin and Megerian (2005) proposed a decentralized algorithm for WSANs for optimal lighting control. Yet, as of 2010 70% of the US national stock of commercial buildings had no lighting controls for energy efficiency (Ashe et al., 2012). Some of the reasons include general lack of encouraging results of lighting retrofit in terms of energy savings and system usability. Rude found that 50% of the intelligent lighting control systems they studied had been deactivated by the users and the remaining 50% operated at 50% of target performance (2006).

However, the drive to move to low energy and

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even net zero energy usage has led to more buildings being retrofitted or commissioned with automated control capabilities. A major challenge is to control the coupled sub-systems of a complex building system or even a cluster of buildings. Moving beyond the capabilities of heuristic control approaches, new systems seek to incorporate predictive models of occupancy, renewable energy availability and price signals (Ma et al., 2012); (Liu and Henze, 2006) to account for interdependencies between energy performance of these subsystems (Mukherjee et al., 2010). The sub-system interdependencies and their influences on the overall building energy performance could be captured by massive deployment of wireless sensor networks (Brambley et al., 2005); (Lin and Megerian, 2005); (Li, 2006) and real-time modelling.

Assuming an energy cost of 16.8 cents/kWh (California Public Utilities Commission, 2011) and an annual energy intensity of 131.0 to 177 kWh/m^2 (California Energy Commission [CEC], 2006), the average annual energy cost of small and medium commercial buildings in California is \$30/m^2; 29% of this energy is used in commercial lighting (CEC, 2006). 50-60% lighting energy savings from daylight harvesting and feedback lighting control would therefore mean an energy cost savings of \$5.20/m^2 per year. A scenario of 2 to 3 wireless sensor platforms per workstation (Deru et al., 2011) including daylight sensors, amounts to 1 platform/6.2 - 9.3 m^2, the standard occupancy being 18.6m^2/person, according to the standards for ventilation set by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) (ASHRAE, 2010). The current price of most commercially available wireless sensor platforms is approximately \$100. Hence, the initial investment for a WSAN-based closed loop lighting control system is approximately \$10.70-\$16.00/m^2 (just for the sensor platform), which is 2-3 times higher than the annual lighting energy cost per unit area of a building.

Thus one major challenge is the development of inexpensive and easy to commission WSANs, along with computationally inexpensive lighting models and intelligent control systems. The question is how minimal sensor deployment could suffice for desired energy and comfort performance of these systems. One strategy is to repeatedly redeploy the same wireless sensor platform in different locations at desktop levels to create parameterized lighting models. This redeployment promises to cut down costs in comparison to sensors permanently fitted in luminaires. This strategy also can increase accuracy, as the overhead sensors tend to over-estimate the light level compared to the human eye at desktop levels. Sensor platform reuse can be facilitated by inclusion of a predictive mathematical model of the indoor light level at key locations (such as desktops) within the intelligent lighting control loop, as a function of the minimum required sensed data points.

In this paper we present a framework for the development of an indoor lighting inverse model as a piecewise linear function of the minimum number of sensed parameters: window light levels and adjoining dimmable lights' statuses, discretized by sub-hourly sun angles at a given time of the day. As part of our on-going research on information-centric smart building control systems, we deployed low power wireless light sensor network for system identification at the Sustainability Base at the NASA Ames Research Center. The training and validation data for the predictive inverse lighting model were obtained after three months of data acquisition at this test bed.

2 ANALYSIS

2.1 Inverse Problem Theory

Inverse problem theory describes methods by which a model of a system is developed by: (1) parameterizing the system in terms of a set of model parameters that adequately characterize the system in the desired point of view, (2) making predictions on the actual values based on physical laws and given values of the model parameters, and (3) using actual results from measurements to determine the model parameters (Tarantola, 2005).

A physics-based lighting model is the best choice for accuracy, requiring the input of accurate building and furniture dimensions. These models estimate the lighting as a summation of the luminaries and daylight at every position in the room. These systems can be difficult to develop and require technicians and professional staff to deploy.

An inverse model, in contrast, does not require complete location information to function. Instead, the system measures lighting data at workstations about the room. The data are mapped to the luminary levels and to the daylight illuminance measured at the windows via a regression model. An inverse model trades some accuracy and extensibility for rapid deployment capabilities and can be set up within a few hours. Moreover, these reduced order models can be computationally inexpensive to perform simulations within a control loop. For these reasons, an inverse model is a promising choice for a predictive lighting control system designed for ease-of-use.

