A Self-Powered Room Occupancy Sensing System

Nayiri Krzysztofowicz, Will Define, Kathryn Wason, Bryan Rombach

***Abstract*—Students spend large amounts of time searching for suitable study areas, as workspaces are often too crowded or loud. Study conditions also vary based on the time of day, and currently no method exists to determine study area conditions in real-time without visiting the location. We propose a system that monitors study area noise, room occupancy, light, and temperature, displaying this information remotely to students. Using public indoor light datasets, we determined that our system requires under 2 mF of energy storage to survive in the lowest 2% of light conditions.**

Keywords—occupancy sensing, indoor light, self-powered system, Internet of Things (IoT)

I. Introduction

The recent rise of the Internet of Things (IoT) has brought on the development of "smart buildings," buildings that allow automated and remote monitoring and control of various operations. One such monitoring application is for room conditions, to efficiently manage interior spaces for large organizations such as businesses or universities. Our proposed system is an indoor light-powered network of ceiling-mounted nodes that sense room noise, occupancy, lighting, and temperature, and periodically transmit this information to a central hub for processing and display.

The feasibility of such monitoring has already been demonstrated. In [1], the number of people in a room was accurately determined using a variety of ambient sensors. In [2], a self-powered Bluetooth occupancy sensor capable of detecting room occupancy and adjusting room lighting was developed. Battery-powered versions of our system are already commercially-available. One such product senses temperature, humidity, noise, atmospheric pressure, and different gas levels such as CO2, ozone, and Radon [3]. Another product, VergeSense, constructs a map of room occupancy using ceiling-mounted sensors [4], with an advertised three-year battery life. Fig. 1 shows cost savings for a battery-less version of VergeSense.

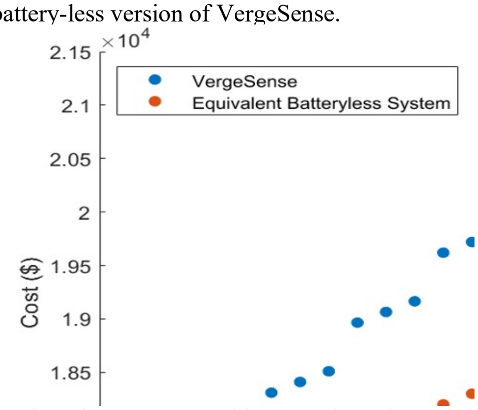

Fig. 1: Total cost for a company requiring 50 sensing nodes, assuming 15 minute battery replacement per sensor every 3 years, $15/hr labor costs, and commercial prices for the 6 AAA batteries required.

II. Architecture and Design

The proposed block diagram for each sensing node is shown in Fig. 2, and the system-level architecture is shown in Fig. 3. A ceiling-mounted setup was selected to use an imaging sensor for the occupancy sensing, which according to literature was the best way to acquire occupancy data.

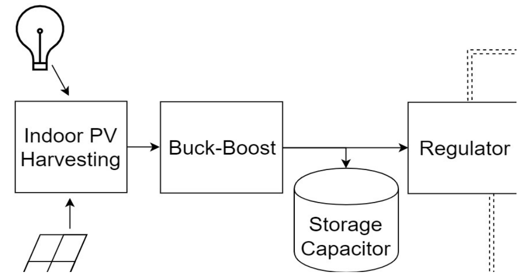

Fig. 2: Sensing node block diagram.

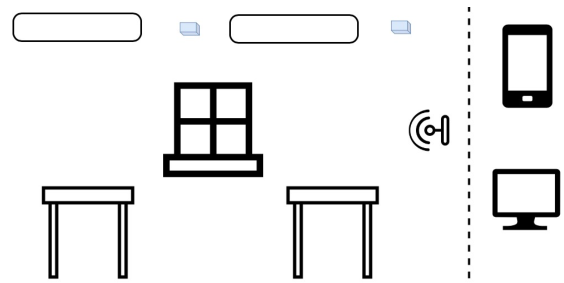

Fig. 3: Proposed system level architecture, with ceiling-mounted nodes.

III. Energy Harvesting Environment

A. Columbia Indoor Energy Availability Study

Columbia University conducted an indoor light energy study by collecting irradiance (W/cm^2) measurements in six different locations in their New York City office buildings. Locations were labeled A-F, described in Table I. Fig. 4 shows plots of key traces for these datasets.

TABLE I. Columbia Light Measurement Locations

Name	Direction	Description
A	South	windowsill; shading always used
B	South	bookshelf far from window; same office as A
C	North	windowsill; large windows, shading use varied
D	S-West	windowsill; shading extensively used
E	South	windowsill; limited shading use; directly below A
F	East	windowsill; window often kept partly open

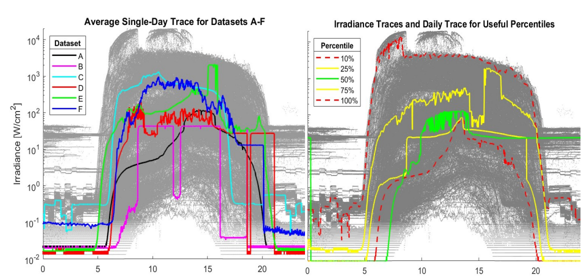

Fig. 4: Left - trace with an average irradiance equal to the average irradiance of the entire location; in other words, these traces reflect what a "typical" trace for a location was. Right - traces representing different percentiles of the data, from the 10th to 100th percentile.

