ENERGY INNOVATIONS SMALL GRANT PROGRAM

FINAL REPORT

Model Predictive Smart Lighting Commissioning System for Emerging Demand Management

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Acknowledgement Page

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Abstract

Studies show that if all the lighting systems in buildings of California were retrofitted with dimming ballasts, then it would be possible to obtain 450 MW of regulation, 2.5 GW of non-spinning reserve and 380 MW of contingency reserve. However, in order to guarantee participation it will be important to monitor and model lighting demand and supply in buildings. Prior work by the PI has shown that wireless sensor networks have the potential to reduce energy use at 50-70%, but they can be expensive due to a dependence on dense sensing. This report presents a sensor-based intelligent lighting system for future grid-integrated buildings. Approximately 60% fewer sensors are deployed compared to state-of-art systems. Sensor modules contain small solar panels that supply power by ambient light. Reduction in sensor deployments is achieved using piecewise linear predictive models of indoor light, discretized by clustering for sky conditions and sun positions. With two weeks of training data from the Sustainability Base at NASA Ames, light levels were predicted with 80-95% accuracy. Day-ahead daylight is predicted from forecasts of temperature, humidity and cloud cover with 92% accuracy. Load shedding and load shifting demand response strategies predicted potential load reduction by 80% and 19%, respectively. An environmental return on investment is estimated to occur after the system has supplemented 148 kWh of grid energy, which can be accomplished in two days with a 70% reduction potential.

Key Words: wireless sensor network, daylight harvesting, inverse model, clustering, support vector regression, solar powered, demand response, life cycle assessment

Executive Summary

Introduction

Prior studies have found that closed loop control of building systems enabled by wireless sensor and actuator networks (WSANs) can result in 28% cooling energy and 40% light energy savings in office buildings. Commercial lighting contributes to 14% of commercial energy use. The researchers' prior work has demonstrated that even without daylight harvesting (controlling artificial lights based on daylight availability), 50% of lighting energy can be saved from personalized control of wireless individually- dimmable luminaires, and an additional 20% of energy savings could be achieved with daylight harvesting.

In spite of the great potential for increased energy conservation, the actual adoption of intelligent lighting control systems in commercial buildings has been very limited. As of 2010, seventy percent of the US national stock of commercial buildings had no lighting controls for energy efficiency, partially due to the high costs of commissioning (installing, customizing and testing). Further, it has been estimated that fifty percent of installed intelligent lighting control systems have been deactivated by the users and the remaining operate well below target performance due to usability problems. These deficiencies have resulted in missed opportunities for energy savings, motivating our proof-of-concept feasibility study of a *rapid low cost performance-oriented* lighting commissioning system using a reusable plug-and-play wireless sensor network (WSN) platform, data processing and modeling software.

Project Objectives

1. **Self-Power and Low Maintenance:** Design and implement tests for energy performance assessment of solar/light-powered sensor platforms. The goal was to achieve continuous data acquisition and light energy harvesting for at least three months without battery replacement.
2. **Expedite Installation:** Plan and deploy real-time data acquisition with solar/light-powered sensor platforms with inverse model algorithms at two operating test beds. Record time for installing data acquisition drivers at different test beds. The goal was to demonstrate easy set-up of the plug-and-play sensor system by reducing new installation and deployment time to less than 30 minutes.
3. **Maximize Accuracy of Virtual Sensors:** Complete inverse indoor light model using test data from the wireless sensor platform. Evaluate time required for consistent model performance. Implement initial optimal sensor placement. The goal was to achieve average accuracy of 90% in instantaneous indoor light prediction (including disaggregation of daylight and artificial light) with less than one month of sensor data.
4. **Minimize Number of Physical Sensors:** Develop a daylight prediction model for each window in the test beds. Prediction accuracy should be high enough to minimize the number of sensors required. The goal was to achieve over 90% accuracy of instantaneous indoor light prediction with 50% fewer sensors than current commercial systems (0.15 sensors/ m^2 to 0.075 sensors/ m^2) .

5. **Implement Demand Response:** Perform energy simulations for different demand response strategies at lighting levels with load shedding at 80% accuracy.
6. **Determine Energy and Environmental Benefits:** Perform lifecycle cost and energy analysis of the retrofit system and user evaluations.

Project Outcomes

Most of the objectives were achieved or exceeded.

1. **Self-Power and Low Maintenance:** Achieved continuous data acquisition and light energy harvesting for the solar/light-powered sensor platforms for six months without battery replacement. It is estimated that the platform can be self-powered for over a year.
2. **Expedite Installation:** Tested the set-up of the plug-and-play sensor system in three test beds and reduced installation and deployment time to less than 30 minutes.
3. **Maximize Accuracy of Virtual Sensors:** Achieved average accuracy of instantaneous indoor light prediction (including disaggregation of daylight and artificial light) to 80-95% with two weeks of sensor data. This accuracy is well within the human tolerance range of ~50%.
4. **Minimize Number of Physical Sensors:** Achieved 80-95% accuracy using 60% fewer sensors than the state-of-art intelligent lighting system. The temporal distribution of error is within 10% for most of the workstations in the test beds.
5. **Implement Demand Response:** Developed a support vector regression model that was able to predict the day-ahead daylight availability to 92% accuracy. Load shedding and load shifting demand response strategies predicted potential load reduction from 19-80%.
6. **Determine Energy and Environmental Benefits:** The system recovers its embedded energy after displacing 148 kWh of US grid energy and provides substantial environmental benefits. With the system reducing lighting demand by 70%, it can achieve an environmental return on investment after only two days of use and can effectively save an estimated 23,000 kg of CO_2 equivalent in emissions over one year (based on a single functional unit of one office space, 500 sq. meters).

Conclusions

A sensor-based intelligent lighting system for future grid-integrated buildings was developed, implemented and tested in several test beds: Center for Information Technology in the Interest of Society and the Berkeley Energy and Sustainable Technologies Lab at UC Berkeley and at the NASA Ames Sustainability Base. With two weeks of training data from the Sustainability Base at NASA Ames, light levels were predicted within 80-95% accuracy. By using piecewise linear predictive models of indoor light, discretized by clustering for sky conditions and sun positions, the system was able to achieve this accuracy while using 60% fewer sensors compared to state-of-art commercial systems. The sensor modules were designed with small solar panels in order to supply power by ambient light. Based on the testing to date, the platform is predicted to be self-energized for over a year of operation.

The estimated energy savings and associated environmental benefits were validated through the research and proof-of-concept testing. Accurate day-ahead predictions could be used to apply load shedding and shifting demand response strategies.

Recommendations

The successful proof-of-concept development and testing motivates moving to the next step for commercialization. The MEMSIC TelosB mote was used as the wireless sensor platform. Although the TelosB platform used in this study was useful for research testing, it would too expensive ($120 each) and unnecessarily complicated for a commercial platform. The next step would be to develop specifications for a simplified platform using off-the-shelf components and a dedicated printed circuit board. The estimated costs could be reduced to $10 each. In addition, the dedicated hardware and software design could be extensible to other sensing modalities and generic data driven modeling for smart building energy management.

Another opportunity is to leverage recent low cost technological advances in internet-accessible LED lights. For example, General Electric has recently announced a series of LED lights that can be controlled through the internet or a smartphone. Smartphones also have light sensors that could be used for the originally commissioning, reducing sensor costs even further.

The target market of the proposed plug-and-play smart lighting commissioning and retrofit comprise 70% of U.S. national stock of commercial buildings, including the new and existing buildings, that do not have intelligent lighting and 50% of the commercial buildings with sub-optimally performing intelligent lighting control systems. Further, new smart meters for residential buildings opens up the residential market as well.

Public Benefits to California

The estimated energy savings is 6,000 GWh per year in California, assuming a 10% market share for the smart lighting system. An environmental return on investment is estimated to occur after the system has supplemented 148 kWh of grid energy. This can be accomplished in two days for single functional unit of one office space (500 sq. meters) and eliminate 23,000 kg-CO_2-eq in emissions over the course of one year when lighting consumption is reduced by 70% from standard. Cost savings will be achieved from reduced installation costs and extended energy bill savings. Moreover, because this plug-and-play system utilizes a predictive inverse model for control, it drastically minimizes commissioning time, which can take months for existing lighting retrofit solutions with no guarantee that the results work after occupancy or room changes.

Introduction

IBM's Instrumenting the Planet report [1] highlights the importance of wireless sensor-actuator networks and distributed analytics in the life cycle management of natural resources and technical infrastructures in agriculture, hydrological systems, land use, power grids, transportation systems, manufacturing and many more applications. Researchers introduce Real-World-Aware (RWA) systems, which extract information about the state of the real world from raw data aggregated from disparate sources and use it to complete the loop through automated and adaptive control. Cyber-physical systems are becoming pervasive in large infrastructures and are viewed as essential components of grid-connected buildings. Expert studies [2] show that if all the lighting systems in the buildings of California are retrofitted with dimming ballasts, then it would be possible to obtain 450 MW of regulation, 2.5 GW of non-spinning reserve and 380 MW of contingency reserve from participation of lighting loads in the energy market. In some cities, such as Amsterdam, dimmable street LED's are integrated within their smart grid [3]. Ceriotti et al. (2011) proposed wireless-enabled closed loop control for lighting in road tunnels [4]. The advantage of controlling lighting loads is that they can be controlled to any intensity with dimming ballasts, unlike HVAC systems. Furthermore, low latency, makes the dimmable lights competitive with generators, which have over one minute response time.

Wen et al. (2011) found that closed loop control of building systems enabled by wireless sensor and actuator networks (WSANs) result in 28% cooling energy and 40% light energy savings in office buildings [5]. Commercial lighting contributes to one of the largest pieces of the commercial energy pie. Intelligent lighting forms an easy and low-cost avenue to energy conservation. According to the U.S. DOE Energy yearbook in 2010 the maximum electricity consumption in commercial buildings (13.6%) is attributed to lighting [6]. The researchers' prior work has demonstrated that even without daylight harvesting (controlling artificial lights based on daylight availability), 50% of lighting energy can be saved from personalized control of wireless-enabled individually- dimmable luminaires, and an additional 20% of energy savings could be achieved with daylight harvesting according to simulation results [7-9]. Furthermore, there have been considerable improvements in lighting and shading controls [10] and in daylight harvesting systems [11, 12]. Singhvi et al. (2005) developed a centralized lighting system to increase user comfort and reduce energy costs by using a WSN [13]. Lin et al. (2005) proposed a decentralized algorithm for WSAN-enabled optimal lighting control [14].

In spite of the growing impetus in lighting control research and some successful pilot projects, the actual adoption of intelligent lighting control systems in commercial buildings has been very limited. As of 2010, 70% of the US national stock of commercial buildings had no lighting controls for energy efficiency [15]. Some of the reasons include general lack of encouraging energy savings from expensive commissioning of lighting systems, particularly when usability was not considered appropriately. Rude (2006) 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 [16]. System usability problems include lack of interoperability between lighting, shading and building automation system drivers, software and database.

Because of dimmable ballasts and the low latency associated with controlling lighting loads, lighting is a prime target for implementing demand response (DR) policies. DR programs aim to lower electricity consumption when market prices are high or when grid reliability is jeopardized by means of incentive payments [17]. DR days are typically announced with one day notice, which leads to day-ahead prediction being necessary for long term DR [18]. Main processes that are often targeted for short notice load reduction include heat, ventilation and air conditioning (HVAC), lighting, and electronic equipment [19]. In the commercial sector, HVAC typically represents the largest potential for load reduction [19,20], but lighting load is also significant [20]. The possible DR methodologies inherently differ between HVAC and lighting, and the low latency and continuous dimming of lighting provides an avenue for rapid load reduction.

Project Objectives

The goal of this project is to develop and test "proof of concept" of a wireless sensing-enabled rapid indoor lighting commissioning and retrofitting system for energy efficiency and emerging demand response.

Project objectives were to:

- **Self-Power and Low Maintenance:** Achieve continuous data acquisition and light energy harvesting for at least three months without battery replacement.
  Achievement of continuous data acquisition at several lighting scenarios is needed to verify "proof of concept". Light energy harvesting for 3 months without battery replacement minimizes power consumption and maintenance. With energy efficiency in lighting as a focus, it is appropriate that the system self-power by light energy.
- **Expedite Installation:** Demonstrate easy set-up of the plug-and-play sensor system by reducing new installation and deployment time to less than 30 minutes.
  A reduced installation and deployment time will make the system convenient and suitable for indoor lighting commissioning.
- **Maximize Accuracy of Virtual Sensors:** Achieve average accuracy of 90% in instantaneous indoor light prediction (including disaggregation of daylight and artificial light) with less than one month of sensor data.
  An average accuracy of 90% maintains that the predictive model light with sufficient accuracy for daily energy efficiency and demand management, while remaining outside the tolerance range for human detection of light changes. The IESNA Lighting Handbook uses 20% as the lowest detectable change. The Commission Internationale de l'Eclairage (CIE), 1986 uses the 50% standard, which is based on the research results of Luckiesh and Moss in The Science of Seeing, 1937 (results Prof. Agogino has validated in her own research). This number was also adopted in Europe through EN 12464-1:2002. By setting a one month maximum to train data, the aim is to create a system that can be rapidly functional.