2.2 Multiple Linear Regression

Multiple linear regression is an efficient and relatively simple procedure that can find a linear relationship between multiple regressors and a regressand. The ordinary least squares (OLS) method functions to create a best linear fit to a given data set by minimizing the sum of the squared residuals (Hayashi, 2000).

For this project, a linear relationship between the illuminance measured at artificial and natural light sources and the illuminance measured at a workstation was found suitable, taking the form:

$$E_w = \alpha_1 E_{a1} + \cdots + \beta_1 E_{n1} + \cdots + \varepsilon \qquad (1)$$

Where E_w, E_a, and E_n are illuminance readings at the workstation, an artificial light source, and a natural light source, respectively, while α and β are constants defined by the model and ε is random error. If we have m samples, the equation becomes:

$$\begin{pmatrix} E_{w_1} \\ \vdots \\ E_{w_m} \end{pmatrix} = \alpha_1 \begin{pmatrix} E_{a1_1} \\ \vdots \\ E_{a1_m} \end{pmatrix} + \cdots + \beta_1 \begin{pmatrix} E_{n1_1} \\ \vdots \\ E_{n1_m} \end{pmatrix} + \cdots + \varepsilon \qquad (2)$$

To solve this equation, the method of ordinary least-squares leads us to find the values of α and β that minimize the sum of the squared residuals. A simple way to do this is to first arrange the data into the form:

$$\begin{pmatrix} \mathrm{E}_{\mathrm{w}_1} \\ \vdots \\ \mathrm{E}_{\mathrm{w}_\mathrm{m}} \end{pmatrix} = \begin{pmatrix} \mathrm{E}_{\mathrm{a1}_1} \cdots \mathrm{E}_{\mathrm{n1}_1} & \cdots \\ \vdots \quad \ddots \quad \vdots & \ddots \\ \mathrm{E}_{\mathrm{a1}_\mathrm{m}} \cdots \mathrm{E}_{\mathrm{n1}_\mathrm{m}} & \cdots \end{pmatrix} \begin{pmatrix} \alpha_1 \\ \vdots \\ \beta_1 \\ \vdots \end{pmatrix} + \varepsilon \qquad (3)$$

Simplifying Equation 3 for clarity:

$$Y = Xb + \varepsilon \qquad (4)$$

From there we assume strict exogeneity, or that the error has a mean of zero and is not correlated to the regressors. We also assume linear independence. This assumption is valid because, while there is some risk of multicollinearity if there is only one light source and the sensor platforms are positioned very close together, this risk is mediated simply by ensuring the sensor platforms are spaced well apart at varying distances from the light source.

Solving for b, the equation can be rearranged to form:

$$b = \left(\frac{1}{n} \sum_{i=1}^{n} x_i \, x'_i \right)^{-1} \frac{1}{n} \sum_{i=1}^{n} x_i y_i \qquad (5)$$

This equation is the Ordinary Least Squares Estimator, and gives us the best fit linear model for the data.

2.3 Piecewise Linear Regression

The complexity of daylight poses challenges to simple linear regression. Daylight is diffused through the atmosphere and is reflected by and diffused through many surfaces within the built environment. The angle of the sun and the spatial geometry, in particular, play significant roles in the distribution of the direct and diffuse light within a space. Direct sunlight falling on a sensor is primarily responsible for the non-linear relationship between the sensed façade light and the sunlight distributed indoors. Because of this, a piecewise linear function discretized by sun angle is better suited to daylight approximation than a single linear model. The angle of the sun can be used as the bounds for the pieces, so that several linear functions now represent small fractions of the entire range of solar angles throughout the day.

2.4 Related Work

There has been prior research in approximating linear functions to daylight illuminances. A. Guillemin (2003) and D. Lindelhöf (2007) have tested a predictive model that assumed a linear relationship between vertical façade illuminance and indoor horizontal illuminance. In his work, his predictive model resulted in standard deviations of 416 lux, roughly double that of the standard deviation of the piecewise linear regression model.

Previous tests for inverse model generation network were performed by the authors in a residential environment in the Spring of 2012. The tests were conducted in a 450 sq. ft. rectangular studio apartment in San Francisco with a west-facing floor-to-ceiling window. The controllable light sources were: a kitchen ceiling fixture and a small bedside lamp. Throughout the test, the space was occupied by two residents on a daily basis. An inverse model was created for each of two workstations. The resulting predictions had an average error of approximately 100 lux with a standard deviation of 250 lux (Paulson, 2012), an improvement over previous studies, but a reduction of the range in error still desirable. This motivated an experiment in an open space commercial office buildings with less interference from walls and other structures.

