Indoor Light Harvesting to Power IoT: Diffuse Light to Structured Information

Richard Freitag
IT-Division
Uppsala University
Dag Hammarskjölds väg 7
753 27 Uppsala, Sweden
richard.freitag@uu.se

Hannes Michaels
Chemistry Department
Ångströmlaboratoriet
Uppsala University
Lägerhyddsvägen 1
751 20 Uppsala, Sweden
hannes.michaels@kemi.uu.se

Dr Marina Freitag
School of Natural and
Environmental Science
Bedson Building
Newcastle University
NE1 7RU Newcastle upon Tyne
marina.freitag@newcastle.ac.uk

CHI'20,, April 25–30, 2020, Honolulu, HI, USA
ACM 978-1-4503-6819-3/20/04.
https://doi.org/10.1145/3334480.XXXXXXX

Abstract

UPDATED—February 11, 2020. The Internet of Things is set to define technology for the next decades, but current designs are strongly limited by their choice of energy supply. Grid-connected devices have to be placed close to available power-outlets, and battery-operated devices have to be designed to save energy and require regular maintenance. Efficient indoor light harvesters provide energy quantities which generally cannot be achieved using other types of energy harvesters. Simultaneously, a new design and energy paradigm to IoT devices is introduced, to maximize their ability to sense, communicate, and predict. The collection of ambient light offers vast universally available energy, which can be used to design near-perpetual smart IoT devices that can directly convert diffuse light energy to computational inferences based on artificial neural networks and other machine learning techniques. We discuss state of the art Indoor photovoltaic (IPV) light harvesters, and their impact on the design of modern IoT devices and sensor networks.

Author Keywords

Indoor Light Harvesting; Self-powered IoT; IoT; Internet of Things; Dye Sensitized Solar Cells; Machine Learning

CCS Concepts

•Computing methodologies → Cooperation and coordination; •Hardware → *Wireless integrated network sensors; Renewable energy;* Impact on the environment; Sensor devices and platforms;

Introduction

Intelligent wireless devices are rapidly evolving into indispensable assistants in numerous facets of our near future world. Merged with machine learning, wireless sensor networks are poised to advance the interchange of information in smart homes, offices, cities or factories. By 2025, an estimated 30 billion IoT devices are expected to be installed, the vast majority of which are to be placed indoors or in diffuse light conditions. IoT devices and wireless sensor nodes (WSN) will need to harvest energy from the environment for long-term deployment and operation. Indoor photovoltaic (IPV) cells have the potential to provide the required energy. The power needed to operate these devices continues to decrease, while conversion efficiencies and hence the power output of indoor photovoltaic cells is rapidly increasing. When located indoors with no access to solar irradiance, IPV cells harvest the energy emitted by artificial light sources, with the illumination intensity typically several orders of magnitude less than sunlight. Dye-sensitized IPV cells have shown considerable efficiency progress of late, with values over 30% measured under 200–1,000 lux light intensity.

The implementation of light-driven autonomous devices leads to a paradigm shift of energy usage, where high entropy diffuse light is transformed into structured information in an autonomous IoT device. Unlike wired or battery-supported systems, all surrounding energy can be harvested and used to the maximum of its availability. A microcontroller with a small energy buffer can be directly powered from harvested ambient light, executing the essential workloads of an IoT device: process, sense, and communicate [4].

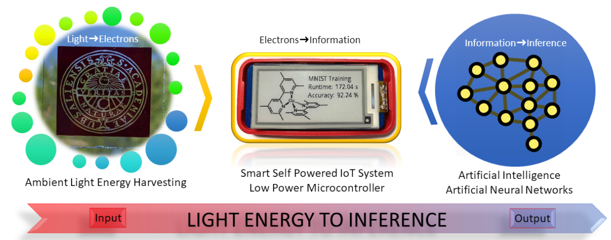

Figure 1: Schematic representation of a self-powered IoT device in indoor light condition, capable of advanced machine learning.

Intermittent and adaptive sleep ensures an equilibrium between harvested and consumed energy, even under ambient light conditions, optimizing its workload execution. As a consequence, the question *if* the implementation of IoT devices will yield direct energy savings becomes a question of *how much* energy savings it will yield [5].

