SMART LIGHTING

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Abstract

Wireless sensor networks (WSN) have great potential to enable personalized intelligent lighting systems while reducing building energy use by 50-70%. However, such systems can be expensive to implement and lack true plug-and-play quality for user-friendly commissioning. We present a combination of WSN and modelling software that holds the potential of improving affordability and user-friendliness. It requires 60% fewer sensor deployments compared to state-of-art systems. The sensor reduction algorithm uses clustering and linear regression and was developed using data from two testbeds. Using an optimal photo-sensor placement, this model was able to predict the light level within 30% accuracy. We estimated that 10% adoption of this system in commercial buildings can save 0.2-0.25 quads BTU energy nationwide.

Introduction

According to U.S. DOE, the maximum electricity consumption in commercial buildings (13.6%) is attributed to lighting. In spite of the growing impetus for lighting control research, the actual adoption of intelligent lighting control systems, with 70% of US national stock of commercial buildings with no lighting control systems and the remaining with deactivated or under-performing systems.

A major challenge is to control the coupled sub-systems of a complex building system or even a cluster of buildings. New systems seek to incorporate predictive models of occupancy, renewable energy availability and price signals to account for interdependencies between energy performance of these subsystems.Thus another major challenge is the development of inexpensive and easy to commission WSANs, along with computationally inexpensive lighting models and intelligent control systems. The question is how minimal sensor deployment could suffice for desired energy and comfort performance of these systems.

Analysis and methods

Our strategy is to repeatedly deploy the same wireless sensor platform in different locations at desktop levels to create parameterized lighting models. This redeployment promises to cut down costs and can increase accuracy, as the overhead sensors tend to over-estimate the light level compared to the human eye at desktop levels.

Inverse Problem Theory

(1) Parameterize the system in terms of a set of model parameters that adequately characterize the system in the desired point of view
(2) Make predictions on the actual values based on physical laws and given values of the model parameters
(3) Use actual results from measurements to determine the model parameters

Parameter identification for virtual sensor model development using quarter scale mockup of office space at Berkeley Energy and Sustainable Technologies Lab.

Demonstration of test-bed at NASA Ames Sustainability Base with 9 sensors

Linear Regression and K-Means Clustering Algorithm

Clustering algorithms are unsupervised learning performed on unlabelled data to discover natural groupings. We have used clustering as a proxy for sky conditions instead of looping clustering with the linear regression algorithm.

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

$$E_w = \alpha_1 E_{a1} + \cdots + \beta_1 E_{n1} + \cdots + \varepsilon$$

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

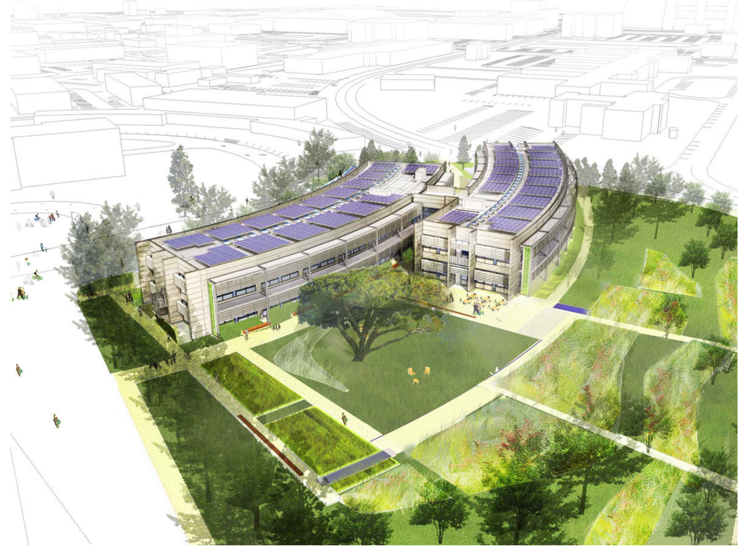
$$\begin{pmatrix} E_{w_1} \\ \vdots \\ E_{w_m} \end{pmatrix} = \alpha_1 \begin{pmatrix} E_{a1_1} \\ \vdots \\ E_{a1_m} \end{pmatrix} + \cdots + \beta_1 \begin{pmatrix} E_{n1_1} \\ \vdots \\ E_{n1_m} \end{pmatrix} + \cdots + \varepsilon$$

$$J(c_k) = \sum_{x_i \in c_k} ||x_i - \mu_k||^2$$

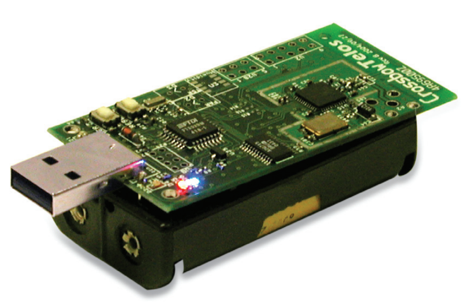
K-means minimizes the J function as:

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

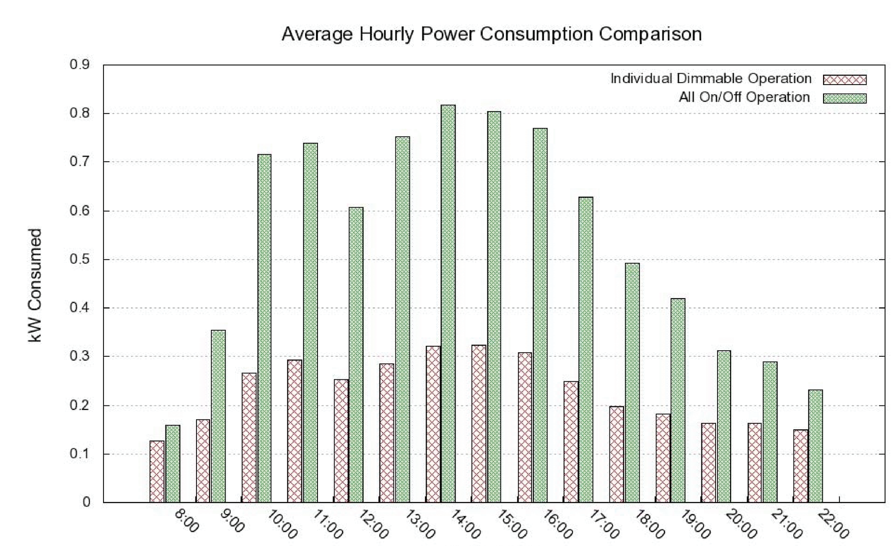
K-Means Algorithm reduces J function to optimally place centroid for cluster of data



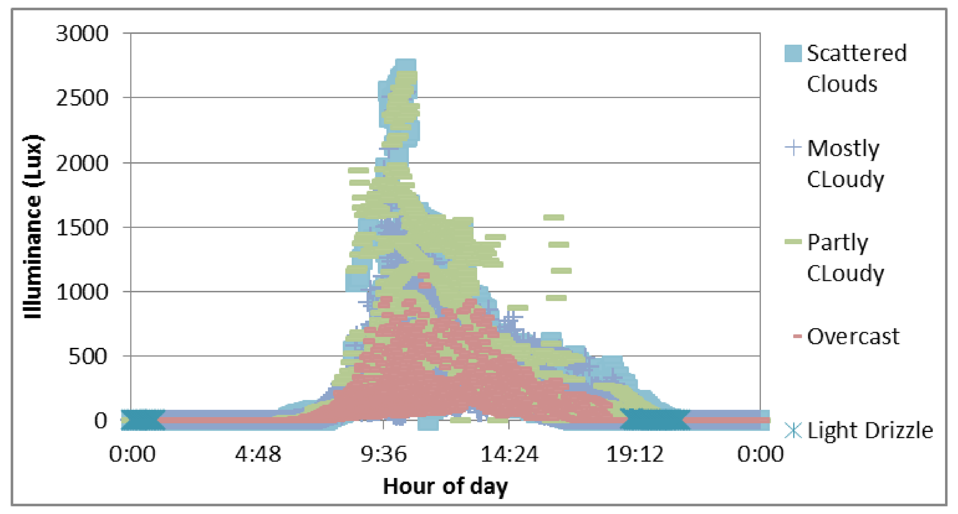
NASA Sustainability Base, Ames Research Center, Mountain View, CA