3 DESIGN AND IMPLEMENTATION

3.1 Hardware

A wireless light sensor network was utilized for inverse modeling. The network was comprised of TelosB mote platforms running on AA-batteries (MEMSIC Inc., 2012). The motes were configured with an ambient illuminance sensor that was sampled at regular intervals. The motes communicated each sample reading over the 802.15.4 layer to another mote connected to a base computer.

3.2 System Architecture

The wireless sensor network was programmed in TinyOS, an open-source platform developed at UC Berkeley (Levis et al., 2005). A flowchart for the software structure can be seen in Figure 1. The motes, each with their own unique ID's, communicate data packages to a base station mote which forwards the data via a serial connection to a computer which saves the data locally and forwards it to an online database following a Simple Measurement and Actuation Protocol (sMAP). sMAP is being developed by UC Berkeley as a single web based platform for accessing large volumes of data from all possible sensor points from a multitude of disparate and distributed data sources such as building management systems of large commercial buildings, ad-hoc sensor networks, grid data from Intelligrid, building models from GreenXML source, pricing data from OpenADR, (Automated Demand Response) and monitoring by Smart Energy Profile applications (Dawson-Haggerty, 2011); (Dawson-Haggerty et al., 2012).

A Java-based program performs several tasks. First, the data are parsed to fill in any gap caused by lost packages. Second, the data from each mote are then divided, depending on the angle of the sun at each time step, which is computed using the *Astronomer Almanac's* sun positioning algorithm (Michalsky, 1988). A daylight model is generated through linear regression on a data set with no artificial light (such as data taken over the weekend) to create a piecewise linear function for each workstation, divided by angle of inclination of the sun. A linear function is estimated for every 1.0° sun elevation. The daylight model is then extended to create a full model using data sets with artificial light.

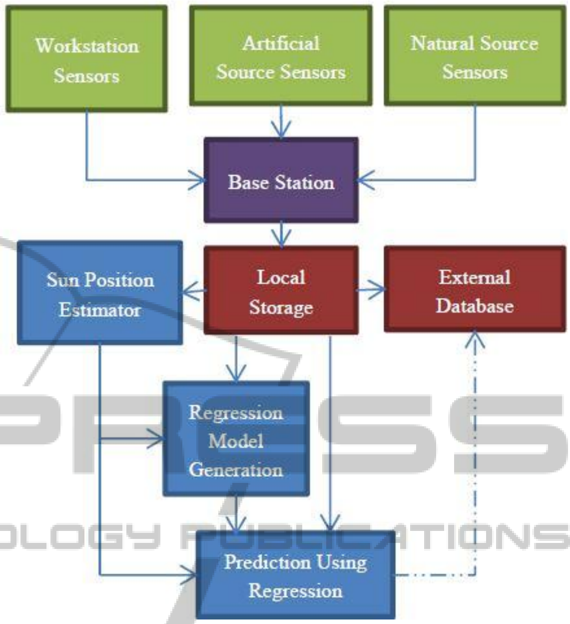

Figure 1: Software flowchart.

3.3 Deployment

Sensors were deployed at the Sustainability Base at NASA Ames Research Center across two cubicles in an open-plan office space. Seven sensors were deployed at or near the workplane and two sensors were placed on the walls near the windows. Sensors 1, 2 and 3 were located at incremental distances from the window mote 8, covering the workplane across the entire cubicle and sensors 5, 6 and 7 were replicated in the adjoining cubicle with 9 being the window mote. Sensor 4 was located on top of a low height partition between the two cubicles. The sensors collected data for several weeks, reporting the data to a local server, which forwarded the data to an online data visualization page for remote access.

Power level data from the controllable luminaries were collected from the luminary system data logs after the tests, to avoid invasive procedures that may void the luminary warranty. The light level data were then input into the inverse model generation package.

Daylight model training data were sampled every five minutes from May 25 – May 27, 2012, a weekend during which no luminaries were turned on. The full model training data were sampled from May 25 – June 5, 2012.

4 RESULTS

The full model was tested from June 11 – June 20, 2012. During this time, the building was occupied and experiencing normal operations. The graphs for the predicted values and measured sensor readings are shown for workstations 1 – 7 in Figures 2 – 8, respectively. The standard deviation of the residuals and the root-mean-square error for each workstation can be found in Table 1.

From Figures 2-8, it is apparent that our model's prediction errors are consistently higher for workstations 1-3 compared to workstations 4-7.