Efficient ambient light harvesting

In outdoor photovoltaics, a significant portion of the sun's spectrum is found in the red region of the visible light and at near-infrared wavelengths, which suits the strong spectral response of crystalline silicon or GaAs-based solar cells in this wavelength domain. On the contrary, the largest part of indoor illumination spectra, most commonly originating from CFL or LED lamps, is found in the visible range between 400 and 650 nm. In this spectral region, diffuse ambient light provides universally available energy, which otherwise remains unused. Fast charge separation in a variety of co-sensitized colored organic dyes and tuneable energy levels in Cu(II/I) electrolyte systems combined with negligible recombinative processes allow DSCs to maintain a high photovoltage, especially under ambient light. Combination of organic dyes enables light absorption over a broad spectral range and therefore the adaption to the majority of light sources that emit in the visible region [12], [3]. Currently stated power densities of less than 10 μW/cm^2 for indoor light harvesting devices [17] are being exceeded by state of the art dye-sensitized solar cells (DSCs) to power densities of 15-100 μW/cm^2 at 200 and 1000 lux [2]. This pushes DSCs beyond GaAs solar cells for use in diffuse light conditions, while being cheaper to produce and more environmentally friendly [9]. The conversion of ambient light offers broadly available energy and paves the way to extensive implementation of self-powered devices.

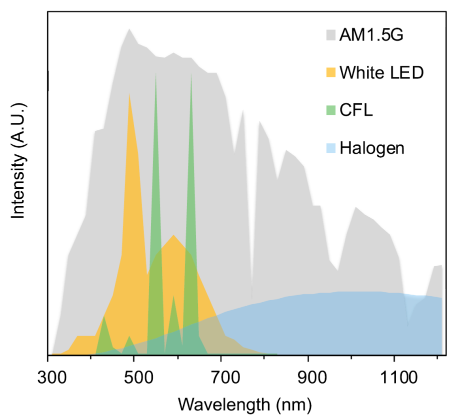

Figure 2: Outline of the different light spectra under which photovoltaic device efficiency is evaluated including the standard solar spectrum (AM1.5G) and typical spectra from White LED, CFL, and Halogen sources. ©2019 Elsevier Inc [8].

Low power IoT

At its core, IoT comprises of a variety of platforms, with the Raspberry Pi being one of the more prominent systems. Self-powered architectures based on these platforms still require relatively large amounts of energy and have to be powered by solar cells under stronger illumination and equipped with an energy buffer for continuous operation [1]. However, using indoor light harvesters at 1000 lux illumination, a 64 cm^2 photovoltaic area suffices to harvest 152J of energy required for training and verification of 60 000 MNIST images with 10 000 verification images, resulting in >90$\%$ prediction accuracy [10]. Using indoor light harvesters, energy-efficient microcontrollers consuming $\sim$10-100μA/MHz in operating mode [11] and <30nA in sleep mode [6] are the currently preferred platform for self-powered IoT devices. Using an approximate value of about 100 μW/MHz (at operating voltages of 3-5V), and 100μW/cm^2 photovoltaic yield at 1000 lux, an average of 1 MHz/cm^2 can be harvested from indoor light using DSC IPV cells.

Current designs of wireless sensor nodes, capable of sensing multiple environemntal variables and communicating them to a base station, are designed based on an energy-saving paradigm [14]. This design shifts to an energy-maximizing paradigm upon the use of IPV light harvesters. Table 1 shows theoretical harvesting times to attain energy quantities similar to those stored in battery types commonly used in IoT devices. Compared to battery-powered devices designed to run for month or years, energy-maximizing harvesting devices can use the additional energy for decreased sensing and communication intervals, or increased data processing, such as inferences through machine learning.

Efficient machine learning

Machine learning (ML), as a subfield of Artificial Intelligence, was established in 1959, and has since then evolved into numerous branches, including artificial neural networks and deep learning [15]. Recent development has shown that microcontrollers are capable of executing Bayesian ma-

Battery	*mAH*	*Joule*	*Days to harvest*
AA	2400	12960	15.8
AAA	1000	5400	6.6
CR2032	200	2160	1.3

Table 1: Days required to harvest power capacities provided by typical batteries, using an $8x8cm^2$ photovoltaic area at 1000 lux constant illumination.

chine learning [7] or pre-trained artificial neural networks, and thus are able to classify and infer information directly on the device, rather than having to rely on server-side execution. In order to suffice to the low memory requirements of microcontrollers, floating-point numbers can be converted to 1-byte fixed-point numbers, reducing the memory requirements by a factor four, with a loss in accuracy found to be no larger than 0.1% with respect to the full precision network [19]. Most recent research even pushes the memory limits towards sub-byte deep neural networks on microcontrollers, promising computation performance and energy efficiency improvements of 1.83x and 2.28x on average, respectively [18].