- **Minimize Number of Physical Sensors:** Achieve over 90% accuracy of instantaneous indoor light prediction with 50% fewer sensors than current commercial systems (0.15 sensors/ m^2 to 0.075 sensors/ m^2).
  Achievement of high accuracy light prediction with 50% fewer sensors reduces the system cost without compromising quality. It allows the intelligent lighting system to be more available to a wider target market.
- **Implement Demand Response:** Predict day ahead lighting needs at 80% accuracy.
  Prediction of day-ahead lighting needs at 80% accuracy allows for demand response policies that don't compromise users' visual comfort, since 80% is within the tolerance for human detection of light levels, as indicated in Objective 3 above.
- **Determine Energy and Environmental Benefits:** Estimate energy savings of 6,000 GWh per year in California with an assumed 10% market share.
  Estimation of 6,000 GWh per year in energy savings demonstrates the financial and environmental benefit of the intelligent lighting system. By considering the impact of the system through its lifecycle, the full impact benefit can be understood.

Project Approach

Intelligent Lighting System Overall Design

Figure 1 provides a flowchart of the system architecture decomposed into the software (above) and WSN hardware (below) components. The WSN consists of two major components: remote light sensors and a base station with a central radio receiver and computer. Remote light sensors are stationed at strategic locations throughout the indoor space and transmit local illuminance data to the base station using radio transceivers. The central base station receiver relays the data to the base computer through a serial port, and the data are stored locally in a SQLite database.

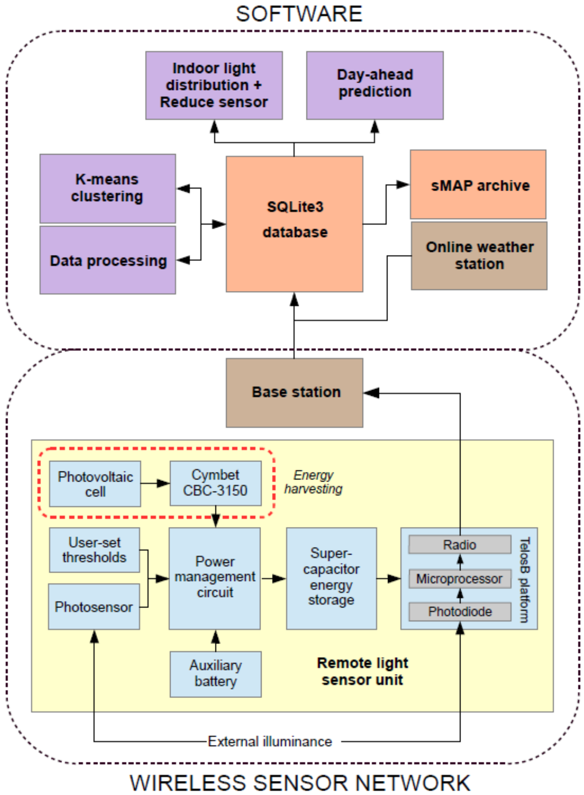

Figure 1: System architecture showing hardware and software components

Once the data are collected from the WSN, the data processing modules are called for regularizing the matrix dimensions, eliminating zero illuminance readings during daytime, eliminating redundant data, and smoothing. The database stores the illuminance readings by mote number, Unix-time stamp (primary key), date and clock time, sky condition at the nearest weather station, solar altitude and azimuth, cluster ID (discussed later). The software modules, written in Python, include a database driver, facade orientation prediction, a sun position calculator and programs for clustering, data processing, indoor light distribution and day-ahead prediction. The database driver module can directly call historical and forecast weather data, like the hourly sky conditions, temperature and relative humidity from the underground repository using their API. Solar altitude and azimuth are calculated using the Astronomer Almanacs solar position algorithm [21]. The same driver module is also used to forward the illuminance readings to an online database following a Simple Measurement and Actuation Protocol (sMAP). sMAP was 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 [22,23]. We will describe the light powered WSN platform in detail in section IV, and discuss the components of the software in section V.

1. Design & implement tests for energy performance assessment of solar/light-powered sensor platforms.

The WSN remote light sensors (Figure 2) are centered on the TelosB platform, an open-source microprocessor-based remote sensing platform developed at UC Berkeley. Illuminance data are collected by the TelosB's onboard Hamamatsu S-1087 photodiode and transmitted to a base station receiver via the IEEE 802.15.4 layer over a five-minute duty cycle. Each remote sensor is fitted with a Sanyo AM-1815 photovoltaic (PV) cell to harvest ambient light energy in the indoor space. The energy harvesting system centers on the Cymbet CBC-3150 energy management module to regulate electrical power generated by the PV cell. In addition to the energy harvesting system, the units have an auxiliary battery to facilitate system start up and ensure reliable operation in low light conditions (Figure 1).

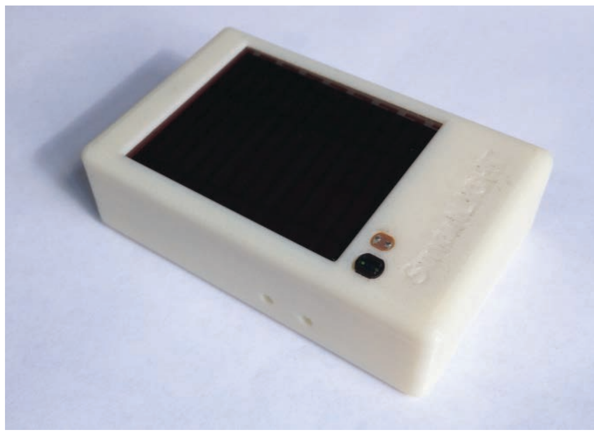

Figure 2: Remote light sensor with Sanyo AM-1815 photovoltaic cell

The TelosB platform's microprocessor is programmed using the open source TinyOS software, and the remote light sensor's default energy consumption during the sleep state and transmission periods were measured. The open source TinyOS code was modified to minimize the remote light sensor's energy consumption. The data transmission period was reduced from 100 ms to 40 ms, the MCU clock speed was reduced from 4 MHz to 1 MHz, and an internal power-saving configuration was used to disable the TelosB microprocessor during the sleep portion of the duty cycle.

Studies have shown that ambient light energy harvesting can be suitably employed to power wireless sensor networks [24,25]. For a light sensor platform, energy harvesting from ambient light is a natural choice. In order to assess the feasibility of this method, the power output of the Sanyo AM-1815 was characterized at several light intensity levels. For each case, the PV cell was exposed to a constant illuminance under varying electrical loads. The electrical output of the cell was recorded at each load point.

2. Plan & deploy real-time data acquisition with solar/light-powered sensor platforms with inverse model platform at 2 operating testbeds. Record time for installing data acquisition drivers for disparate data sources.

An installation guide was written to guide users through the software installation and sensor configuration process for operating the Smart Lighting system. This installation guide was used in alpha testing at Sutardja Dai Hall in UC Berkeley and in the Berkeley Energy and Sustainability (BEST) Lab. A six node wireless sensor network collected data at the full-scale test beds for two months. The data were subsequently used for software training and validation. Although this alpha test of the software installation was achieved in 30 minutes, some optional features were not included. The alpha testing also revealed that the system would benefit from some additional features, such as on the fly installation from a smartphone, sensor identification and relational database creation.

As a result, a Guided User Interface (GUI) and written instructions were developed to ease the installation process. After the installation GUI for a Linux operating system was completed, the process was tested with four novice users. Total installation time and encountered problems, if any, were recorded. Another novice user tested the installation program from scratch on a separate Linux computer; the user provided detailed feedback and the breakdown of time required for each step.

Sensors were deployed across two cubicles in an open-plan office space in the Sustainability Base (SB) at the NASA Ames Research Center. The Sustainability Base is a 50,000 sq. ft. LEED Platinum certified high performance office building at NASA Ames Research Center. The SB aims to redeploy innovations and technologies originally developed by NASA for aerospace missions to monitor and control building systems while reducing energy and water consumption. The ultimate vision of the SB is to provide a research test and demonstration site for different sustainable technologies and concepts. The three primary research objectives involved in this vision are to reduce building energy consumption and operating and maintenance costs, as well as to improve employee comfort levels.

Seven sensors were deployed on workstations and two sensors were placed on the walls near the windows. Layout of the test bed cubicles in 3D model with sensor locations (left), heat map of indoor light distribution (middle) and a photograph of the test bed (right) are presented in Figure 3. Sensors 1, 2 and 3 were located at incremental distances from the window node 8, covering the work plane across the entire cubicle and sensors 5, 6 and 7 were replicated in the adjoining cubicle. Sensor 4 was located on top of a low height partition between the two cubicles. Sensors 1 through 7 will be referred to as workstation sensors in the rest of the report. The goal is to use all of the above sensors for model training, but only deploy 50% or fewer of these eight sensors to predict the light level across all the workstations during the operational phase of intelligent lighting system. The sensors collected data for several weeks, reporting the data to a local server. Real-time trends could be accessed and viewed from sMAP and a dedicated webpage. The artificial light statuses from four controllable luminaries were collected from lighting system data logs and were fed into the same database. Training and validation data were sampled from May 25 - June 5, 2012 and June 8 - June 20, 2012, respectively. During the training and validation period, the building was occupied and experienced normal operations. Illuminance data continues to collect from the same test-bed at SB. One of the SB nodes is equipped with a solar panel for indoor light harvesting.

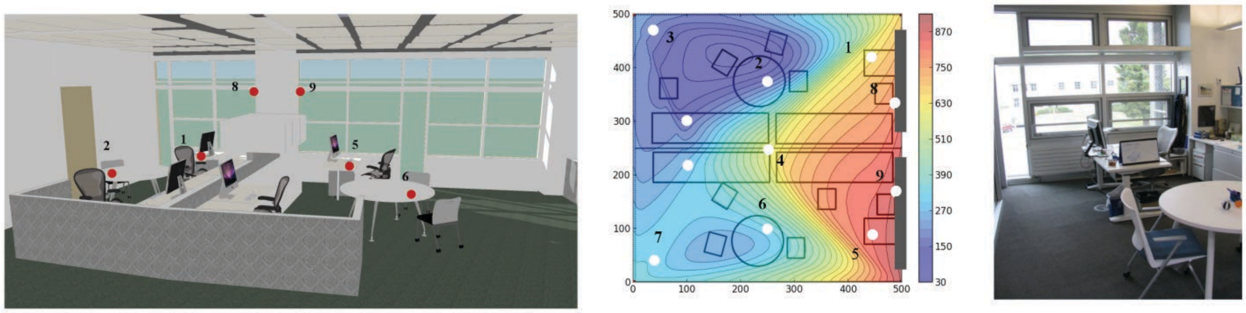

Figure 3: Cubicles at Sustainability Base from various perspectives: 3D CAD model with sensor locations (left), heat map of light distribution with sensor positions (middle) and photograph of test bed (right)

3. **Complete inverse indoor light model using data from WSN. Evaluate time required for consistent model performance. Implement initial optimal sensor placement based on sensed data.**

The raw light data can be noisy due to dropped packets, redundant communication between the receiver and the sender nodes and low sensor accuracy. Other errors may stem from sensors that are shadowed or covered due to human activities or due to battery power drainage. Such errors must be handled with sensor validation algorithms prior to basic data processing. The patterns in the data generated by each of these errors could be simulated and labeled for comparison with future data. Alternatively, the error patterns could be learned when the lighting system is running. The latter was chosen to avoid intervention in real buildings.

A tolerance was proposed based on the moving average of 30-minute windows of light data. If the difference between the current light level and the immediate past light level is greater than the difference between the moving average and the past light level by a threshold percentage, chosen as a function of the light levels, then the current light level is assumed to be erroneous, as shown by equation 1.

$$m_i = \frac{\sum_{n=1}^{N} x_{i-n}}{N} \qquad \text{If } x_{i-1} - x_i \geq a(x_{i-1} - m_i) \text{ then replace} \tag{1}$$

Here x_i is the illuminance reading at current time step i, m_i is the moving average until time step *i-1* and *N* is the averaging window. The quantity a in equation 1 is a function of $x_{i-1} - m_i$, determined iteratively. The erroneous reading is replaced by an average light level from the same half hour from the past seven similar days. The similarity between each pair of 30-minute time spans is calculated based on the day-to-day difference between averages of illuminance readings in that time span. The average light values over seven 30-minute time spans closest to the current 30- minute average were chosen to replace the erroneous readings.

After the above processing we performed exponential smoothing of over 40 minutes windowed data and moving average over one hour windowed data, which were archived along with raw illuminances. Imputation was not performed as data points from various sensors with the nearest time stamps were fused for the inverse models.