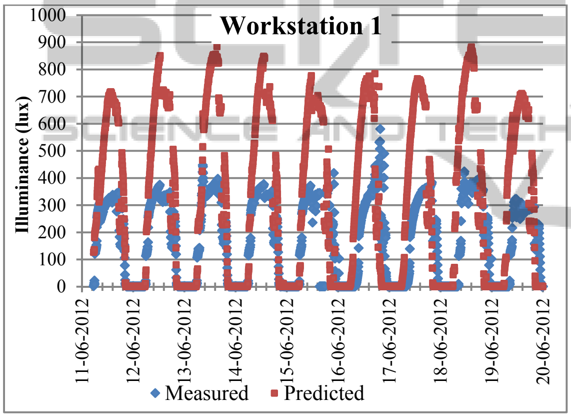

Figure 2: Measured and predicted values of illuminance for Workstation 1.

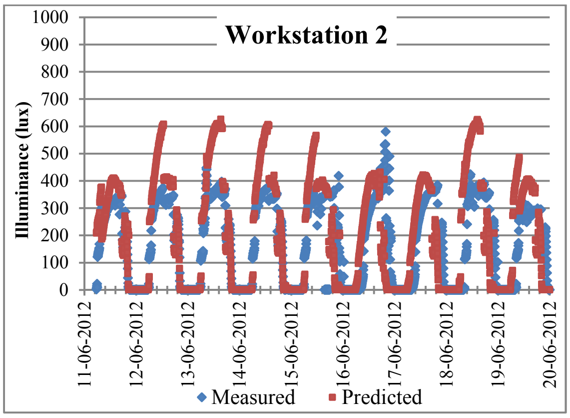

Figure 3: Measured and predicted values of illuminance for Workstation 2.

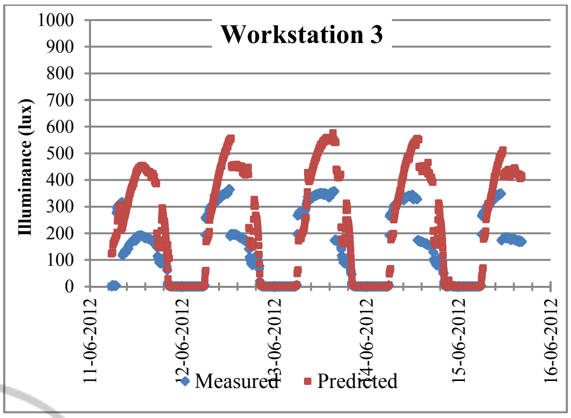

Figure 4: Measured and predicted values of illuminance for Workstation 3.

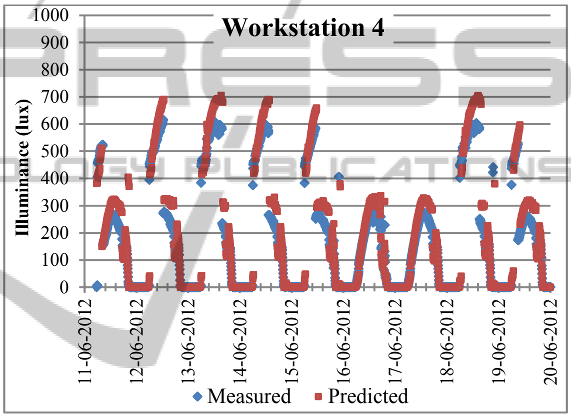

Figure 5: Measured and predicted values of illuminance for Workstation 4.

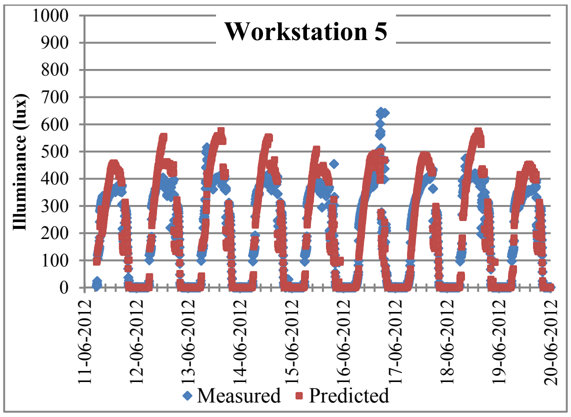

Figure 6: Measured and predicted values of illuminance for Workstation 5.