Architecture, Integration, and Interaction

Having an abundance of near-perpetual IoT devices in place requires adjustments to existing designs for wireless sensor networks [16], or even require the development of completely new architectures, implementing the energy-maximizing paradigm of energy harvesting. Integration of hundreds or even thousands of maintenance-free wireless nodes will result in topologies considering varying amounts of available energy, but also optimize the trade-offs between energy-intensive wireless communication and on-device decision making. Interaction paradigms will be defined by the scope of the sensor networks. For human-device interaction, low-energy interfaces will be used (e.g., e-ink displays for unidirectional information exchange). Machine to machine (M2M) interaction will strongly be influenced by its energy-availability, resulting in highly adaptive architectures.

Conclusion

The global market for artificial intelligence is estimated to exceed 3 trillion USD by 2024. This will partially be driven by an abundance of ubiquitous sensing devices, providing coherent information for augmented intelligence systems. These systems will provide environmental information not only for human-to-machine communication, but mainly for machine-to-machine communication required for many robotics and autonomous systems currently being developed [13]. This requires a large amount of near-perpetual and maintenance-free IoT devices whose energy-requirements can be met by harvesting diffuse light. Driving forces for the improvement of these systems will be

- stability and efficiency improvements in commercially available IPV light harvesters,
- improvements in energy-storage techniques, especially alternative energy storage methods,
- energy-efficient CPUs/MCUs, wireless communication devices and sensors,
- and the development of efficient computing techniques

enabling self-powered IoT devices and topologies with higher levels of environmental- and self-awareness.

Ambient light harvesters provide a new generation of self-powered and “smart” IoT devices powered through an energy source that is largely untapped. Indoor photovoltaics combination of high efficiency and low cost with non-toxic materials is of paramount importance to IoT sustainability.

Acknowledgements

This work was supported by the Royal Society University Fellowship (URF\R1\191286), Swedish Energy Agency (43294-1), Swedish Research Council (2018-04570), Göran Gustafsson Young Researcher Prize and Olle Engkvist Byggmästare Stiftelsen (184-482).

REFERENCES

[1] 2020. How to Build a Low-tech Website? (2020). https://solar.lowtechmagazine.com/2018/09/how-to-build-a-lowtech-website.html

[2] Marina Freitag, Joël Teuscher, Yasemin Saygili, Xiaoyu Zhang, Fabrizio Giordano, Paul Liska, Jianli Hua, Shaik M. Zakeeruddin, Jacques-E. Moser, Michael Grätzel, and Anders Hagfeldt. 2017. Dye-sensitized solar cells for efficient power generation under ambient lighting. *Nature Photonics* 11, 6 (June 2017), 372–378. DOI:http://dx.doi.org/10.1038/nphoton.2017.60

[3] Anders Hagfeldt, Gerrit Boschloo, Licheng Sun, Lars Kloo, and Henrik Pettersson. 2010. Dye-Sensitized Solar Cells. *Chemical Reviews* 110, 11 (Nov. 2010), 6595–6663. DOI: http://dx.doi.org/10.1021/cr900356p

[4] R. Haight, W. Haensch, and D. Friedman. 2016. Solar-powering the Internet of Things. *Science* 353, 6295 (July 2016), 124–125. DOI: http://dx.doi.org/10.1126/science.aag0476

[5] Eric Hittinger and Paulina Jaramillo. 2019. Internet of Things: Energy boon or bane? *Science* 364, 6438 (April 2019), 326–328. DOI: http://dx.doi.org/10.1126/science.aau8825

[6] Hrishikesh Jayakumar, Arnab Raha, and Vijay Raghunathan. 2014. Hypnos: An ultra-low power sleep mode with SRAM data retention for embedded microcontrollers!. In *2014 International Conference on Hardware/Software Codesign and System Synthesis (CODES+ISSS)*. 1–10. DOI: http://dx.doi.org/10.1145/2656075.2656089