Ray-tracing light models can accurately approximate the indoor light distribution of buildings. These models, however, require accurate building and furniture dimensions and can be difficult to develop, requiring technicians and professional experts for calibration. An inverse model, by contrast, is a reduced-order model with only statistically significant inputs or features, and hence 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. 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 relatively simple physical laws and given values of the model parameters, and (3) using actual results from measurements to determine the model parameters [26].

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 of a given dataset by minimizing the sum of the squared residuals. Based on this performance improvement achieved by the Sun Position-Based Model, a piecewise linear relationship between artificial and natural light sources and the illuminance measured at a workstation was assumed, with model parameters varying with solar altitude and half of the day. The time scale of each linear model is 30 minutes. Considering the periodic nature of daylight, unpredictability of sky conditions and mismatch between onsite sky condition and weather station data, the daylight data were clustered into smaller sub-spaces using half-hourly means and standard deviations of light levels as features. Figure 4 shows a wide and comparable distribution of daylight under different clouded sky conditions obtained from the weather data. The lack of identifiable relationship between weather station data and onsite light distribution precludes the use of regional sky conditions as a potential feature in the light models.

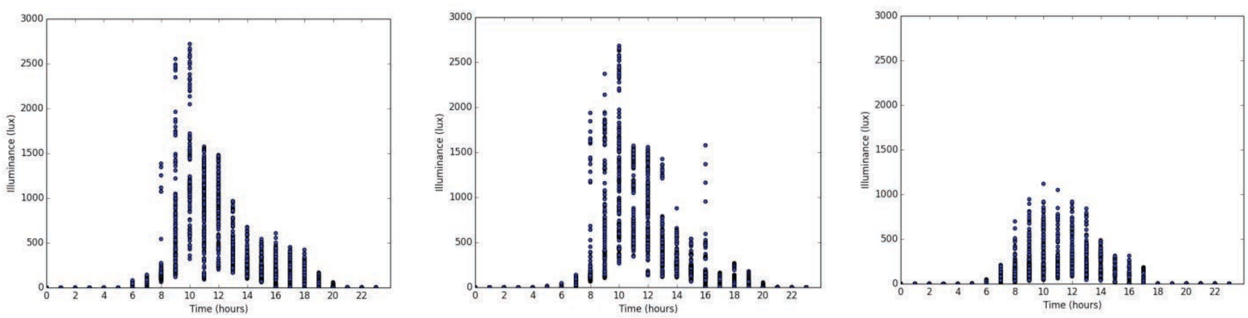

Figure 4: Hourly daylight distribution under scattered clouds (left), partly cloudy (middle) and overcast sky conditions (right).

Dividing the data into half-hourly bins takes into account variations in the solar altitude at a lower resolution than our prior consideration [27]. The choice was made to accommodate tradeoffs between data requirements for convergence of clustering and model accuracy. Clustering was used as a proxy for sky conditions, with a constant number of clusters. Clustering algorithms use unsupervised learning to discover natural groupings in unlabeled data. Clustering allowed the diverse onsite sky conditions to be accounted for without using actual weather data. The K-means clustering algorithm provided simplicity [28] and availability of variants [29]. Letting $z = \{z_i\}$ for $i=1,2,\ldots n$ gives a 2D vector of mean and standard deviation of measured sunlight at the window for every half an hour during the day. Letting $c = \{c_k\}$ for $k=1,2,\ldots K$ creates K clusters in each 30 minutes interval. In this case, $K=3$ was used as a constant, due to limited data points on one hand and empirical observations of the mean and standard deviation of daylight levels on the other. K-means clustering partitions the data by minimizing the sum of squared distance between centroid of cluster c_k, identified as μ_k and $z_i \in c_k$. The squared error between each z_i and c_k is given by equation 1 and equation 3.

$$J(c_k) = \sum_{x_i \in c_k} \| z_i - \mu_k \|^2$$
$$J(C) = \sum_{k=1}^{3} \sum_{x_i \in c_k} \| z_i - \mu_k \|^2 \qquad (2)$$

One limitation of K-means is that the optimization problem presented in equation 2 can converge to local minima, which may differ with different random initializations of the centroids. However, most random centroid initializations resulted in only one or two different final centroids, thereby obviating refined initializations. For this work, the K-means module of Scipy Python was used with 20 initializations of cluster centroids and 100 iterations per model. The centroids were initialized randomly as subsets of z_i.

The smoothed illuminance m_w at each workstation for $w=1$ to W (W is the number of workstations) for each cluster can be modeled as a linear function of artificial light statuses e_s for $s=1$ to S artificial lights in the influence zone and illuminances measured at other workstations $\{m_1, \ldots m_{w-1}, m_{w-1}, \ldots m_W\}$. The following multivariate regression model was trained on the clustered photo-sensor data at each workstation.

$$m_w = \alpha_1 m_1 + \cdots + \alpha_{w-1} m_{w-1} + \alpha_{w+1} m_{w+1} + \cdots + \alpha_W m_W + \beta_1 e_1 + \cdots + \beta_S e_S + \varepsilon \qquad (3)$$

α_w and β_s are model parameters which can be grouped together in a vector $\boldsymbol{b}$, and ε is random error. To solve this equation, the method of ordinary least-squares provides α and β such that they minimize the sum of the squared residuals. Aggregating across all the workstations and simplifying in matrix formulation gives:

$$\boldsymbol{Y} = \boldsymbol{Mb} + \boldsymbol{\varepsilon} \qquad (4)$$

Where $\boldsymbol{Y}$ is a vector $\{m_1, \ldots m_w, \ldots m_W\}$ of workstation illuminances and M is the input vector consisting of regressor illuminances and artificial light statuses. Solving for $\boldsymbol{b}$ produces equation 5 below. This equation is the Ordinary Least Squares Estimator (OLS), which provides the best-fit linear model for the data.

$$\boldsymbol{b} = \left(\frac{1}{W}\sum_{w=1}^{W} m_w m_w'\right)^{-1} \frac{1}{W}\sum_{w=1}^{W} m_w y_w \qquad (5)$$

One of the challenges in multivariate regression using large-scale distributed sensor data are the choice of appropriate regressors that minimize over-fitting and improve prediction accuracy of the inverse model. The goal is to use sensor data as regressors and the optimization problem is to decide the location of the sensors for optimal prediction across the workstations. Spatial or geometric information about the distribution of photo-sensors and artificial lights would be useful in initial screening of regressors. For example, the physics of light attenuation as a quadratic distance relation can be used in regressor selection. Precise location information of the sensors was used at the windows, which are likely to be places with highest variance in the light field. The rest the algorithm is automated to iteratively pick the best set of regressors that maximize prediction accuracy based on the percentage root mean square error of prediction. The algorithm selects those sensors that carry the maximum information about the rest of the light field. For example, the initial set of optimal sensors in the developed algorithm only contains a daylight sensor located near the window. The rest of the regressors are iteratively added from a set of W sensors, resulting in optimal sensor subset. By restricting the total sensor deployment to 50%, the number of iterations per workstation amounts to $\frac{w!}{(w-r)!}$ for $r = 1,2,3...0.5w$. The optimal sensor sets for all the workstations are saved in a matrix. A set of sensors with size less than or equal to $0.5w$ and the highest occurrence in the optimal sensor matrix is picked. This method is sufficient for the small number of sensors that are deployed ($w = 8$). The above approach would be computationally expensive without at least low-resolution spatial information, such as room or hall dimensions.

With data collected at NASA Sustainability Base, several combinations of prediction and validation sets were tested. The inverse model was tested on new and old data sets, and the selected regressors were compared. Testing training data of various lengths allowed the amount of training data required for consistent performance to be determined. Prediction and validation data sets for the inverse indoor light model were also tested across seasons and over multiple years, such as validating March 2014 data based on training data from March 2013.

4. **Develop daylight prediction model for each window in the test beds. Prediction accuracy should be enough to minimize the number of sensors required.**

The goal of day-ahead prediction of light distribution is to predict the available lighting load shedding from a building, which could be reliable contingency reserve, spinning and non-spinning reserves. Most of these load participations require a short response time of one second to a few minutes and a total commitment of one to two hours. If a minimum lighting load shed for two hours could be guaranteed, it could be determined whether continuous load shed would be comfortable to human eyes. Experiment shows that dimming artificial lights by even 80% is tolerable for most people in presence of sufficient daylight. Therefore, this reduces the problem to prediction of daylight availability in the next two hours. Such predictions will be important for spaces with low solar penetration.

Many researchers have focused on short-term predictions of daylight. For example, Lu et al. (2012) proposed a short-term prediction of daylight using weighted linear function of historical data, with the weights being determined by a mean square error based similarity metric between current day and historical day [12]. Day-ahead prediction is more challenging and would be necessary for long-term demand response (DR) . Most day-ahead predictions use numerical weather models. Several researchers have proposed day-ahead prediction of building energy components from smart meter data using Gaussian Process models as function of temperature and time [30], and as neural network support vector functions of forecasted temperature, humidity and solar radiation [31].

Data-driven models of PV power output have also been investigated, with solar radiation as the connecting variable. In fact, neural networks are the most popular approaches for PV output prediction. A day-ahead prediction of indoor light is proposed as a support vector regression (SVR) model. The predictive model of daylight focuses on the windows, owing to high hourly and daily variance of daylight compared to relatively uniform artificial light schedule. For introduction to SVR refer to Smola and Schölkopf [32] and LibSVM guide [33]. The advantages of epsilon-SVR over OLS regression include flatness of function and error tolerance, in addition to the ability to handle non-linearity via kernels. The flatness of the function means SVR algorithm searches for small weights resulting in a more generalizable model. Studies have shown that accuracy of support vector machine (SVM) based models of day-ahead PV power prediction can be improved by including more weather parameters in the features. In fact a complete ensemble of solar radiation, humidity, cloud cover and temperature results in the highest model accuracy. For this model, temperature, sky conditions and the hourly moving average of past three days of daylight are used as features.

5. **Perform energy simulations in different demand management scenarios. Develop demand response strategies at lighting levels with 10%, 15% and 20% load shedding.**

A robust daylight prediction model using Support Vector Regression (SVR) was developed for the purpose of demand response (DR). With an accurate daylight prediction model, DR policies can be implemented with a single days' notice in commercial buildings. In order to evaluate the potential benefit of select DR policies, real data were used instead of predicted data. It is important to note that energy savings from DR policies are additional savings on top of the everyday reductions due to daylighting. Since the artificial lights at the Sustainability Base have not yet been controlled based on these algorithms, the artificial light demand is estimated based on the difference between the lighting target and the daylight availability over the course of the day (Figure 5).

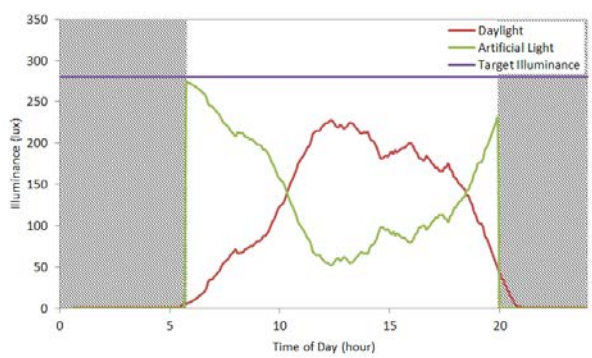

Figure 5: Sample data at a central desktop (Sensor #2) with estimated artificial light demand. Daylight represents the average sensed data over one weekend, and the desktop achieved a target illuminance of 280 lux over the time frame. Non-work hours are hatched in grey.

Demand response policies were created for different lighting and usage scenarios. It was determined that continuous dimming and load shifting (e.g., changing work hours to accommodate more use of artificial light) held the most potential as DR policies in lighting. Dimming takes into account the fact that the sensitivity of the human eye is relatively low at 500 Lux. The recommended lux level for standard office work is 500 lux [34], however sensor data showed that desk spaces at the Sustainability Base often operated at lower illuminance levels. According to experiments conducted by Luckiesh and Moss (1937) the human tolerance range at any light level is approximately 50% [35], which means at 300 lux the perceivable change is 150 lux (adopted as the European standard). Load shifting on the other hand provides an unique solution where energy can be saved by simply shifting the work hours rather than adjusting the light intensity.

Data over four months at the Sustainability Base was used to assess the impact of two DR policies. A worst-case scenario was represented by evaluating the policies at Sensor #2 (see Figure 3 for placement), which had on average the lowest illuminance compared to other locations. It was assumed that since the artificial lights are off during weekends,[1] the weekend data could represent the daylight contribution to the total illuminance during an adjacent week. Current artificial light data were calculated as the difference between the sensed data during the week and the daylight profile, taken from weekend data. From this, the times when artificial lights were on and off and the total number of work hours in a day could be evaluated. The artificial light illuminance required was calculated to be the difference between the set target and the daylight profile over the workday. The two DR policies were evaluated for four separate time frames in 2012 (late May, early June, mid-June, and early August).

