Making Sense of Intermittent Energy Harvesting

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ABSTRACT

Batteryless, energy harvesting sensing devices enable new applications and deployment scenarios with their promise of zero maintenance, long lifetime, and small size. These devices fail often and for variable lengths of time because of the unpredictability of the energy harvesting source; be it solar, thermal, RF, or kinetic, making prediction and planning difficult. This paper explores ways to make sense of energy harvesting behaviors. We take known energy harvesting datasets, and create a few of our own, then classify energy harvesting behavior into modes. Modes are periodic or repeated elements caused by systematic or fundamental attributes of the energy harvesting environment. We show the existence of these Energy Harvesting Modes using real world data and IV surfaces created with the Ekho emulator, and then discuss how this powerful abstraction could increase robustness and efficiency of design and development on intermittently powered and energy harvesting computing devices.

CCS CONCEPTS

• **Hardware** → **Power and energy**; • **Computer systems organization** → *Sensor networks*;

KEYWORDS

Energy harvesting, Intermittent computing, IV surface

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1 INTRODUCTION

For more than a decade, the wireless sensing community has worked together to enable long-term, affordable, and sustainable sensing across many application domains, ranging from wildlife tracking [7] to infrastructure monitoring [3], the built environment [2, 6], wearables [10, 19, 20], autonomous vehicles, and even space exploration. These applications and deployments have yielded significant value to the scientific community. However, ultra long term, massive scale sensing remains elusive. Energy harvesting in-situ, on a device often without batteries, provides a means to extend these deployment lifetimes as well as reduce battery replacement and overall maintenance costs.

These systems do not always have the energy necessary to maintain operation because of the unpredictability of energy harvesting [16]; resulting in an *intermittently powered computer system*, with frequency of power failures ranging from ten times a second in the smallest sensor nodes, to days or weeks in larger systems. However, these devices are essential to a sustainable future of computing [14], enabling global-scale applications in personal healthcare (wearables), infrastructure monitoring (road wear, bridge scour, and pipeline leak detection sensors), agriculture, and other areas where long term sustainable monitoring and compute is critically important.

Recently, sensors without batteries have begun to replace the traditional battery powered mote [13, 21]: the reasons are many, sustainability concerns as well as the need for longer device lifetime. Even industry has begun to recognize the need to leave batteries behind [1, 17]. This combination of factors has brought the intermittent computing paradigm to the forefront of sensor networks research. Intermittent computing is fundamentally different from conventional computing and wireless sensing, because intermittent devices violate one of the most basic assumptions of computing—a stable power supply.

We envision these tiny intermittent sensors harvesting energy, executing complex tasks, communicating and monitoring their application, for long periods in deployment. Achieving this vision will require a new approach to understanding and adapting to environmental conditions in the wild. This paper attempts to show that energy harvesting, while often treated as stochastic and unpredictable from the systems perspective (especially on small scale, RFID like sensors), energy harvesting environments present *modes* that can be taken advantage of to deliver quality of application. Modes are repeated signal elements of the energy environment, inherent to the actuation of the harvester or the environment itself.

Contributions: We show preliminary data and algorithms to support this hypothesis, detail practical challenges of using mode-like behavior, then discuss future directions and implications of these energy harvesting modes. This paper makes the following contributions:

- Defining the Energy Harvesting Mode (EHM) abstraction and demonstrating its occurrence in multiple energy harvesting environments.
- Preliminary results for capturing and compressing realistic representations of energy harvesting environments.
- A first method for extracting EHMs from the energy harvesting environment.
- Discussion and outline of future directions in deployment planning and test for batteryless devices.

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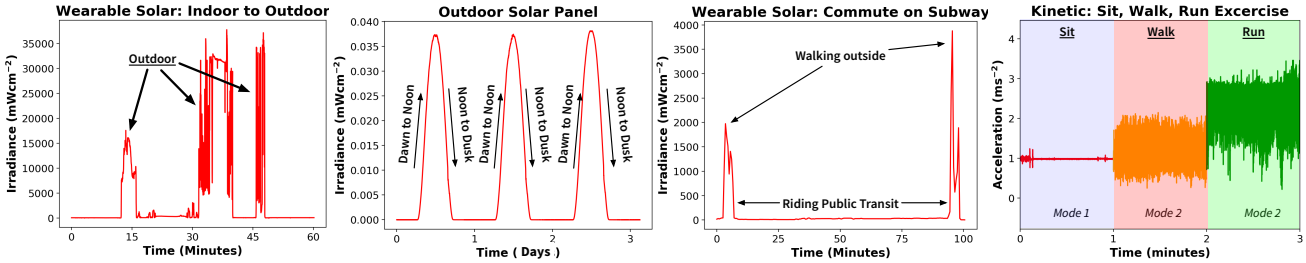

Figure 1: Energy harvesting is based on environmental features or physical attributes. Our intuition is that many energy harvesting behaviors are predictable and classified into "modes." Shown are multiple mode like energy harvesting scenarios.