[7] Charles Leech, Yordan P. Raykov, Emre Ozer, and Geoff V. Merrett. 2017. Real-time room occupancy estimation with Bayesian machine learning using a single PIR sensor and microcontroller. In *2017 IEEE Sensors Applications Symposium (SAS)*. 1–6. DOI: http://dx.doi.org/10.1109/SAS.2017.7894091

[8] Ian Mathews, Sai Nithin Kantareddy, Tonio Buonassisi, and Ian Marius Peters. 2019. Technology and Market Perspective for Indoor Photovoltaic Cells. *Joule* 3, 6 (June 2019), 1415–1426. DOI: http://dx.doi.org/10.1016/j.joule.2019.03.026

[9] Ian Mathews, Gerard Kelly, Paul J. King, and Ronan Frizzell. 2014. GaAs solar cells for Indoor Light Harvesting. In *2014 IEEE 40th Photovoltaic Specialist Conference (PVSC)*. 0510–0513. DOI: http://dx.doi.org/10.1109/PVSC.2014.6924971 ISSN: 0160-8371.

[10] Hannes Michaels, Michael Rinderle, Richard Freitag, Iacopo Benesperi, Tomas Edvinsson Edvinsson, Richard Socher, Alessio Gagliardi, and Marina Freitag. 2020. Dye-sensitized Solar Cells under Ambient Light Powering Machine Learning: Towards Autonomous Smart Sensors for the Internet of Things. *Chemical Science* (2020).

[11] Masami Nakajima, Ichiro Naka, Fumihiro Matsushima, and Tadaaki Yamauchi. 2016. A 20uA/MHz at 200MHz microcontroller with low power memory access scheme for small sensing nodes. In *2016 IEEE Symposium in Low-Power and High-Speed Chips (COOL CHIPS XIX)*. 1–3. DOI:http://dx.doi.org/10.1109/CoolChips.2016.7503677

[12] Brian O'Regan and Michael Grätzel. 1991. A low-cost, high-efficiency solar cell based on dye-sensitized colloidal TiO 2 films. *Nature* 353, 6346 (Oct. 1991), 737–740. DOI:http://dx.doi.org/10.1038/353737a0

[13] Javier Andreu Perez, Fani Deligianni, Daniele Ravi, and Guang-Zhong Yang. 2018. Artificial Intelligence and Robotics. *arXiv:1803.10813 [cs]* (March 2018). http://arxiv.org/abs/1803.10813 arXiv: 1803.10813.

[14] Felix Pflaum, Robert Weigel, and Alexander Koelpin. 2018. Ultra-low-power sensor node with wake-up-functionality for smart-sensor-applications. In *2018 IEEE Topical Conference on Wireless Sensors and Sensor Networks (WiSNet)*. 107–110. DOI:http://dx.doi.org/10.1109/WISNET.2018.8311577 ISSN: 2473-4624.

[15] A. L. Samuel. 1959. Some Studies in Machine Learning Using the Game of Checkers. *IBM Journal of Research and Development* 3, 3 (July 1959), 210–229. DOI:http://dx.doi.org/10.1147/rd.33.0210

[16] TiwariAnkit, BallalPrasanna, and LewisFrank L. 2007. Energy-efficient wireless sensor network design and implementation for condition-based maintenance. *ACM Transactions on Sensor Networks (TOSN)* (March 2007). https://dl.acm.org/doi/abs/10.1145/1210669.1210670

[17] Rudd J.M. Vullers, Rob van Schaijk, Hubregt J. Visser, Julien Penders, and Chris Van Hoof. 2010. Energy Harvesting for Autonomous Wireless Sensor Networks. *IEEE Solid-State Circuits Magazine* 2, 2 (2010), 29–38. DOI:http://dx.doi.org/10.1109/MSSC.2010.936667

[18] YuJiecao, LukefahrAndrew, DasReetuparna, and MahlkeScott. 2019. TF-Net. *ACM Transactions on Embedded Computing Systems (TECS)* (Oct. 2019). https://dl.acm.org/doi/abs/10.1145/3358189

[19] Yundong Zhang, Naveen Suda, Liangzhen Lai, and Vikas Chandra. 2018. Hello Edge: Keyword Spotting on Microcontrollers. *arXiv:1711.07128 [cs, eess]* (Feb. 2018). http://arxiv.org/abs/1711.07128 arXiv: 1711.07128.