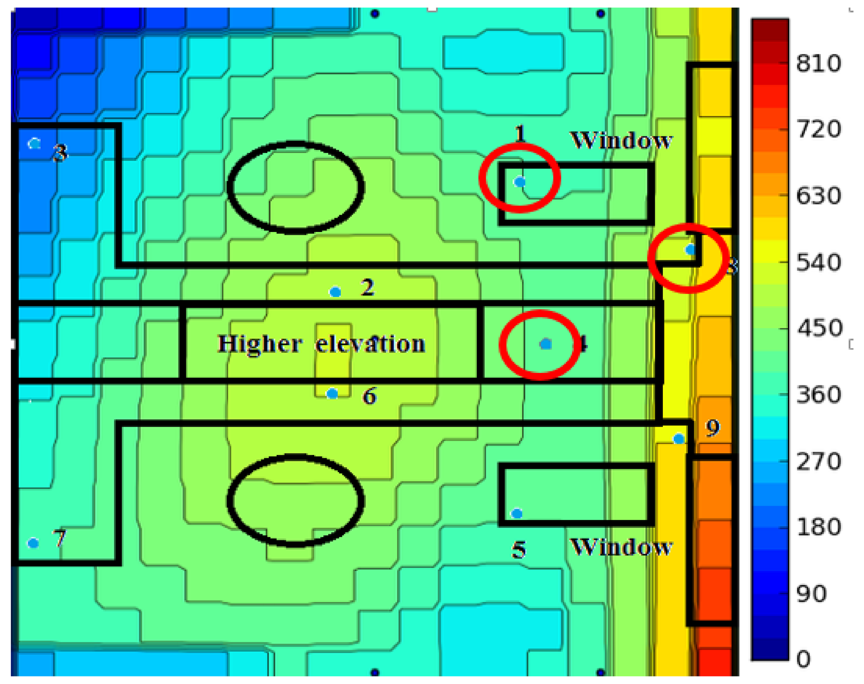
TelosB mote



Energy savings data for BEST lab lighting system



Distribution of daylight level for different cloudy sky conditions shows lack of consistency between weather station data and on-site condition.



Distribution of light for areas of a square meter to compute daylight autonomy, a major component of LEED green building certification.

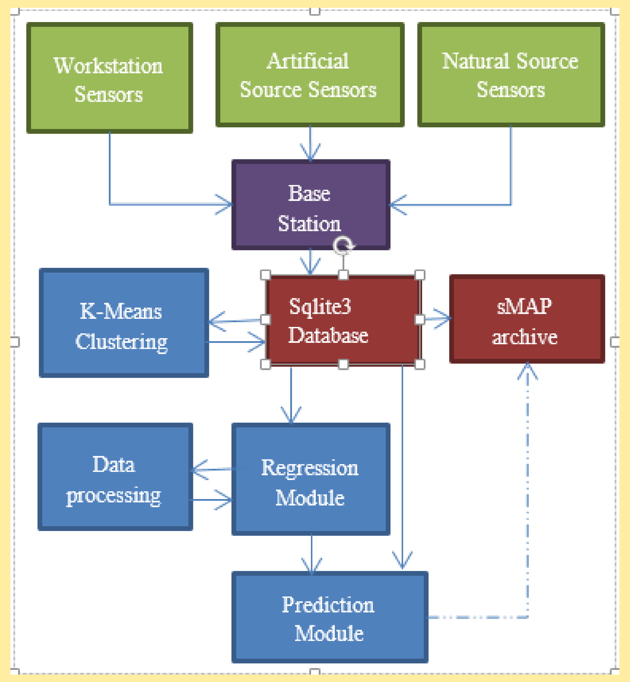
Technology design

Software

Calibration phase:Wireless sensors are deployed and the local server builds a probabilistic inverse model that can predict the light level within error bounds.

Optimal Sensor Placement Phase: The local server computes an optimal sensor placement that places a subset of the sensors in the room to minimize prediction error.

Operation Phase: The inverse model predicts the light level at any point in the building and this prediction gives way to intelligent actuation of lights.

