Dataset: Tracing Indoor Solar Harvesting

Lukas Sigrist
ETH Zurich
Computer Engineering and Networks Laboratory
Zurich, Switzerland
sigristl@ethz.ch

Andres Gomez
ETH Zurich
Computer Engineering and Networks Laboratory
Zurich, Switzerland
gomeza@ethz.ch

Lothar Thiele
ETH Zurich
Computer Engineering and Networks Laboratory
Zurich, Switzerland
thiele@ethz.ch

ABSTRACT

Energy harvesting is finding widespread use as a long-term energy supply for the Internet of Things (IoT). The dependency of these devices on the spatially and temporally variable environment further complicates reliable application design. We present a long-term indoor solar harvesting dataset to support the modeling, analysis, calibration and evaluation of energy harvesting systems. More than 2 years of joint high accuracy power and ambient condition traces were collected at 6 diverse indoor locations. The dataset provides a solid foundation for the design and validation of energy prediction, energy management and run-time adaptation schemes. The detailed description of the measurement setup and the resulting dataset is accompanied by the public release of the dataset, as well as the hardware design of the measurement platform and code examples for post-processing the dataset in R and Python.

CCS CONCEPTS

• **Hardware → Sensor applications and deployments**; **Energy generation and storage**; **Renewable energy**; • **General and reference → Measurement**.

KEYWORDS

Energy Harvesting, Dataset, Solar, Environment, Internet of Things

ACM Reference Format:
Lukas Sigrist, Andres Gomez, and Lothar Thiele. 2019. Dataset: Tracing Indoor Solar Harvesting. In *Proceedings of DATA '19: 2nd Workshop on Data: Acquisition to Analysis (DATA '19).* ACM, New York, NY, USA, 4 pages. https://doi.org/http://dx.doi.org/xx.xxxx/xxxxxxx.xxxxxxx

1 INTRODUCTION

Energy Harvesting is seen as key enabler to supply the emerging Internet of Thing (IoT) in a long-term and efficient manner. Extracting energy from the ambient makes these systems and their operation inherently dependent on the non-deterministic and highly variable environment conditions. Systems relying on energy harvesting as energy supply therefore need to tolerate [2] or adapt [1] to variable harvesting conditions. Data from the spatial and temporal variable environment and the energy that can be extracted through harvesting are highly valuable for dimensioning, calibrating and testing such systems. For outdoor solar harvesting extensive irradiation data is available from weather service stations around the world, typically reaching back many decades. In contrast, indoor solar harvesting data is only sparsely available, but becoming increasingly critical for many Internet of Things applications that target deployment in this environment like building automation and assisted living.

DATA '19, November 10, 2019, New York, NY

ACM ISBN 978-1-xxxx-xxxx-x/19/11.
https://doi.org/http://dx.doi.org/xx.xxxx/xxxxxxx.xxxxxxx

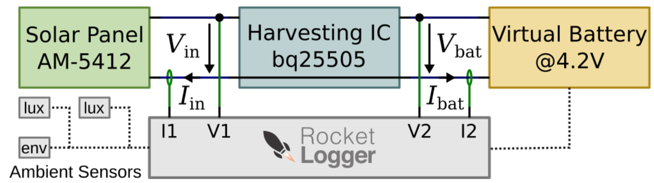

Figure 1: High-level schematic of the measurement setup. For details see the publicly released hardware design.

We present an extensive dataset that addresses the lack of long-term indoor solar harvesting traces. While others have performed illuminance measurements in indoor environments [3], we are the first to jointly monitor the extracted energy from the solar panel, the energy stored in the battery, and the ambient conditions. The combination of power measurements using a real harvesting system implementation and rich ambient sensor data enables diverse opportunities for analysis and evaluation, including power estimation, energy harvesting source modeling, and harvesting system efficiency analysis, to mention a few. The co-location with the widely adopted FlockLab testbed for distributed network protocol evaluation [4] enables energy aware design and testing of network protocols based on real-world harvesting traces.