2 EXPLORING ENERGY HARVESTING MODES

We propose a new abstraction to help developers adapt and understand the energy harvesting environments their devices are deployed in: Energy Harvesting Modes. Energy harvesting availability is often hard to predict, with the volatility of the energy availability varying widely between harvester types, and an imperfect predictive interface (Power or Voltage). Energy from an RF source is highly volatile, while solar or thermal based sources are usually stable and slowly change. The magnitude of the energy differs depending on the source; with solar usually producing an order of magnitude higher energy for the same device size.

Different "modes" or "trends" of energy harvesting availability often appear in the environment from recorded IV surfaces. For example, in an outdoor deployment environment with a solar energy harvester, distinct times of the day have different amounts of harvest-able energy. Night time has next to nothing, while daytime has an abundance. Figure 1 shows how solar and kinetic energy harvesting can naturally form into these modes. In this figure, we investigated data from energy harvesting datasets [5, 9] accompanying [8], as well as our own data (acceleration data on the far right). These data show how modes present in the natural environment.

Understanding the energy availability in the deployment environment, as well as its volatility, is a key insight for developers of intermittently powered devices. Different "modes" or "trends" of energy harvesting availability that appear in the environment must be gathered from recorded IV surfaces and processed. These will give the developer more flexibility to decide what tasks to execute, and also determine which tasks are more likely to succeed and produce useful data. This type of analysis can also investigate modes stemming from multiple harvesters: for example a solar powered sensing device equipped with an RFID harvester that is rarely but consistently activated, providing a brief but intense spike of energy.

In order to investigate energy harvesting environments to extract modes and trends we need to gather very long energy traces. Energy harvesting information can be gathered via Ekho [11] for short periods of time. However, to get to the point where energy harvesting modes can be determined, the actual energy harvesting environmental data must be gathered for weeks in the wild which cannot be done with the current implementation of Ekho. This is done currently using variants of Ekho, that are equipped with a large battery, low power processor, and analog front end for recording raw IV surfaces in-situ.

We discuss the challenges associated with the development of a variant of Ekho in the next section and then present, in Section 4, our algorithm and preliminary results for extracting EHMs.

3 COMPRESSING ENERGY HARVESTING ENVIRONMENTS

Recording environments over the course of many weeks poses problems for current techniques, as IV surfaces for existing mobile Ekho systems are gathered raw in the field, without compression or further processing, leading to deployments of less than a week [12]. This is done so that raw data can be converted to IV curves once the data is retrieved from the field. On current platforms, a single IV curve is represented by 512 bytes, gathering a curve a millisecond (a common requirement for fast changing RFID based energy harvesting), **this means recording a week long energy harvesting environment requires 309.6 gigabytes of data storage.** This is completely not practical for a small embedded device . Therefore, compression and processing techniques are required in-situ to reduce the storage needs for mobile Ekho devices that provide the raw data to inform pre-deployment testing.

However, compressing IV curves is not trivial, as quick moving features need to be recorded at a high resolution, and the IV curves themselves must be completely captured to be useful. There are two different areas to compress IV surfaces: the *representation* of the IV curve itself, and the *frequency* of IV curves gathered in the surface. Methods for modulating the frequency dynamically in-situ to reduce the number of IV curves gathered is beyond the scope of this paper, but compressing the individual IV curves from the 512 byte format is discussed here. We attempted three different methods of IV curve compression with, shown in Figure 2. These methods trade off one or more of computation power, energy cost, memory cost, and accuracy of representation. We detail the three methods below in descending order of accuracy of representation and computational cost. Table 1 shows an example of raw IV data that is converted into a IV curve representation using simple approximation techniques.

2-Polynomial regression: The most accurate method, but the method with the highest computational (and therefore energy and time) costs. A polynomial regression fits an n-polynomial function to a set of (x, y) data. The unsorted raw (i, v) pairs gathered

Table 1: Compression methods for IV curves, trade-offs in accuracy and cycle count shown for MSP430FR5994.