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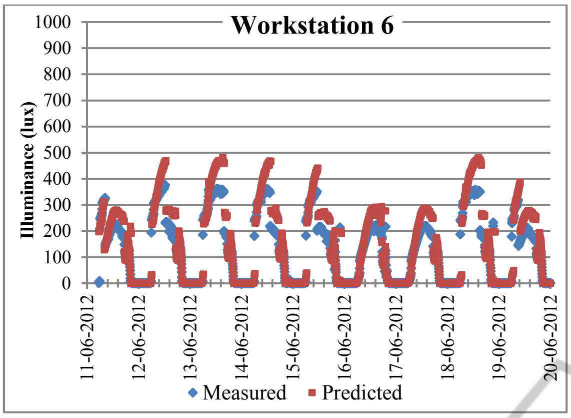

Figure 7: Measured and predicted values of illuminance for Workstation 6.

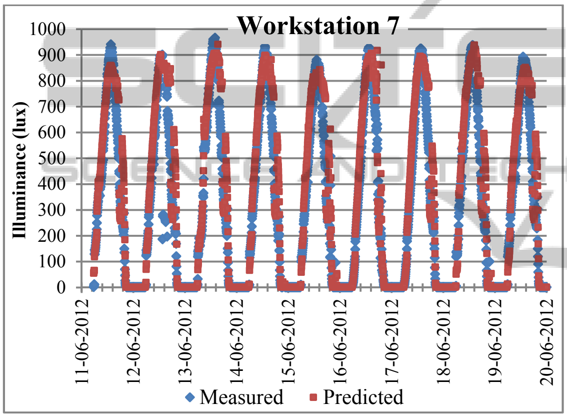

Figure 8: Measured and predicted values of illuminance for Workstation 7.

Table 1: Standard deviation of residuals and root mean-square error for predicted values for workstations 1-7.

Workstation	SD (lux)	RMSE (lux)
1	204.32	257.76
2	108.65	142.715
3	211.61	213.06
4	86.90	91.44
5	58.78	61.56
6	55.66	62.17
7	92.51	101.93

5 DISCUSSION

The inverse model implemented from the dataset obtained from our second test bed at NASA Ames appears to predict the workstation light level with higher accuracy than the previous tests on an average. The root mean square error of the models tended toward 100 lux or less on an average across the monitored workstations except for a few of workstations (1, 2 and 3), probably due to various disturbances such as installed position and varying traffic levels. The recommended lux level for standard office work is 500 lux (IESNA, 2000) and, assuming a logarithmic sensitivity of the human eye, an average error of 100 lux is hardly perceivable. While the standard deviation of the residuals for some workstations is still very high, the majority of the models exhibited standard deviations below half of those reported in previous tests. Note that accuracy and predictive capability of physically based models of lighting, which use sophisticated and computationally expensive ray tracing algorithms, vary widely depending on the expertise and the experience of the modellers, the average being 20% (Ibarra and Reinhart, 2009).

The linear daylight regression model discretized by solar tilt appears to be more accurate than single linear regression models, with standard deviations of residuals being up to 87.6% lower than those reported in previous related work depending on the sensor position (Guillemin, 2003).

5.1 Error Sources and Corrections

The possible major errors were expected to stem from sensor accuracy and precision followed by the complex nature of daylight spatial geometry like distance from the windows, solar shading, distribution of indoor reflective surface and miscellaneous disturbances like occupant traffic, change in sensor position and so on. The complex nature of daylight is attributed to unpredictability of weather parameters such as sudden cloud cover and relationship of the building geometry to solar geometry. Fluctuating weather patterns could affect the correlation of illuminance values between the motes at the workstations and those at the windows. One solution to the first error would be to use multiple motes and take advantage of data redundancy, facilitated by temporary sensor platform deployment for model identification (Wen, 2008).

Alternatively, an adaptive modelling algorithm could be designed to appropriately deploy means of data validation and fusion iteratively until a shared performance goal is reached. For example, in our study, a preliminary comparison of window sensor 8 readings with three on-site roof-mounted radiometer data showed a good correlation between the two, but not for sensor 9. Results of further comparison with other reliable explanatory variables could eventually be used to weigh the sensor 9 readings based on data validity. We expect that sampling over a set of cloudy and sunny days can indicate the possible reasons for high standard deviations of the residuals at workstations 3 and 4. This methodology calls for interoperability with various information sources in the building such as shading systems, BMS etc. – an opportunity offered by sMAP. sMAP comes with drivers written in Python for various data sources found in standard building applications.