We release the dataset together with data processing examples for the popular Python pandas and R data analysis frameworks. Furthermore, we make the hardware design available that can be used for consistent and comparable tracing of the harvesting power and ambient conditions.

2 MEASUREMENT SETUP AND DEPLOYMENT

For measuring the harvested energy and the ambient conditions we use a custom designed monitoring platform. The platform consists of a solar panel (AM-5412, 50 mm × 33 mm) connected to a maximum power point tracking DC-DC boost converter (bq25505) that stores the harvested energy in a virtual battery circuit. The battery emulation circuit keeps the harvester output operating point fixed at a typical battery voltage level of 4.2 V to guarantee consistent and comparable harvesting measurements. Two TSL45315 light

Table 1: Overview of the monitoring positions: characteristics, measurement timespan, and co-located FlockLab nodes.

#	Deployment Description and Sunlight Exposure	Timespan (YYYY-MM-DD)	Daily Energy	FlockLab
06	Employee office, wall mounted at 2.4 m, little natural light with increased level in the late afternoon and during summer, no direct sun exposure	2017-07-27 – 2019-06-17	2.02 ± 1.64 J	004
13	Student office, wall mounted at 2.0 m, some natural light with increased level in morning hours and during summer, no direct sun exposure	2017-07-27 – 2019-08-01	1.57 ± 1.28 J	032
14	Laboratory, wall mounted at 2.1 m, significant natural light with increased level and potential direct sunlight in morning hours and during summer	2017-07-27 – 2019-08-01	14.18 ± 11.67 J	011
16	Employee office, table mounted and facing towards ceiling, significant natural light with increased level in the afternoon, no direct sun exposure	2019-06-18 – 2019-08-01	7.07 ± 1.50 J	*N/A*
17	Employee office, wall mounted at 2.4 m, significant natural light with increased level in the afternoon, no direct sun exposure	2017-07-27 – 2019-08-01	2.87 ± 2.36 J	016
18	Hallway, wall mounted at 2.2 m, no natural light, only little, indirect artificial light due to high wall mount mounting position	2017-07-27 – 2019-08-01	0.19 ± 0.12 J	023

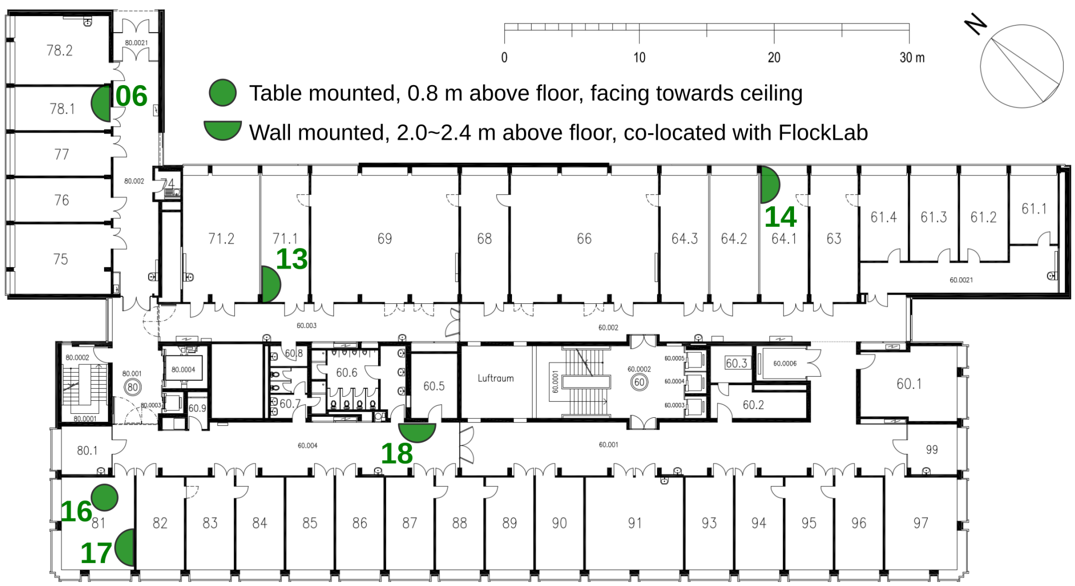

Figure 2: Floor plan with the deployed measurement positions. The rounded part of the position markers indicate the directions from which light reaches the solar panel.

sensors placed on opposite sides of the solar panel monitor the illuminance level, while a BME280 sensor logs additional ambient conditions like temperature, humidity and air pressure.