A MATLAB script was written to evaluate the two proposed DR policies in a way that allowed for rapid iteration. To estimate load shedding, the area under the artificial light curves was evaluated by means of the trapezoid rule. While a scaling factor between energy and illuminance can provide an energy measurement, the load shedding (percentage) can be evaluated from the illuminance-time plot directly, assuming the scaling factor does not vary with system load. For the load shifting, the time period that maximizes the total amount of daylight was calculated based on the area under the daylight prediction model. For the load shedding, the average illuminance target was decreased such that the illuminance would not drop below the detectable light level for a human (50% of current level) [35,34]. For both policies, load shedding was calculated based on the area under the artificial light curves for the DR day and the non-DR day.

6. Perform lifecycle cost and energy analysis of the retrofit system and user evaluations.

The lifecycle cost was determined through a life cycle assessment (LCA) in Sustainable Minds. Sustainable Minds is a cloud-based LCA software package that evaluates products against the TRACI 2.1 impact categories, which are: acidification, ecotoxicity, eutrophication, global warming, ozone depletion, fossil fuel depletion, carcinogenics, non carcinogenics, respiratory effects, and smog formation [36]. The objective was to determine the environmental return on investment of the intelligent lighting system and identify which components within the intelligent lighting system are most impactful.

The system was analyzed from cradle through the use phase for the base station and sensors (Figure 6). End of life considerations and the dimmable ballasts were excluded because of insufficient data, and it was assumed that the required computer is non-dedicated, therefore excluding it from the analysis. The functional unit was set as the lighting needs for a 500 square meter office space for one year with an average intensity of 500 lux, the recommended light level for standard office work [37]. This was chosen to aid comparison to a previous life cycle

[1] Confirmed by employees and the pattern of the data.

study by Dubberley et al. (2011), where a previous version of this intelligent lighting system was analyzed through the Economic Input Output Life Cycle Assessment (EIO-LCA) [38]. Previous research indicated that a sensor pair (one desk sensor and one window sensor) is needed approximately every 36 square meters [9]. Therefore, the functional unit scaled the model to include 28 sensors and 2 base stations.

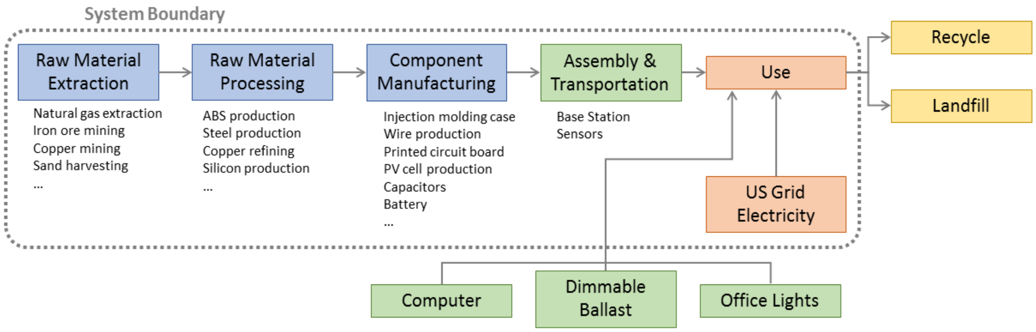

Figure 6: Simplified process flowchart with analysis boundary

Individual components of the base station and sensor were inventoried and weighed. In order to more conveniently evaluate impacts across component types, components were broken down into nine categories: casing, printed circuit board (PCB), PV cell, electrical connectors, mechanical connectors, capacitors, batteries, other electrical components, and external components. In instances when individual components could not be weighed directly, estimates were taken based on material and component volume.

The standard lighting energy demand for a 54 square foot office space was estimated at 12 kWh per day based on a previous study by Wen & Agogino (2008) [9]. Since the wireless sensors do not rely on an external power supply, the energy consumption during the use phase is only dependent on building lighting demand and savings due to the installed system. Previous research with this system demonstrated that 50% of lighting energy can be saved from personalized control of wireless-enabled individually dimmable luminaires, and an additional 20% of energy savings could be achieved with daylight harvesting [7-9]. However since the actual energy savings are variable and this value has not yet been verified with the current sensor platform, several energy saving scenarios were examined. Outcomes were evaluated by Sustainable Mind's single score (millipoints), which represents the yearly environmental load for one person in the United States [39], as well as the global warming potential (kg CO_2 equivalent) over 100 years.

User evaluations were provided through student and user feedback as part of an introductory course to new product development (ME 110, Spring 2014, Agogino). The intelligent lighting system was tested with members of the Pinoleville Pomo Nation, a federally recognized Native American in Northern California. After seeing and using the sensors, tribal members provided feedback verbally, while students filled out an online survey at a course tradeshow.

Project Outcomes

1. **Design & implement tests for energy performance assessment of solar/light-powered sensor platforms.**

When using the default open-source code available from TelosB, it was found that the remote light sensor consumes 0.849 ± 0.003 mW of power when in the sleep state and 54 ± 3 mW during a 100 ms data transmission period. This equates to a total energy consumption of 260 ± 1 mJ over the nominal five-minute duty cycle. After reducing the data transmission period and MCU clock speed, the TelosB platform consumed 0.2019 ± 0.0003 mW in the sleep state, and a maximum of 45 ± 3 mW during the 40 ms data transmission period. Given these performance characteristics, the platform uses 62.4 ± 0.2 mJ of energy over the five-minute duty cycle, roughly a 75% reduction from the original configuration, without noticeable effects on data transmission range or reliability.

The resulting performance curves from testing the PV cell under varying electrical loads and several light intensity levels are shown in Figure 7. Figure 7 shows that at every illuminance level, a load point exists, which maximizes the PV cell's power output. Table 1 shows that the maximum output of the PV cell at an incident illuminance of 200 Lux is roughly equal to the TelosB's power consumption in the sleep state. At the OSHA mandated minimum indoor workspace illuminance of 30 foot-candles (~ 320 Lux) [40], the maximum power output of the PV cell exceeds the TelosB's power consumption in the sleep state by 0.090 ± 0.004 mW. This excess power is stored in the system's super-capacitor, providing 1.8 ± 0.2 mJ of energy required during the TelosB's data transmission period. At an incident illuminance of 320 Lux, the capacitor takes about 20 seconds to store the required transmission energy, and 166 seconds to charge to a maximum capacity of 14.9 ± 0.7 mJ at the nominal operating voltage of 3V. In this way, the energy generated by the PV cell and stored by the super-capacitor over the remote light sensor's 5-minute duty cycle is well within the TelosB platform's energy consumption requirements.

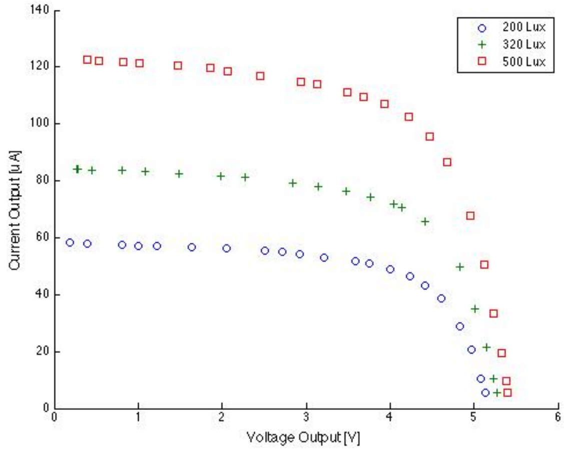

Figure 7: PV cell power output at different controlled light levels

Table 1: Maximum PV cell power output

Incident Illuminance (lux)	Maximum power output (mW)
200	0.196 ± 0.004
320	0.292 ± 0.004
500	0.433 ± 0.004

However, these experiments also showed that the PV cell's power output is extremely susceptible to changes in both lighting conditions and electrical load, demonstrating the need for a management circuit to regulate and maximize this fluctuating output. The CBC-3150 module is equipped with an impedance matching function that varies the load on the PV cell to maximize the power output. This impedance matching function optimizes the PV cell's power output with fluctuating incident illuminance. The CBC-3150 subsequently regulates this optimized PV power to maintain a maximum output voltage of 3.3 V to the TelosB platform.

A coin cell battery was added to the aforementioned energy harvesting system to address two major shortcomings. Firstly, the system ceases to operate when exposed to illuminance levels below 200 Lux. At this incident illuminance, the power generated by the PV cell is roughly equal to the power consumption of the TelosB platform in the sleep state. Consequently, no excess energy can be stored in the system's super-capacitor over the sleep portion of the duty cycle to power the TelosB platform during the data transmission period. For the purpose of collecting data during building occupancy, it was deemed necessary to operate the remote sensors at a minimum illuminance of 50 Lux. Below this illuminance level, the space is deemed too dark for occupancy, and data collection is no longer required.

Secondly, the energy harvesting system was identified as having difficulties "waking up" following extended periods of complete shutdown, typically overnight. When the remote light sensor's TelosB platform and Cymbet CBC-3150 initially boot up, they require a surge in power to initialize various systems. It was found that the PV cell was typically unable to energize the super capacitor to the levels required to overcome this boot up surge until light levels reached about 500 lux. This often led to the remote light sensors remaining non-functional until late morning or early afternoon. These two observations led to the conclusion that an auxiliary battery was required to enhance the system's operational reliability.

Adhering to these requirements, auxiliary battery power should only be provided to the TelosB platform during periods when the incident illuminance is between roughly 50 and 200 lux, as illustrated in Figure 8. A window comparator enables auxiliary battery power to the platform when the voltage generated by a photo-resistor resides within a defined range. The lower and upper thresholds of this voltage range are initially calibrated to correspond to an incident illuminance of 50 and 200 Lux, respectively. In this manner, the auxiliary batteries both extend the effective data collection period, and provide the energy surge required to boot up the sensors in low light conditions. If needed, users can adjust the thresholds of the voltage range using potentiometers, to control the illuminance range during which auxiliary battery power is enabled. This feature allows users to control the sensor's boot up and shut down threshold, and modulate the period over which energy harvesting is enabled. Moreover, this flexible power management system enables users to easily configure the sensor units to operate efficiently in a wide variety of locations and incident illuminance levels.

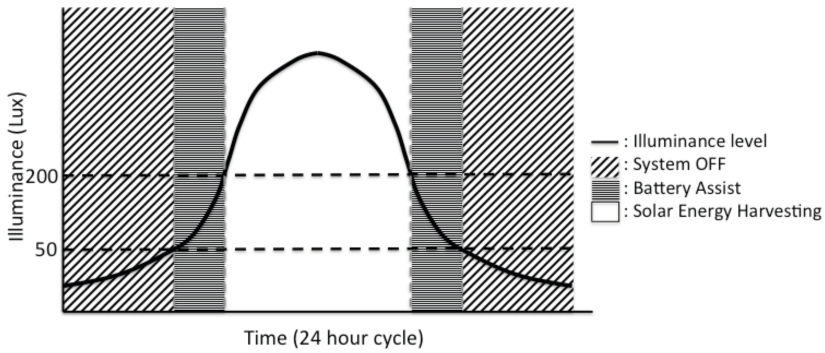

Figure 8: Remote Light Sensor Power Management

Testing over two months showed that the sensor units were typically shut down for roughly 12 hours a day, using auxiliary battery power four hours a day, and harvesting light energy for eight hours a day. Given these performance characteristics, the system had a daily current consumption of 0.55 ± 0.09 mAh at a nominal voltage of 3V. The remote light sensor utilizes a CR2032 lithium battery, with a capacity of 240 mAh at 3V, allowing the sensor to operate over a year before requiring battery replacement. It should be noted, however, that the performance of the system is entirely reliant on ambient illuminance levels and the auxiliary battery management thresholds set by the user.

Testing at the NASA Sustainability Base has shown that in three months of continuous testing the auxiliary battery voltage has only dropped 7% and thus is expected to meet the goal of operating for a year without maintenance. The current sensor platforms operate for an average of 14 hours per day over the course of testing. Over the same timeframe of 3 months, the solar cell reliably supplied power to the sensor unit at an average voltage of 2.93 V, with natural fluctuations due to changes in incident light throughout the day.

2. **Plan & deploy real-time data acquisition with solar/light-powered sensor platforms with inverse model platform at 2 operating test beds. Record time for installing data acquisition drivers for disparate data sources.**

Data were collected at three distinct test beds: Sutardja Dai Hall (CITRIS) in UC Berkeley campus, the Berkeley Energy and Sustainable Technology (BEST) Lab, and the NASA Ames Sustainability Base. A six node wireless sensor network collected data at CITRIS for two months, while 4 sensors collected data at BEST for 6 months. Two sensors were set up to collect temperature and relative humidity data in addition to light in the BEST Lab for over a week. These sensors, onboard the TelosB motes, could provide additional insight into the indoor environmental quality and could be used to initiate additional energy reduction policies. Data collection at the Sustainability Base began December 2, 2013 and continues to be collected. SB data collection at seven workstations occurred while the office was fully in use.