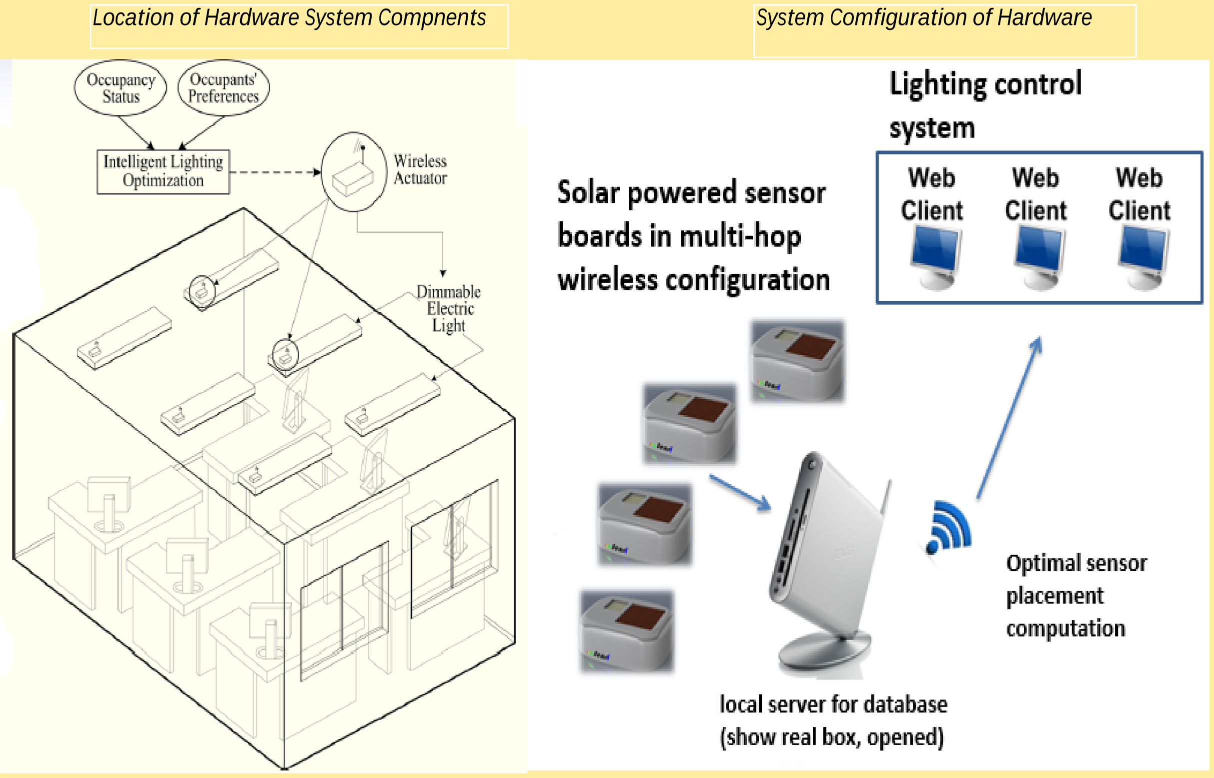


Software flowchart

Hardware

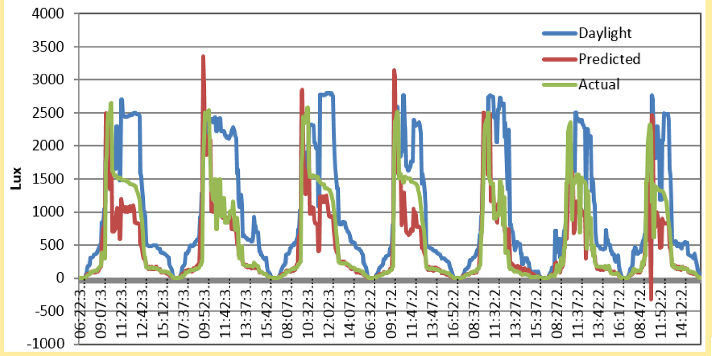
A network of wireless light sensors send data via a multi-hop network to a local server, located on each floor of a building, which carries out computations for light level predictions and optimal sensor placement.

The local server communicates with a web client that carries out actuation via wireless dimming ballasts embedded in each light.



Results

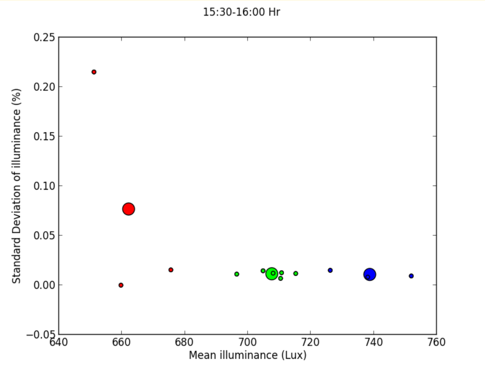
Best Lab Testbed



After training our models on the data received by the full set of deployed sensors, an optimally-placed subset of the sensors achieved 75-95% accuracy when predicting the readings of the other sensors with 1 of the sensors.

NASA Ames Testbed

The inverse model algorithm was able to achieve approximately 70% accuracy across the testbed at NASA Ames Sustainability base. Research shows that this is within the human percievable change in light level.



Measured light data from 12:30 P.M. -1:00 P.M. clustered by 30 minutes of mean and standard deviation

comparative analysis

Technology	Components	Features	Costs
Enlighted Inc.	Multi-sensor board per fixture, a few gateways per floor, central energy management software	automated Sensor placement template, occupancy based control	$8.35/square meter
inSense	Multi-sensor board, a few gateways per floor, data mining software with virtual sensors	Optimal sensor placement customized to each building, indoor lighting condition model	$4/square meter

Beats Best of Market: Our sensor technology is half the cost of Enlighted's sensor technology, the current best in the field of smart lighting sensor technology. Our system optimizes the number and placement of sensors for a building's architecture and a company's energy and cost budget.

Potential Partner: NEXT Lighting offers a full sensor and lighting system, but is more focused on efficient lighting. We would extend the capabilities of their sensor systems through our robust probabilistic models and increase affordability

Impacts

- Extends capabilities of current smart lighting systems
- Energy cost savings in commercial buildings: $5.20 per squared meter
- Installation Cost Savings: 84% over systems with sensors at every light fixture
- Resultant nationwide energy savings in commercial buildings: 60,000 GWh/year
- Increases adoption of smart lighting systems nationwide

Components of Sensor Package showing wireless mote and power management board for solar panel

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http://best.berkeley.edu/drupal/node/27

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Tyndall Institute:
http://www.tyndall.ie/
Cymbet Corporation (Energy Harvester Kits):
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