The solar harvesting and ambient monitoring platform is designed as an I^2C extension for the RocketLogger platform [5]. The logger is used for measuring of the energy flow at the input and the output of the bq25505 harvesting circuit and for logging the ambient sensors. The energy extraction and control circuitry of the battery emulation and the ambient sensors are supplied from the RocketLogger. The high level schematic of the fully integrated measurement setup is shown in Figure 1. More details are found in the hardware design of the monitoring platform, which is also released to the public as part of this publication[1].

Five of the measurement platforms are deployed in office rooms of our institute at ETH Zurich, Zurich, Switzerland. The exact locations of the deployment and the alignment of the rooms are shown on the floorplan in Figure 2. The locations were selected to have high diversity in terms of orientation, mixture of artificial and natural light, direct or indirect sunlight exposure at different times of the day, and occupancy patterns. The chosen rooms are either used as permanently occupied employee offices, part-time occupied student offices, or sporadically used labs. Furthermore, the positions are co-located with existing observer nodes of the FlockLab testbed [4] to facilitate the use in network protocol design. The details on the positions and their specific characteristics are summarized in Table 1.

[1]available at: https://gitlab.ethz.ch/tec/public/employees/sigristl/harvesting_tracing

Table 2: The data columns of the processed power measurements. These values are sampled at a rate of 10 Hz.

Name	Description	Unit
index	Network synced measurement timestamp	timestamp
`V_in`	Converter input/solar panel output voltage	Volt
`I_in`	Converter input current (solar panel output)	Ampere
`V_bat`	Battery voltage (emulated through circuit)	Volt
`I_bat`	Net Battery current, in/out flowing current	Ampere
`dt`	Time delta between measurements	Seconds

Table 3: The data columns of the processed sensor measurements. These values are sampled at a rate of 1 Hz.

Name	Description	Unit
index	Network synced measurement timestamp	timestamp
`Ev_left`	Illuminance left of solar panel	Lux
`Ev_right`	Illuminance left of solar panel	Lux
`P_amb`	Ambient air pressure	Pascal
`RH_amb`	Ambient relative humidity, between 0 and 1	Unit-less
`T_amb`	Ambient temperature	degree °C
`dt`	Time delta between measurements	Seconds

3 DATASET

The dataset [6] consists of power and ambient measurement traces from the positions described above. The ongoing measurement campaign was started in July 2017, the data availability for all positions is listed in Table 1. Furthermore, the table includes the average daily energy yield, including the 75 % percentile of the absolute deviation from the mean. For each position we include the raw RocketLogger measurement traces that are split into many parts and separated by power and ambient measurements. The power measurements are sampled at a data rate of 10 Hz, while ambient measurements are performed at a rate of 1 Hz. Beside this raw data, we provide a merged and filtered series of all measurements for each position in the HDF5 data format. This allows for fast import and processing in a wide range of analysis tools.

The HDF5 dataset stores the data timestamps as UNIX nanoseconds in the `dataset/axis1` data block. The actual measurement values are stored in the `dataset/block0_values`, and the corresponding column names in the `dataset/block0_items` data blocks. The individual columns and their units are listed in Table 2 for the power and in Table 3 for the ambient measurements. The file structure allows direct loading of the data using the Python pandas' DataFrame import functionality, or generating a timeseries sturcture in R. The import procedures and further post processing sample code for Python and R are provided along with the dataset. An overview of two analysis use cases included in these scripts is given below.

4 DATASET ANALYSIS USE CASES

We complement the dataset with two Jupyter notebooks that demonstrate the import and use of the dataset in both Python and R. Here we discuss the results of two use cases included in the notebooks.