Alpha testing of the installation program at CITRIS yielded an installation time of less than 30 minutes by a novice user; however optional features were not included. The developed GUI includes program features such as windows, buttons, loading bars, and entry boxes, and a supplemental instruction guide was developed (Appendix I). Four novice users tested the revised installation process. All demonstrated an install time of less than 30 minutes. All of these installation tests were completed in under 30 minutes.

Another user installed the software from scratch on a separate Linux computer in over an hour. The most significant error was due to a small coding mistake that caused the TinyOS build to fail, and this was later fixed in the code. There was also confusion in the order of installing the sensors and base station, and this was clarified in the instruction guide (Appendix I). Lastly, the user recommended that the error detection be improved. In another installation attempt, it was discovered that the installation program encounters problems when a new version of the TelosB mote is used, while the program encounters no problems with the previous model. These final errors are currently being addressed and will continue next month.

3. **Complete inverse indoor light model using data from WSN. Evaluate time required for consistent model performance. Implement initial optimal sensor place based on sensed data.**

Figure 9 shows the results of clustering between 10:30 A.M. to 11:00 A.M. (left) and 5:00 P.M. to 5:30 P.M. (right). As per the results of clustering, the distribution of light level follows a diurnal pattern, justifying the use of 30-minute data bins. For example, in Figure 9 (right), the mean light level has a narrow range towards the end of the day, 100-370 lux and a wider range and a higher mean (300 to 750 lux) in late morning. The latter range, however, is much smaller than the natural fluctuation of daylight. The narrow range can be attributed to building geometry, lack of exposure to direct sunlight or the limited data acquisition period. Furthermore, the clusters are distinct in Figure 9 (right) showing high light level with low standard and low light level with high standard deviation, as expected in clear and partially cloudy conditions respectively.

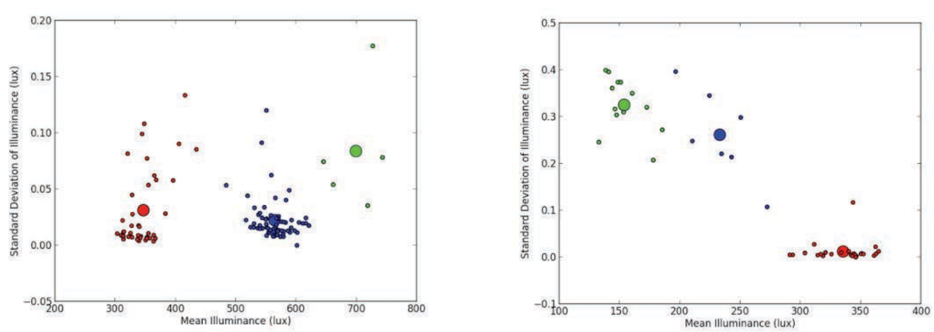

Figure 9: Clustered 30 minutes light data showing 3 clusters, 10:30 AM - 11:00 AM (left) and 5:00 PM - 5:30 PM (right)

The comparison of actual and predicted light levels at workstations 2,3,6 and 7 are displayed in Figure 10. The two cubicles at SB are mirror images of each other, resulting in sensor positioning at identical locations with respect to the window. For example, workstations 2-6 and 3-7 have similar light profiles over the prediction period. Workstation 5 is a mirror image of workstation 1.

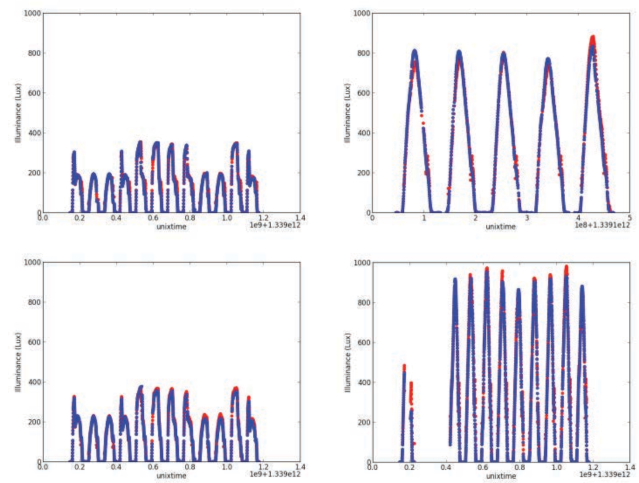

Figure 10: Measured and predicted values at workstations 2 (top left), 3 (top right), 6 (bottom left) and 7 (bottom right)

The Root Mean Square Error (RMSE) of the prediction model (shown in both absolute value and as a percentage) calculated for the validation period (June 8 - June 20, 2012) is presented in Table 2. Note that artificial lights have been identified by small letters a, b, c and d. The bottom row indicates the set of regressors used. Table 2 also lists the optimal set of regressors for best predictability of light distribution across the workstations. Therefore only three physical sensors out of eight sensors deployed in the test bed were sufficient to predict the indoor light field with desirable accuracy. This amounts to 60% fewer sensors deployment compared to state-of-the-art intelligent lighting systems, which typically place a sensor in each luminary above each workstation. Results of the Sun Position-Based Model, applied to the same dataset and using same set of regressors (as Table 2), are presented in Table 3. The average prediction error across the workstations in the developed algorithm has dropped to approximately 5-15% (see Table 2) with adequate data processing and clustering compared to 20-45% error using sun position-based data binning (see Table 1). Moreover, the new clustering-based model shows a more consistent prediction across the workstations with a narrower error range. The current RMSE is approximately 15-40 lux as opposed to previous 60-250 lux across the workstations, reported by Paulson et al. (2013) [27]. As observed in Paulson et al. (2013), the prediction accuracy increases away from the window.

Table 2: Root mean-square error for workstations 2, 3, 5, 6 and 7 using clustering-based model

Workstation	2	3	5	6	7
RMSE (lux)	15.0	33.5	41.0	15.0	31.0
RMSE (%)	8.0	7.0	12.0	8.0	6.0
Regressors	8,1,4	8,4	8,4,a, b	8,1,4	8,d

Table 3: Root mean-square error for workstations 2, 3, 5, 6 and 7 using sun position-based model

Workstation	2	3	5	6	7
RMSE (lux)	14.0	111.0	57.0	30.0	80.0
RMSE (%)	30.0	45.0	25.0	30.0	35.0

In order to test the long term model performance, the inverse model was trained and tested further on new data collected from the NASA Ames Sustainability Base from December 2, 2013 to February 4, 2014. The training times used on the test set were over the first ten days, from December 2, 2013 to December 12, 2013. Results of root mean square percent error were within ±1% of prediction results obtained for summer months. Based on these results, time required for consistent model performance has been identified as 7 to 14 days.

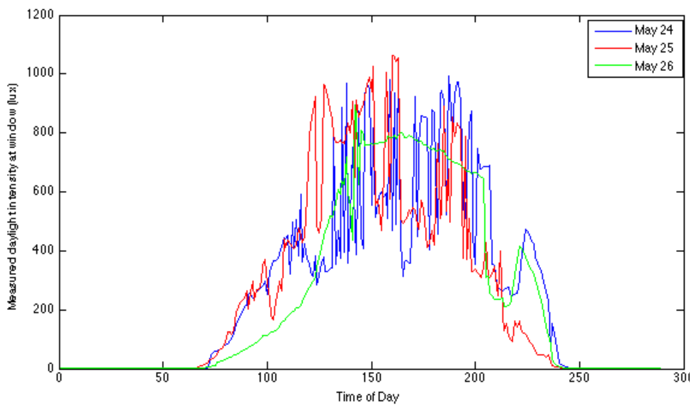

Figure 11: Distribution of light level on three days of May in 2012, May 24, May 25 and May 26

Figure 11 illustrates the daily distribution of light level on May 24-26, 2012. While light distributions on May 24 and 25 are highly fluctuating, May 26 shows a generally similar but much smoother profile of light distribution, indicating the time dependence of light distribution. Therefore a simple regression model using historical values of hourly light levels may give a good result when May 24 data are used to compute the day-ahead prediction, but the same does not hold for May 25. RMSE between daily light level on May 24 and May 25 is 11 lux while on May 25 and May 26 is 10 lux. However hourly difference between two consecutive days may be as high as 600 lux.

The goal was to use season adjustment for the training data to predict for any month of the year. Cross-seasonal tests of the inverse model demonstrated significant errors, which appear to be caused by changes in sun angle and/or sensor placement between training and validation data. At the Sustainability Base sensors were moved and reinstalled on December 2, 2013. As a result, the data were validated with training data from the same season but different years, and high errors still remained. Data are being further collected at the SB to address the varying seasonal performance of the model. Clustering based on sun angle rather than time will also be investigated further.

One of the major goals of adaptive regressor selection is to ensure that the prediction accuracy demanded by the control system for occupant visual comfort and energy savings is not compromised. Therefore the impact of prediction accuracy of the inverse model on the above was analyzed and determined as an appropriate error threshold. The analysis assumes that unless the energy savings target is stringent and/or there is a demand response event, any under-estimation or over-estimation leading to prediction within 300 lux - 500 lux will lead to inaction. Any under-estimation below actual 300 lux will lead to energy wastage while an over-estimation greater than 67% above actual 300 lux is likely to cause visual discomfort due to inadequate light; whereas when the actual light level is greater than 800 lux, inaction resulting from under-prediction may cause glare.

4. **Develop daylight prediction model for each window in the test beds. Prediction accuracy should be enough to minimize the number of sensors required.**

Using 5-fold cross validation, it was determined that forecasted hourly outdoor temperature, hour of the day and hourly sky conditions are the most important features affecting the sunlight measured at the window. For similar days, past light levels appeared to be a better predictor than any of the above features. Besides these, average hourly light level of past three days was considered as a feature for the SVR. The scatter plot in Figure 12 (left) shows an approximately linear relationship between hourly light levels measured on two similar days. Figure 12 (right) on the other hand illustrates the deviation from linearity due to dissimilar sky conditions. While a linear kernel produced the least mean square error of cross validation when similar historical days compared to the test period were used in the training, Radial Basis Function (RBF) kernel was better able to handle occasional non-linearity as shown in Figure 12 (right).

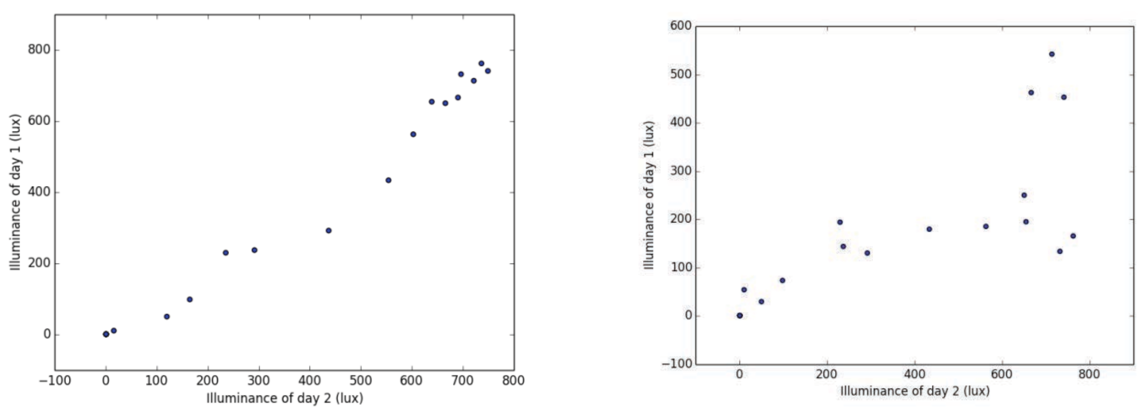

Figure 12: Scatter plots showing an approximate linear relationship between hourly light levels of two similar days (left) and deviation from linearity due to dissimilar sky conditions (right)

Sky conditions 'clear', 'scattered clouds', 'partly cloudy', 'mostly cloudy' and 'overcast' were converted to numeric values from 1-5, for convenience of SVR. The similarity between the days was determined by the root mean square error between the sky conditions over 24 hours period. Depending on the similarity between the forecasted sky condition of the prediction day and the previous three days, model cost function *C*, error tolerance ε and the RBF kernel parameter γ were adapted for improved prediction accuracy. In SVR, C determines the trade-off between model complexity and error tolerance. The best set of parameters was found by an exhaustive search over a range of *C*=[1:1:10000], while ε and γ were fixed at 0.1. The result of SVR based day-ahead prediction of light level on three consecutive days, June 2-4 2012 is illustrated in Figure 13. The training data consisted of past six days of hourly temperature, sky conditions and hourly average light level of the past three days. The minimum RMSE was approximately 48 lux while the maximum error was 204 lux. The average accuracy of the SVR model over three days is approximately 92%. The prediction error expressed as root mean square error (RMSE) was found to be 112 lux on average with smaller error between similar testing and training light environment.