Compression Method	Cycle Cost	Code Size	Accuracy
2-Poly	150464	Med	High
MPP (SW)	148848	Low	Low
MPP (LEA)	2176	Low	Low

by an Ekho recording device are used to calculate a 4x4 vandermonde matrix (a matrix with the terms of a geometric progression in each row), the coefficients of the 2-order polynomial are then determined using a brute force Gauss-Jordan Elimination (GJE) algorithm, which runs in $O(n^2)$ Because the matrix is small, the simple implementation of GJE is preferred to more advanced methods. We implement this method on a MSP430FR5994 device with FRAM and a Low Energy Accelerator (LEA). The LEA is a separate processor inside the MSP430 and speeds up matrix and vector operations by an order of magnitude. This method serves as a good representation of the IV curve, as the 2-order polynomial captures the MPP, or the "knee" ov the IV curve, and compresses to only the three coefficients needed to fix the polynomial, representing a $170x$ improvement in storage space. However, the computation cost is high, especially as the number of raw IV pairs grows.

Linear regression: A linear regression simply calculates the best fitting linear function for the unsorted raw (i, v) pairs gathered from the Ekho recorder. This method misses the MPP (or "Knee") of the IV curve, but gives an approximation of the available energy and at much faster speed than the polynomial. Additionally, only two coefficients are needed, reducing the storage space by $256x$. However,this compression technique results in a very lossy representation of an IV curve. Cycle count results for this method were not gathered before submission.

Max Power Point: The maximum power point is the voltage at which the most current / power can be harvested from the energy harvesting source. The MPP can be roughly calculated from the raw IV pair data, assuming that the Ekho recorder is sampling the curve at a rate such that the entire curve is covered. There are two methods for calculating the MPP: the software only method, and the method that uses the newly developed LEA of the MSP430FR5994. With the LEA, the IV pairs are put into two $1xN$ matrices (one for Voltage, one for Current) and multiplied to get a vector of power (Watts) values. The maximum is determined from this vector, and the index is used as the MPP. This method is much faster than either regression method, with the LEA method giving a 68x improvement over the software MPP method. However, the MPP is a single data point, and does not give the slope of the curve after and before the knee, which is crucial to many applications that run on the edges of the IV curve. This method could be augmented by prior knowledge of the harvester, to get a general shape of the IV curve, and then estimate the curve from MPP readings. These methods were implemented on the MSP430FR5994 and cycle counts are shown in Table 1.

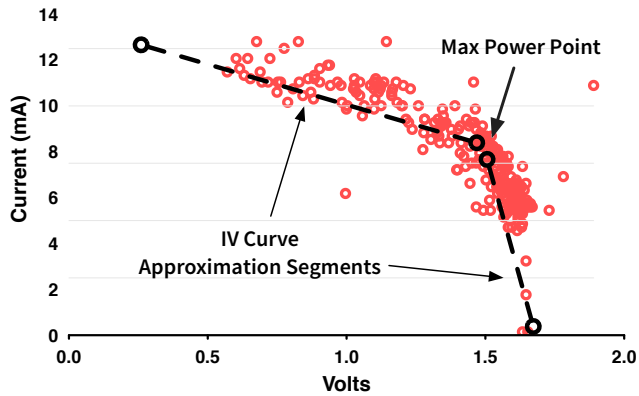

Figure 2: Raw IV data gathered by Ekho, along with MPP calculation and two regression lines for the endpoints. This method provides reasonable recording accuracy and low memory footprint.

Each of these three methods of representing raw IV surface data give trade-offs for accuracy, energy, and compute costs. Further investigations are required. We believe that an optimized version of the polynomial regression, coupled with checking by the speedy MPP method, offers the best path forward, along with careful adaptation and duty cycling to increase in-situ Ekho recording lifetimes.

Once an energy trace is recorded, the extractor algorithm can be applied to extract its EHMs. We detail the experimental setup and algorithm in the next section.

4 PRELIMINARY EXPERIMENT

We conducted a study to explore energy modes, including developing a software tool to break up similar sections of an IV surface and categorize them based on total energy. First we recorded a solar IV surface using Ekho, in an indoor laboratory setting, while flashing an LED or turning the LED on and off (reducing illumination but not to pitch black levels). We also partially obscured the LED in some cases. The IV surface recorded is shown in Figure 3. This surface has different energy harvesting modes visible to the naked eye, the "lights on" and "lights off" modes, and the intermediate modes. Due to movement of the harvester during the recording (total of 18 seconds), some parts of the surface had higher energy levels (the third peak).