B. Intel Berkeley Research Lab Study

The Intel Berkeley Research Lab deployed 54 sensors in their lab area and collected light data (in Lux) over a few months. Key traces are plotted in Fig. 5.

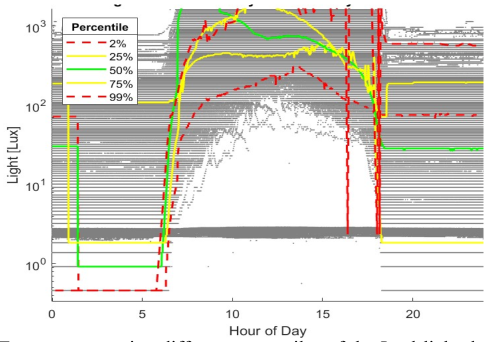

Fig. 5: Traces representing different percentiles of the Intel light data, from the 2nd to 99th percentile.

IV. Load System

The required load components for our system were benchmarked, with selected components listed in Table II. The component power consumption was plotted as a function of duty cycle in Fig. 6, with operating points along each curve selected based on sensor sampling requirements. From these operating points, the load trace was generated in Fig. 7, with the system sensing for 3 seconds every five minutes.

TABLE II. Load system

Type	Name	Voltage [V]	Active Power [uW]	Idle Power [uW]
Microphone	ADMP803	0.9	15.3	9
Image sensor	Hanson_VLSI 2009	0.5	1.2	0.7
Temp sensor	TSYS02D	1.5	27	0.03
Light sensor	OPT3001DNPR	1.6	5.92	0.48
MCU	PIC16F1503	1.8	864	0.468

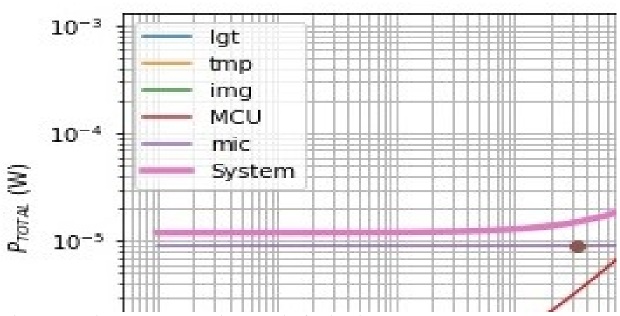

Fig. 6: Total power versus duty cycle for load system

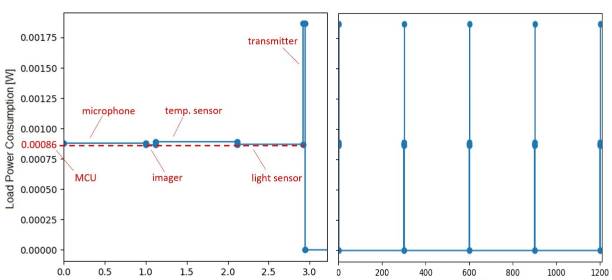

Fig. 7: Load power usage for one sample (left) and over 20 minutes (right).

V. System Modeling

The indoor light data had to be combined with the load model to assess the performance of our system. In [5], amorphous silicon photovoltaic cells were shown to generate the most power in the presence of indoor light, and this linear relationship was applied to the Intel light dataset percentile traces to generate power traces. These traces were simulated with our load model while sweeping storage capacitance values. The minimum storage capacitance for which the capacitor did not discharge overnight was selected. Fig. 8 shows the percentile light traces and corresponding capacitor voltages plotted for a two-day period. The capacitor values were all around 1 mF, varying very little with percentile amount. Fig. 9 shows the "minimum" trace (2%) and corresponding capacitor voltage plotted over a week, demonstrating that the system would survive even with abnormally sustained periods of low light.

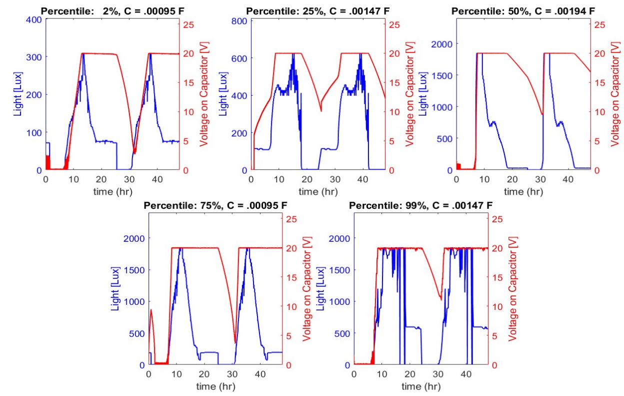

Fig. 8: Intel Lux traces and corresponding capacitor voltage and capacitance.

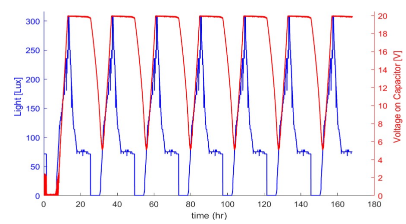

Fig. 9: Minimum Lux trace (2%) and capacitor voltage over a week.

VI. Conclusion

In this paper we presented a battery-less, self-powered room condition sensing platform. Using two public datasets comprising millions of indoor light values, our load system was simulated over a range of indoor light traces, having an average Lux in the lowest 2% to the highest 99% of the data.

Acknowledgments

Benton Calhoun, Henry Bishop, and Shuo Li for their guidance on this project.

References

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