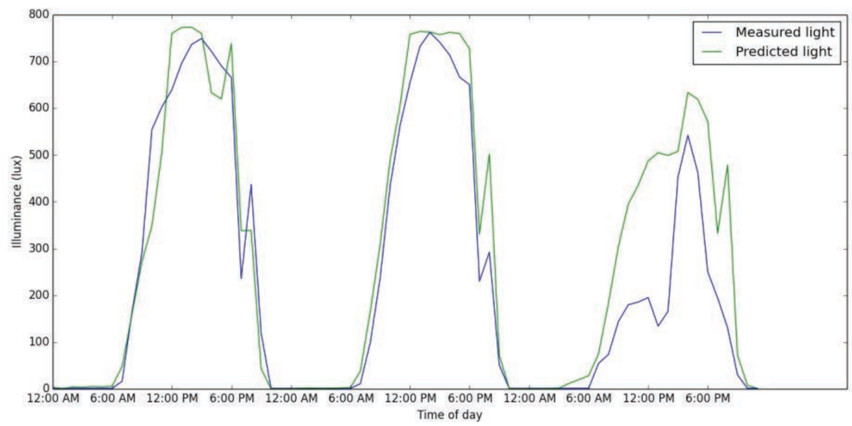

Figure 13: Day-ahead prediction of light level on June 2-4, 2012 from forecasted temperature, sky conditions and past 3 days hourly average measured light level.

The accuracy and predictive capability of first principle models of lighting, using sophisticated and computationally expensive ray tracing algorithms, vary widely depending on the expertise and the experience of the modelers, the average accuracy being 20% [42]. In comparison, ~ 80%-95% accuracy across the test bed, as obtained in this work indicates a model accuracy sufficient for occupant comfort. Moreover, the spatial distribution of the errors was found to be consistent except for workstation sensor 3. The temporal distribution of error is within 10% for most of the workstations in the test bed. Due to negligible under-estimation, the problem of energy wastage will presumably not be encountered.

Furthermore the model achieved prediction accuracy of 80% - 95% using 60% fewer sensors than the state-of-art intelligent lighting system, which use one photo-sensor and actuator per light fixture. A scenario of two to three wireless sensor platforms per occupant workstation, including daylight sensors, amounts to one platform/6.2 - 9.3 m^2, assuming a standard occupancy of 18.6m^2/person as recommended by the ASHRAE standards for ventilation (ASHRAE, 2010) [43].

5. **Perform energy simulations in different demand management scenarios. Develop demand response strategies at lighting levels with 10%, 15% and 20% load shedding.**

Demand response strategies of load shifting (adjusting work hours to accommodate natural light) and load shedding (decreasing target illuminance) were developed. These strategies were tested over four months data at the NASA Sustainability Base. Analyses were completed for four separate cases (late May, early June, late June, and early August), and results were then averaged across all four cases. Table 4 below summarizes those results.

Table 4: Mean and standard deviation of estimated savings when two DR policies are implemented. Saving percentages represent percent reduction in energy load on a DR day compared to a baseline non-DR day.

Policy	Quantity	Mean	Standard Deviation
Load Shift	Energy Savings (%)	19	18
	Time shifted forward (min)	130	76
Load Shed	Maximum Energy Savings (%)	80	2.4
	Target Reduction to Achieve 10% Energy Savings (lux)	13	1.5
	Target Reduction to Achieve 15% Energy Savings (lux)	20	2.2
	Target Reduction to Achieve 20% Energy Savings (lux)	27	3.0

Depending on the case, load shifting could be a simple and effective way to decrease the load for office lighting. The potential savings from shifting the load (moving the work hours during periods of higher levels of sun light) showed much variability across the four examined cases. For example, around 40% load reduction could be achieved by shifting the work day forward 3 hours and 50 minutes in early June, while in early August shifting hours can not achieve any noteworthy savings (Figure 14). The total amount of load shedding possible and the desirable start and stop time for a DR work day are highly dependent on the building configuration, type of work and time of year, to name a few.

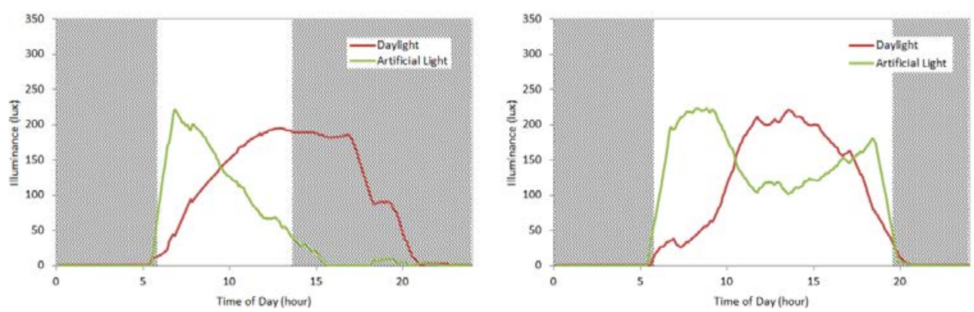

Figure 14: Sample data at a central desktop (Sensor #2) with average calculated artificial light demand for one work week in early June (left) and early August (right). Daylight represents the average sensed data over one adjacent weekend. Non-work hours are hatched in grey.

Load shedding through dimmable ballasts can be an effective and flexible way to meet various DR targets. For the tested days at the Sustainability Base, decreasing the illuminance target demonstrated the potential to produce significant load reductions without dipping below the noticeable threshold for the human eye. Furthermore, goals of 10%, 15% and 20% load reduction can be achieved by decreasing the illuminance target by only 10 to 30 lux. These target percent reductions are also on top of any load reductions that occur on a daily basis due to daylighting and adjusting for user preferences.

6. **Perform lifecycle cost and energy analysis of the retrofit system and user evaluations.**

Based on the analysis in Sustainable Minds, the intelligent lighting system represents 123 kg CO_2e per functional unit and 10.5 mPts per functional unit from cradle to gate (resource extraction to factory gate, before it is transported to the user). The printed circuit board contributed the largest impacts to the overall system, and most of this impact is in carcinogenics (Figure 15). Transportation was found to contribute negligible effects to the overall impact. As determined by this analysis, materials and manufacturing of intelligent lighting system has paid itself off environmentally once the system has reduced energy consumption by 148 kWh during its use.

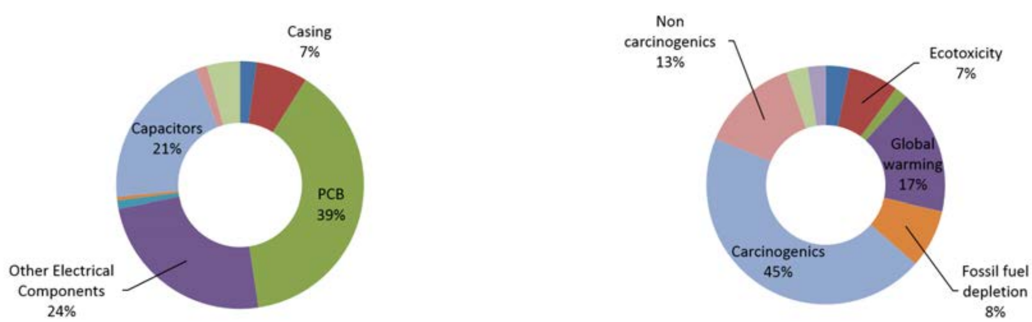

Figure 15: Cradle-to-gate assessment of intelligent lighting system demonstrating total impacts by component (left) and category (right). Only impact contributions greater than five percent of total are listed.

1. Since the intelligent lighting system may reduce building light energy consumption at different rates depending on the circumstance, several efficiencies were evaluated. Figure 16 below illustrates the payback time to the environmental cost of the wireless devices as a function of efficiency. If the intelligent lighting system is able to reduce building energy consumption by 70% (50% by user adjustments and 20% by daylight harvesting), as indicated possible by previous studies [7-9], the cost of the devices environmentally will have already paid for itself off in energy savings after two working days. In this use scenario and per functional unit, implementing this system could save approximately 23,000 kg-CO_2-eq in emissions over the course of one year of use (based on a single functional unit of one office space, 500 sq. meters).

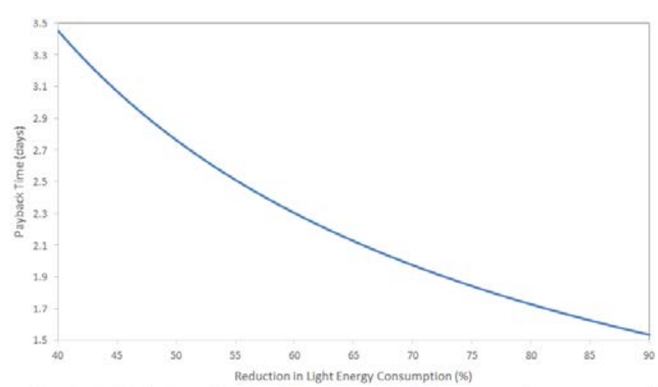

Figure 16: Environmental payback time with respect to building energy savings from the standard lighting demand [9], represented per one functional unit.

User studies were conducted to evaluate the plug-and-play features of the sensor system. Although the 30 min. set-up target was reached, users provided useful suggestions in regards to integration with cell phones and specific user interface improvements. User evaluations were also conducted for potential residential applications. The results indicated the potential for allowing the sensor and light-harvesting casing to be customizable for residential use. More details for improvements are included in the Recommendations section.

Conclusions

A wireless sensor network with onboard solar panels was developed, deployed and tested at independent test beds. With the assistance of an auxiliary battery, the solar panels can self-power the devices with little to no required maintenance. While the PV cell provides power during hours when incident light is sufficient, the auxiliary battery supplements the cell's capabilities in times of low light and upon startup. Over three months of testing at NASA Ames Research Center, the auxiliary battery voltage has only dropped 7%, indicating that the platform is capable of sustaining self-power for over a year.

As part of this research endeavor to enable data-driven model-based predictive control of building systems with the Sustainability Base at the NASA Ames Research Center, a computationally inexpensive predictive model of indoor lighting has been developed. To this end, a low power wireless sensor network (with PV-energy harvesting) has been deployed at three test beds, and a piecewise linear regression model of clustered workstation illuminance, built on a month of data at seven workstations, has been developed. In this work, clustering accounts for the complex nature of daylight resulting from unpredictable weather parameters such as sudden cloud cover and the relationship between building geometry and solar geometry. The clustering based model was capable of predicting the light levels with 80%-95% accuracy across the workstations. This was a significant improvement over the researchers' prior work using sun position based piecewise linear model. Clustering light data by mean and standard deviation revealed patterns in the data that could be utilized in refining the linear models.

A support vector regression model was able to predict the day-ahead daylight availability within approximately 92%. The predicted day ahead hourly daylight availability as a function of forecasted hourly temperature, sky conditions and hourly average measured daylight of historical days is a potential valuable input to model predictive lighting control of grid-integrated buildings. From this model, accurate day-ahead predictions were used to estimate potential load savings on demand response days. Load shifting (adjusting the work hours to accommodate maximum daylight) and load shedding (decreasing the target illuminance) policies were developed for this purpose. On the examined days at NASA Ames, load shifting and load shedding policies could potentially save 19% and 80% lighting energy, respectively.

Estimated energy savings and environmental benefits were examined through a life cycle analysis of the intelligent lighting system. Within the devices, it was discovered that the printed circuit board was responsible for the majority of negative impacts, but this was minor compared to the advantages of the increased energy savings. The materials and manufacturing of this system easily pays itself off environmentally once the system has reduced energy consumption by 148 kWh during its use. This can occur after only two days, for example, when the system is effectively reducing light energy consumption by 70%, as indicated possibly by previous research [7-9]. In this scenario, it is estimated that the system effectively eliminates 23,000 kg of CO_2 equivalent in emissions over one year of use.

Recommendations

This research project has produced an easy-to-deploy, low-maintenance distributed sensor network that effectively monitors, predicts, and has the ability to be integrated into the control of indoor lighting conditions. However, the current version of the sensor network is the product of preliminary research efforts, and consequently suffers from a number of design inefficiencies that should be remediated through a pre-commercial product development process. Recommendations are presented to facilitate this development process, and allow for large-scale implementation and commercialization of the sensor platforms.

The current remote sensors rely on TelosB mote platforms and Cymbet CBC-3150 power management modules. While these products are highly effective and easy-to-use, they are also expensive and contain a wide range of integrated capabilities not required for our application. Consequently, it is recommended that future versions of the remote sensor utilize cheaper, less capable hardware that is more specifically tailored to the application. For example, the CPU, radio transmitter, and power management circuit could be integrated into a purpose-built PCB. This would also allow for a drastic reduction of the sensor's physical dimensions, lowering material costs and allowing for more inconspicuous deployment of the sensor network in the indoor space.