In places where both mean and standard deviations of the errors are large, longer sampling will allow disaggregating the effect of weather and sun position from those of local disturbances on the measured data at a given workstation. After sensor placement, it was discovered that workstation 1 was placed on a table that was raised and lowered by nearly a foot and a half on a fairly regular basis, likely contributing to the higher residuals and standard deviation for that workstation. This highlights a drawback to inverse modelling, in that if the sensors are moved after initial placement, the model becomes much less accurate. However, occasional data exchange between motes and comparison between the spatially distributed sensor readings could again be used here to detect such disturbances.

Sensor blockage due to occupant traffic could be another potential source of error, which can be addressed partly through sensor processing. Our initial investigation of weekend and weekday data, however, did not indicate any sharp change in data pattern due to occupant presence.

Sun tilt cannot adequately explain the relationship between solar geometry and building geometry. The effect of 10° sun tilt might be completely different in the morning and evening depending on the building orientation. In our next model we are trying to account for this factor by dividing the data further by morning and afternoon.

From the above analysis, it is apparent that our model should be capable of using several explanatory variables when required, customized to individual lighting scenarios with nodes that exchange readings for time to time comparison. Such a feature would be increasingly important for the platform reuse model. Sandhu, Agogino A.M., and Agogino A.K. (2004) had proposed an Multi-agent system (MAS) for distributed data processing and Influence Diagram (Bayes' net)-based decision making in closed loop lighting control, the main goal was to achieve flexibility of distributed computation. We could formulate our case in a MAS framework, in which individual workplane sensor may have its own set of explanatory variables, while the common goal of the supervisory algorithm would be to minimize the average prediction error across the spatially distributed agents.

6 FUTURE WORK

6.1 Extending Inverse Model for Annual Energy Performance Prediction

Some of the challenges of data driven-models are the number of samples and perturbations required in each of the model parameters to achieve a fairly robust inverse model of a process. Developing a calibrated physically-based model of the process can address some of these challenges by obviating long term data acquisition. We are creating and calibrating a physically-based lighting model of the monitored workspace at the Sustainability Base using the RADIANCE lighting simulation software. Outputs from the annual simulations of this model will be used to extend and validate the reduced order light model, which in turn will then predict the energy and comfort performance of the control algorithm.

6.2 Extending Inverse Model for Model Predictive Control

The inverse light model of workstation lighting was developed for the purpose of controlling individually addressable luminaires. However, control of the sub-systems of a complex system such as a building, or even a cluster of buildings, must be more coupled as engineers move beyond heuristic control approaches and seek to incorporate predictive models of occupancy, renewable energy availability and price signals (Ma et al., 2012); (Liu and Henze, 2006), accounting for interdependencies between energy performance of these subsystems (Mukherjee et al., 2010). This invites the challenge of controlling a multi-input multi-output system where the response time of the sub-systems varies from a few seconds to several hours. Keeping in mind this challenge of future smart building energy and comfort management, we are using a modular approach to augment our system identification platform. We are extending the inverse lighting model for predictive control of multiple smart shading systems, the setpoints being instantaneously desired light level at multiple workstations and desired zone temperature, several time steps in the future.

7 CONCLUSIONS

Current market intelligent lighting control systems seldom include a predictive light model within the control loop and the implementations of these systems have proven to be ineffective in the majority of installations. The light sensors are mostly overhead and tend to over-estimate the light level at the workplane due to a different field of view than the human eye at the workplane. Predictive models of indoor lighting could also be integrated within the framework of model predictive control of building systems, an emerging strategy in the realm of smart buildings on the smart grid.

As part of our research endeavour with the Sustainability Base at the NASA Ames Research Center we are developing a computationally inexpensive predictive model of indoor lighting. To this end we have deployed a low power wireless sensor network at this test bed and developed a piecewise linear regression model of workstation illuminance, built on a month of data at seven workstations, that was capable of predicting the light levels within 36%-60% on average across the workstations. We found that linear models discretized by sun angles were able to explain and predict the influence of daylight on workplane illuminance better than previous related work that considered only a single linear model as function of vertical façade illuminance. However, in spite of a low spatially averaged error we still noted higher fluctuations of errors in the proximity of the windows, in cubicles with higher occupant traffic or when window motes receive more direct solar. In order to address these error fluctuations we are planning to develop an adaptive model that can adjust the model coefficients based on system state. Further using data from annual simulations of a calibrated physically based model of the monitored space, the current inverse model will be extended for annual control algorithm generation and energy performance evaluation. In addition we are incorporating future daylight prediction capability within the current model for better integration into a model predictive control framework, including systems of multiple response times.

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