This three dimensional surface represents all possible *execution paths* for a energy harvesting sensor node in terms of the harvesting current (I) and the supply voltage (V). Each point on the path across the surface represents a harvesting power (P), by integrating P over time, the sum energy can be measured per path. The paths with the highest energy cross the Maximum Power Point (MPP) of each (discretized) IV curve. If energy harvesting modes are known, then the MPP can be guessed and harvesting efficiency, and therefore total energy gathered, will increase.

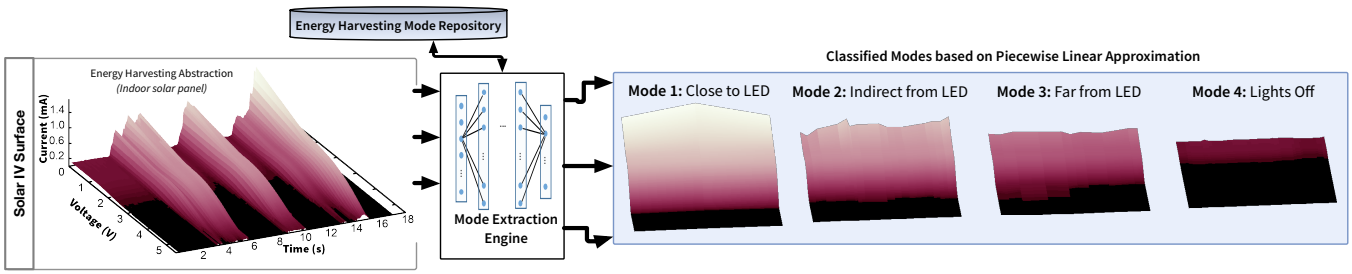

Figure 3: Overview of mode analysis tool and preliminary experiment. An IV surface recorded from a solar panel harvesting energy while lights were turned on and off in a laboratory with low ambient light. Energy harvesting modes identified by implementing MPP driven mode segmenting algorithm.

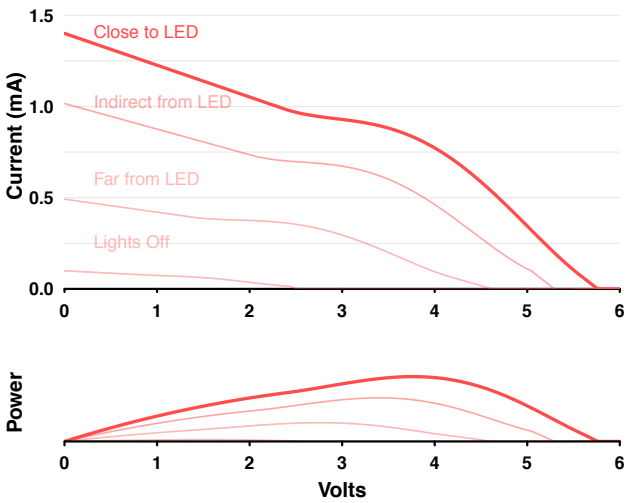

Figure 4: Representative IV curve of each mode and the power output versus voltage of each mode.

4.1 EHM Extractor Algorithm

We developed a preliminary algorithm and software implementation to extract these different energy harvesting modes from an arbitrary IV surface. The goal of the algorithm is to break up the IV surface into the minimum number of energy harvesting modes that covers the majority of the recorded IV surface. The key concept is that we can use the Maximum Power Point (MPP) of each IV curve (many of which make up the IV surface) to differentiate the mode. First, the MPP of the IV surface is calculated, where for each IV curve a unique point exists. This converts a 3-dimensional problem into two dimensions where we can segment the calculated MPP data with piecewise linear approximation using an arbitrarily sized sliding window and linear regression. For each segment that is produced, we differentiate the individual modes by the slopes of the lines using a reasonable threshold we calculated by trial and error. We use the slope of the segments to bin the segments into their requisite modes. While this method is not robust to noisy IV surfaces, such as RFID, the results are good enough for breaking up solar surfaces into a small number of modes. Our software tool implements this algorithm, and produced the results show in Figure 3, generated from the solar IV surface in Figure 3. Representative IV curves and PV curves are shown in Figure 4.