The current version of the intelligent lighting system utilizes a central small computer (PC) as the network's central data receiving node, also known as the 'base station'. This approach has created complications with regard to operating system compatibility, as the current radio receiver hardware must be configured to communicate with the PC, requiring a host of drivers unique to individual operating systems, and even individual versions. In addition, the current system requires that the PC be wastefully turned on at all times to complete a very simple task that only requires a tiny fraction of its processing power. Consequently, it is recommended that a purpose-built base station be developed. This system could be based on open source CPU platforms, such as the Arduino series, or emerging "Internet of Things" platforms, such as Marvell's Kinoma or Samsung's "SmartThings". Regardless of platform, the system could utilize a smartphone as both an interface and a central node. Independent of the platform type, the CPU should be configured to receive, log, and process the data from remote sensors and to subsequently transmit control commands to lighting actuators.

To expand the capabilities of this system, the current sensor technology has been adapted to collect relative humidity and temperature data (onboard the TelosB) in addition to lighting. Data has been collecting on these three sensors in the BEST Lab (230 Hesse Hall) continuously for three weeks. With the addition of these sensors, it is possible to get a picture of the indoor environmental quality in addition to the illuminance. This could prove beneficial when monitoring the effects of demand response policies, for example, since decreasing the lighting in a space may also cause a drop in temperature. Further investigations should examine how collecting data on these additional sensors affects power management. Generic data such as these could additionally drive modeling for smart building energy management and indoor localization enhanced by environmental data.

Lastly, it is recommended that a set of standardized lighting actuators be developed to carry out the commands output by the lighting control algorithm. One promising actuation approach is to integrate a radio receiver and dimmer into standard light switches. When turned on, these wall switches would receive control inputs from the base station to effectively modulate lighting levels in accordance with the indoor data collected by the distributed network. Additionally, significant opportunities exist with actuated lights, such as web-connected dimming LED bulbs by GE and Phillips [44,45]. These bulbs can receive dimming signals directly from smartphones, for example.

The PI has had significant prior work in closing the system loop with lighting actuation and control [7,8,9]. Lighting adjustments based on daylighting and user preference have both been quantified. The goal of this current research was to develop a "proof of concept" sensing system for improved and less costly commissioning with lighting estimation and prediction that could be used in conjunction with such actuation and control strategies. Prior to commercialization, additional development and testing will be needed to integrate prior actuation and control algorithms with new smart lights now available on the market. Additional next steps should also include further testing of the sensing method to identify failure cases and refine the user interface.

Based on user feedback from a demonstration home near Ukiah, California, there is potential to develop the wireless sensor network for residential applications. The wireless system could provide generalized energy reduction practices as well as feedback on consumption habits and indoor environmental quality. In addition to these benefits, flexibility in the case design and material allows the system to be tailored towards the target market's preference. For example with the demonstration home with the Pinoleville Pomo Nation, users desired a case made from a natural material such as willow because of values of maintaining cultural relevance and environmental harmony. Furthermore, culturally informed visualizations of the sensor data could enhance the societal impact and business value of the system. Since fewer sensors are required when using a predictive model, the system can be available at a lower cost, making it feasible for both residential and commercial applications.

The recommendations above are intended to reduce the cost of the system, while simplifying its implementation in individual buildings and homes. In future product development efforts, it is suggested that a typical household system be designed with a cost that reflects the amount consumers are spending on thermostats and other household control items ($100 to $500). The final implementation of the system should only require the user to install the standard actuators, plug in the central base station, and deploy the remote sensors. Periodically, the user would extract data from the central base station (via a USB stick), and input this data to software that provides performance outputs, such as the energy saved and average light level maintained in the space. In addition, the software will implement the "virtual "sensor algorithms that were developed, allowing the user to see if any of the remote sensors are providing redundant data, or could otherwise be replaced with a virtual sensor, so that the remote sensor hardware can be more effectively deployed to another room or space.

Public Benefits to California

A recent study at Lawrence Berkeley National Laboratory has shown that similar lighting control infrastructures, when coupled with shading control, could save 57% lighting energy and 28% cooling energy [5]. In spite of a few successful pilot studies, as of 2010, 70% of US national stock of commercial buildings does not have intelligent lighting included in the new and existing buildings. Of the 30% commercial buildings with lighting systems, 3% have dimmers, 5% motion detectors, 4% timers and 18% use EMS [15].

For calculating the energy savings over and above existing products, the intelligent lighting controls scheme indicated are considered as the baseline [15]. It is assumed that 70% of the office and educational buildings across the country not using intelligent lighting controls is our target market because these buildings have the largest energy footprint which is 32% [47] of the total lighting and cooling energy consumption of 6.33 quads Btu [46]. 70% is a conservative number as this system can also improve the energy performance of 50% of the remaining 30% non-functioning lighting control systems. In reality, in terms of cooling energy savings, the fraction of this 70% commercial space should be considered that have active cooling. Therefore this system will offer savings over 1.32 quads Btu of commercial primary energy. Furthermore, it is estimated that a 10% adoption of this intelligent lighting system in commercial buildings could save 0.2-0.25 quads BTU of energy nationwide [48]. The total average estimated energy savings is approximately 20% for lighting and 10% for cooling with some extended energy savings assuming that better controllability over heat gain will facilitate adoption of more energy efficient cooling technologies in moderate climates in California. In addition, we estimated that the system could eliminate 23,000 kg of CO_2 equivalent in emissions over one year of use with 10% market penetration.

A breakup of expected energy savings by components of this product is as follows:

- Operation and control: Lighting energy savings from granular occupancy detection based dynamic light zoning, conflicting user preference satisfaction over and above baseline intelligent lighting controls: 20%. Cooling energy savings from active heat gain control as part of integrated lighting and smart shading control: 10%. These numbers are over the savings achievable per building using bests of the market
- Streamline commissioning method: A streamlined and less resource intensive commissioning and retrofitting process coupled with accurate model based prediction of expected energy and cost savings could enhance the implementation of lighting retrofit in 20% of the target commercial buildings (assuming increase in the commercial building stock by the time of product commercialization and licensing).
- A further 15-50% of indirect cooling energy savings is possible depending on the climate zone due to better adoption of thermally active systems.

Cost savings will be achieved from reduced installation costs and extended energy bill savings. Moreover, because this plug-and-play system utilizes a predictive inverse model for control, it drastically minimizes commissioning time, which can take months for existing lighting retrofit solutions with no guarantee that the results work after occupancy or room changes.

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Glossary

CAD	Computer Aided Design
DR	Demand Response
HVAC	Heating, Ventilation, Air Conditioning
LCA	Life Cycle Assessment
MAS	Multi-Agent System
MI	Mutual Information
OLS	Ordinary Least Squares
PC	Personal Computer
PPN	Pinoleville Pomo Nation
PCB	Printed Circuit Board
RBF	Radial Basis Function
RWA	Real-World-Aware
RMSE	Root Mean Square Error
SVM	Support Vector Machine
SVR	Support Vector Regression
SB	Sustainability Base
WSAN	Wireless Sensor and Actuator Network
WSN	Wireless Sensor Network

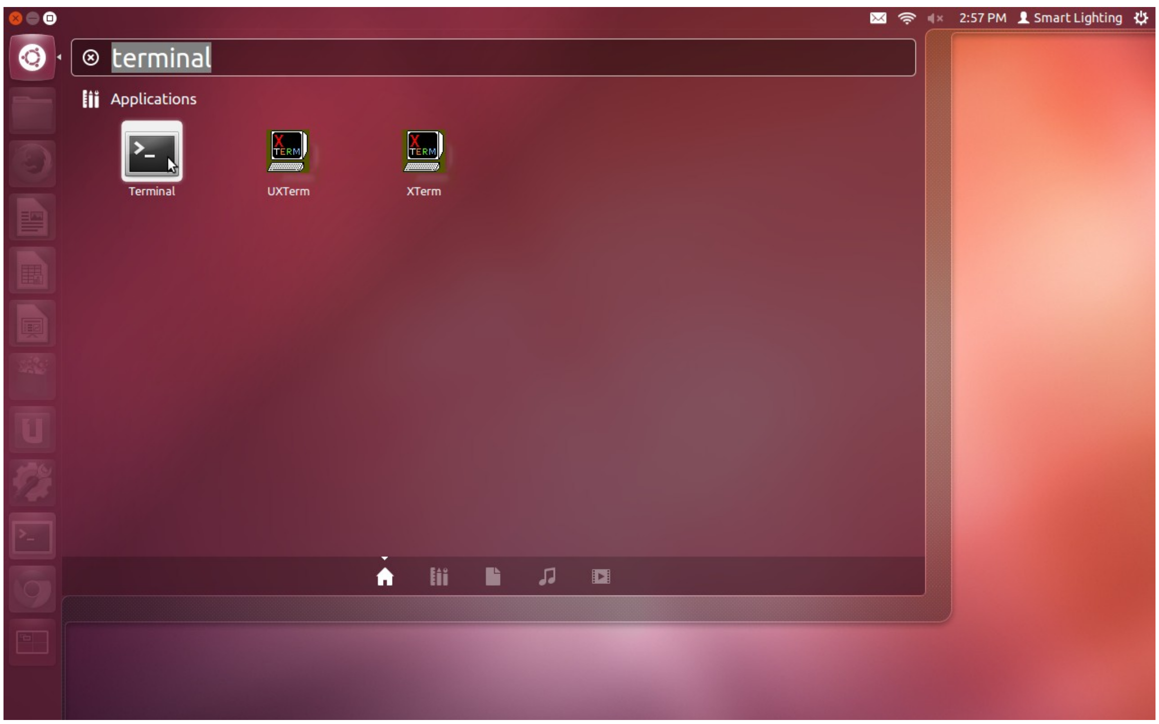
Appendices

Appendix I: Installation Guide

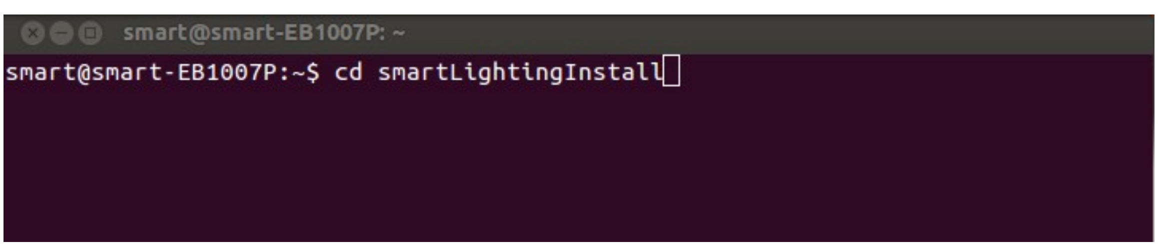
Smart Lighting Wireless Sensor Network: User's Guide

I. Ubuntu Installation

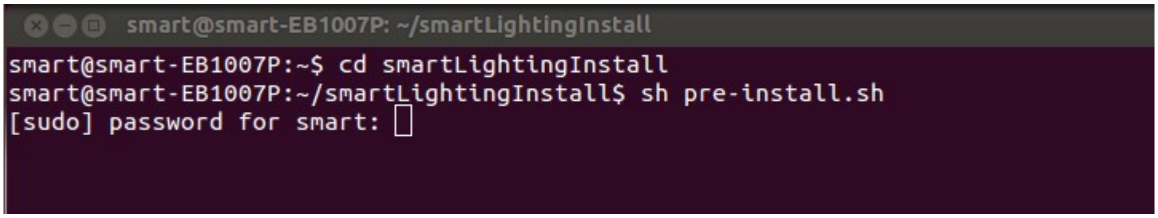
1. Open your terminal.
    a. Search for terminal.
    b. Double click the terminal icon.
    c. Type **'git clone git@github.com:elizabethcheng/smartLightingInstall.git'** into your terminal and press **'Enter.'**



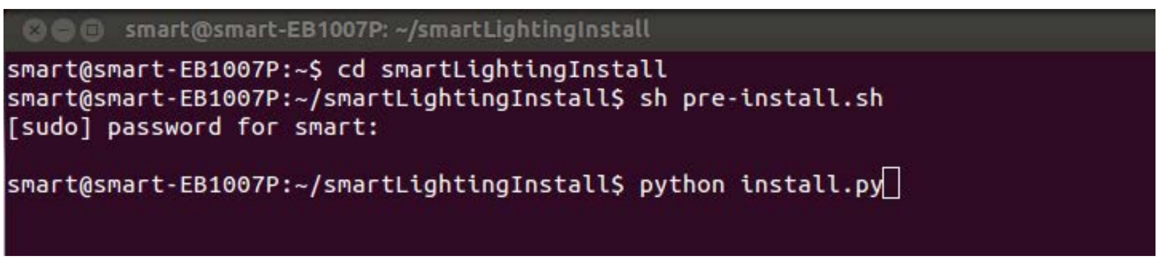
2. Open your **'smartLightingInstall'** folder using terminal.
    a. Type **'cd smartLightingInstall'** into your terminal and press **'Enter.'**