Energy Prediction Performance As part of the Python notebook we compare the performance of three prediction schmes that predict the average power for the next 5 min interval. The result of this analysis is shown in Figure 3 and demonstrates that a simple conservative prediction of the value observed in the current interval achieves a high prediction accuracy.

DC-DC Conversion Efficiency In the provided R notebook the energy efficiency of the bq25505 harvesting chip is analyzed. The analysis shown in Figure 4 reveals that a high conversion efficiency is achieved already at input power levels only minimally above the minimum required input power.

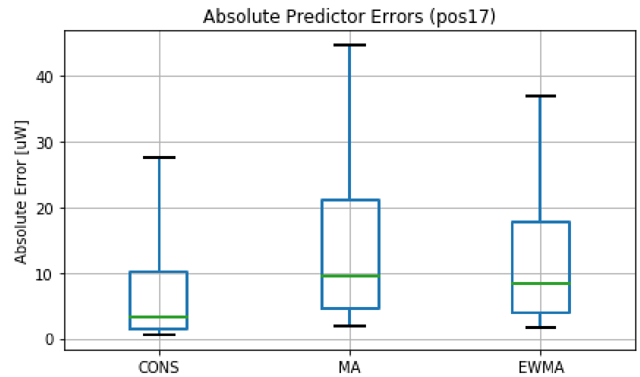

Figure 3: Error analysis for short-term energy prediction for the data of position 17. The simple conservative predictor (*CONS*) demonstrates a very good performance in comparison to the moving average (*MA*) and exponentially weighted moving average (*EWMA*) predictors.

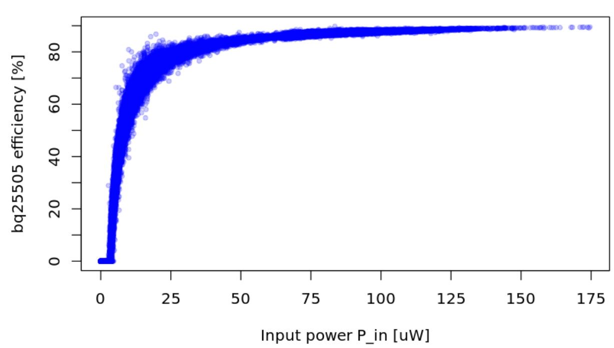

Figure 4: Efficiency of the bq25505 as a function of the input power for all operating points observed at position 06. After reaching the minimal input power of about 6 µW to get the harvesting chip operating, the efficiency of the bq25505 increases very quickly and is close to the optimal efficiency for input power levels higher than 20 µW.

ACKNOWLEDGMENTS

This research was funded by the Swiss National Science Foundation under grant 157048: Transient Computing Systems.

REFERENCES

[1] R. Ahmed, B. Buchli, S. Draskovic, L. Sigrist, P. Kumar, and L. Thiele. Optimal Power Management with Guaranteed Minimum Energy Utilization for Solar Energy Harvesting Systems. *ACM TECS*, 18(4), 2019.

[2] A. Gomez, L. Sigrist, T. Schalch, L. Benini, and L. Thiele. Efficient, Long-Term Logging of Rich Data Sensors using Transient Sensor Nodes. *ACM TECS*, 17(1), 2017.

[3] M. Gorlatova, A. Wallwater, and G. Zussman. Networking Low-Power Energy Harvesting Devices: Measurements and Algorithms. *IEEE TMC*, 12(9), 2013.

[4] R. Lim, F. Ferrari, M. Zimmerling, C. Walser, P. Sommer, and J. Beutel. FlockLab: A testbed for distributed, synchronized tracing and profiling of wireless embedded systems. In *IPSN ’13*, 2013.

[5] L. Sigrist, A. Gomez, R. Lim, S. Lippuner, M. Leubin, and L. Thiele. Measurement and validation of energy harvesting IoT devices. In *DATE ’17*, 2017.

[6] L. Sigrist, A. Gomez, and L. Thiele. Long-term tracing of indoor solar harvesting. https://doi.org/10.5281/zenodo.3363925, 2019.