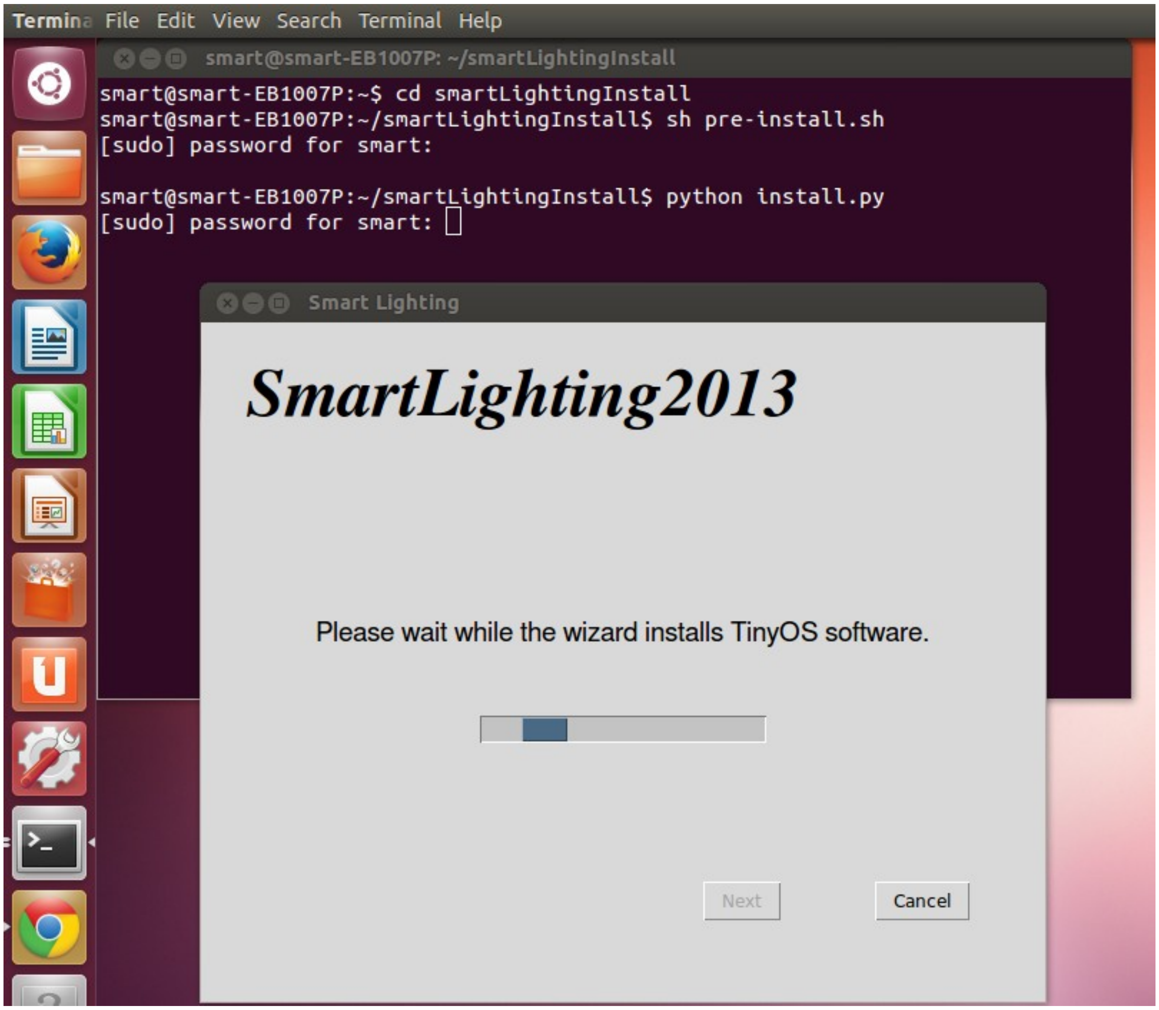
3. Run the pre---installation program from the terminal
    a. Type **'sh pre---install.sh'** in the terminal and press **'Enter.'**
    b. You may be prompted by the terminal to enter your password. If you are, enter your computer password and press **'Enter'** to continue. **NOTE: the password text may not be displayed while typing.**
    c. The pre---install.sh program should run for approximately 10---15 minutes.



4. Run the installation program from the terminal.
    a. Type **'python install.py'** in the terminal and press **'Enter.'** The Smart Lighting Installation Wizard window will open.
    b. You may be prompted by the terminal to enter your password. If you are, enter your computer password and press **'Enter'** to continue. **NOTE: the password text may not be displayed while typing.**



5. Step through the installation wizard to set up your sensor network.
    a. Follow the instructions of the installation wizard to install TinyOS, sMAP, light sensor motes, the base station mote, and to start the WSN.
    b. Throughout the installation, the terminal may prompt you to enter your password. If you are, enter your computer password and press **'Enter'** to continue. **NOTE: the password text may not be displayed while typing.**
    c. Throughout the installation, the terminal may ask whether or not you want to continue installing programs. Type **'yes'** in the terminal and press **'Enter'** to continue the installation.
    d. Note on sensor installation:
        i. **For LIGHT SENSOR MOTES**: Unplug each light sensor mote from the USB port after you finish installing it (have one sensor plugged into the computer at a time).
        ii. **For the BASE STATION**: After the base station is installed, leave it plugged into the computer.



6. Once you have exited the installation wizard, you have installed all necessary components of your WSN. Congratulations!

7. (Optional) Create your local database
    a. Wait two weeks for sMAP to collect data before creating your local database.
    b. Open your **'smartLightingInstall'** folder from terminal (see instructions in Step 4).
    c. Type **'python Database.py db_info.txt'** into the terminal and press **'Enter.'**
    d. Your new local database, **'data.db'** will be in your **'smartLightingInstall'** folder.

California Energy Commission Energy Innovations Small Grant (EISG) Program **PROJECT DEVELOPMENT STATUS**	**Questionnaire**

Answer each question below and provide brief comments where appropriate to clarify status. If you are filling out this form in MS Word the comment block will expand to accommodate inserted text.

Please Identify yourself, and your project: **PI Name** ___________________**Grant #** ___________

Overall Status

Questions	Comments:
1) Do you consider that this research project proved the feasibility of your concept?	*Yes, the research proved the feasibility of our proposed concept.*
2) Do you intend to continue this development effort towards commercialization?	*Although the research proved feasibility of the proposed concept, the lessons learned also indicated that a commercial platform could be made smaller and less expensive if we integrated our own sensors and computing platform.*
Engineering/Technical	
3) What are the key remaining technical or engineering obstacles that prevent product demonstration?	*The product has been demonstrated.*
4) Have you defined a development path from where you are to product demonstration?	*Not yet. This is our next step.*
5) How many years are required to complete product development and demonstration?	*One year for a prototype of a commercial platform, depending on whether funding is obtained.*
6) How much money is required to complete engineering development and demonstration?	*$100,000 for research staff time and components.*
7) Do you have an engineering requirements specification for your potential product?	*No, we are developing specifications now as part of our next year effort.*
Marketing	
8) What market does your concept serve?	*Originally we focused on the commercial market. The advance of the Nest thermostat, however, and new internet-accessible LED lights leads us to believe that a residential market exists as well.*
9) What is the market need?	*Faster commissioning of smart lighting systems. We believe we can also add smart energy features in general with temperature and humidity sensing.*
10) Have you surveyed potential customers for interest in your product?	*We have performed observations and qualitative research.*
11) Have you performed a market analysis that takes external factors into consideration?	*We have performed a competitive analysis of existing products and have identified possible strategic partnerships.*

12) Have you identified any regulatory, institutional or legal barriers to product acceptance?	*No regulatory barriers have been identified; in fact, they are helpful.*
13) What is the size of the potential market in California for your proposed technology?	*A recent study in Lawrence Berkeley National Laboratory has shown that similar lighting control infrastructures, when coupled with shading control, could save 57% lighting energy and 28% cooling energy [5]. In spite of a few successful pilot studies, as of 2010, 70% of US national stock of commercial buildings does not have intelligent lighting included in the new and existing buildings. Of the 30% commercial buildings with lighting systems, 3% have dimmers, 5% motion detectors, 4% timers and 18% use EMS [15].* *For calculating the energy savings over and above existing products, the intelligent lighting controls scheme indicated are considered as the baseline [15]. It is assumed that 70% of the office and educational buildings across the country not using intelligent lighting controls is our target market because these buildings have the largest energy footprint which is 32% [47] of the total lighting and cooling energy consumption of 6.33 quads Btu [46]. 70% is a conservative number as this system can also improve the energy performance of 50% of the remaining 30% non-functioning lighting control systems. In reality, in terms of cooling energy savings, the fraction of this 70% commercial space should be considered that have active cooling. Therefore this system will offer savings over 1.32 quads Btu of commercial primary energy. The total average estimated energy savings is approximately 20% for lighting and 10% for cooling with some extended energy savings assuming that better controllability over heat gain will facilitate adoption of more energy efficient cooling technologies in moderate climates in California.*
14) Have you clearly identified the technology that can be patented?	*The algorithms developed may be patentable.*
15) Have you performed a patent search?	*Not yet.*
16) Have you applied for patents?	*Not yet.*
17) Have you secured any patents?	*No.*
18) Have you published any paper or publicly disclosed your concept in any way that would limit your ability to seek patent protection?	*Yes, but we are still within one year for a U.S. patent.*
Commercialization Path	
19) Can your organization commercialize your product without partnering with another organization?	*Probably not. We have identified potential strategic partners and are evaluating suppliers.*

20) Has an industrial or commercial company expressed interest in helping you take your technology to the market?	*Yes, this is one of our potential strategic partners.*
21) Have you developed a commercialization plan?	*Not yet.*
22) What are the commercialization risks?	*Mostly time and money for the development.*
Financial Plan	
23) If you plan to continue development of your concept, do you have a plan for the required funding?	*Not yet.*
24) Have you identified funding requirements for each of the development and commercialization phases?	*Not yet.*
25) Have you received any follow-on funding or commitments to fund the follow-on work to this grant?	*No, but we have identified potential funding from a strategic industrial partner or from a grant to the National Collegiate Inventors and Innovators Alliance..*
26) What are the go/no-go milestones in your commercialization plan?	*Commitment from research personnel.*
27) How would you assess the financial risk of bringing this product/service to the market?	*We believe the benefits are huge, and risks low.*
28) Have you developed a comprehensive business plan that incorporates the information requested in this questionnaire?	*Not yet.*
Public Benefits	
29) What sectors will receive the greatest benefits as a result of your concept?	*Initially commercial; but we believe there is a residential market with benefits as well.*

30) Identify the relevant savings to California in terms of kWh, cost, reliability, safety, environment etc.	*We estimate a savings over 1.32 quads Btu of commercial primary energy. For calculating the energy savings over and above existing products, the intelligent lighting controls scheme indicated are considered as the baseline [15]. It is assumed that 70% of the office and educational buildings across the country not using intelligent lighting controls is our target market because these buildings have the largest energy footprint which is 32% [47] of the total lighting and cooling energy consumption of 6.33 quads Btu [46]. 70% is a conservative number as this system can also improve the energy performance of 50% of the remaining 30% non-functioning lighting control systems. In reality, in terms of cooling energy savings, the fraction of this 70% commercial space should be considered that have active cooling. Therefore this system will offer savings over 1.32 quads Btu of commercial primary energy. The total average estimated energy savings is approximately 20% for lighting and 10% for cooling with some extended energy savings assuming that better controllability over heat gain will facilitate adoption of more energy efficient cooling technologies in moderate climates in California.*
31) Does the proposed technology reduce emissions from power generation?	*No, other than less power generation will be needed with the increased energy conservation.*
32) Are there any potential negative effects from the application of this technology with regard to public safety, environment etc.?	*No.*
Competitive Analysis	
33) What are the comparative advantages of your product (compared to your competition) and how relevant are they to your customers?	*The system requires fewer sensors than competitive products due to our virtual sensor system. We also offer faster and more effective commissioning.*
34) What are the comparative disadvantages of your product (compared to your competition) and how relevant are they to your customers?	*We require initial testing in order to collect data and develop the virtual sensors.*
Development Assistance	
The EISG Program may in the future provide follow-on services to selected Awardees that would assist them in obtaining follow-on funding from the full range of funding sources (i.e. Partners, PIER, NSF, SBIR, DOE etc.). The types of services offered could include: (1) intellectual property assessment; (2) market assessment; (3) business plan development etc.	
35) If selected, would you be interested in receiving development assistance?	*Yes for refining the prototype for a commercial market, market assessments and business plan development.*