Alternatives: This preliminary method is by no means the best one. Relying on arbitrary thresholds may be useful when the harvester topology and input is known beforehand, leveraging domain data, and when the energy harvesting environment presents modes that tend to be stable for long periods at similar energy levels. However, modes may present as gradients (for example sun rising and setting), or stochastic, complicating division of an arbitrary IV surface into modes. Exploration of statistical methods like autocorrelation to determine groupings of modes, or unsupervised learning methods could be fruitful.

4.2 Usage and Implications

Our preliminary experiment does not cover a full evaluation of the extractor algorithm. However, we believe that extracting these modes can help a developer at compile time to write a task based program with multiple control flow options for each task. These multiple options provide different execution paths, have different energy profiles and thus can be adapted based on the current EHM. These paths and tasks can be designed by gracefully compromising the accuracy of the application. Such compromise will decrease the confidence in sensed value but could keep the device active for longer durations.

5 DISCUSSION AND FUTURE WORK

This paper focuses on some of the challenges and promise of deployment planning for energy harvesting batteryless sensors; however, the work presented here is preliminary, and only a first step towards a batteryless future. Future hardware and software systems must enable better preparation for deployment of batteryless sensing device in the real world; especially in exploring the energy harvesting environment, and then conducting realistic testing against it. In this section we describe potential avenues for future research.

Dynamic Compression for IV Surfaces Not considered in this paper but an appealing area of future work is a dynamic compression scheme for in-situ IV surface capture. By capturing IV curves only after large changes, or capturing points of interest based on the harvester type (RF sources are volatile and solar or thermal based

sources are usually stable and slowly change - sampling frequency can be adapted) or application needs, the memory and resource footprint required could be reduced.

Profiler Hardware: Hardware that can gather realistic energy harvesting information in the form of IV surfaces in the wild, for long periods of time, and store those environments is crucial. This profiler device will be deployed in the location where future batteryless sensors will be deployed, for example, on a wrist or item of clothing when profiling a mHealth wearable networks deployment. The hardware will gather useful data (in the form of IV surfaces and sensor readings) for later processing by the developer, to inform on deployment conditions and provide useful testing data and test cases. The hardware platform must focus on generality and flexibility for the developer, allowing for different types of energy harvesters to be plugged in, as well as different sensor modules (such as a Gyro or Accelerometer), depending on the application.

Sensor Data: While we did not discuss sensor data in this paper, it is a crucial aspect of deployments that must be considered, and accounted for. Recording and compressing sensor data in the wild, or gathering statistical information, will inform application developers on how and when to sense, and provide a foundation for inventing testing suites.

Energy Aware Testing: Test cases can be generated from the actual energy harvesting IV surfaces recorded by the profiler hardware discussed previously, These test cases can then be replayed on an Ekho emulator, closely matching the deployment conditions. In addition, the sensor data that is gathered alongside the energy harvesting data can be replayed into the device using the Energy-Interference-Free Debugger.

Adaptation in the Wild: Adaptation will be key to long lived batteryless sensing applications with high quality of service, using this papers contributions to inform on adaptation is an interesting area of future work. While the tools mentioned here could make planning and preparation for deployment easier and more rigorous, their is no mechanisms for adaptation in the wild. The large amount of data gathered and stored in environmental profiles could enable novel methods of adaptation in the wild; when coupled with a predictive framework for energy environment changes. Extending task based language models like Chain [4] or Mayfly [15] with primitives that enable adaptive task scheduling, informed by the environmental profiles, could enable this long term adaptive future.

Applicability to Energy-Neutral Systems: We focused in this paper on enabling simple and effective deployments for tiny, batteryless, energy harvesting systems—which can lose power many times a second, and have volatile power supplies and energy harvesting. However, the tools and techniques can be easily applied to other larger classes of sensing systems that deal with less frequent, or longer- term interruptions, such as energy-neutral sensing systems [18]. These sensors have more compute resources, larger energy harvesters, and rarely experience power failures.

6 CONCLUSIONS

Intermittently powered, energy harvesting computers and sensing devices **will** revolutionize computing; but first we must learn how to effectively test, then deploy these devices longterm in sometimes hostile environments. This paper has discussed some of the challenges of deploying batteryless sensors, and explored ways to deal with these difficulties through the Energy Harvesting Mode abstraction. This abstraction could serve a variety of purposes; generally extending the IV surface abstraction to provide a more robust and generalized view of an energy environment. In the future, ways to recognize and adapt to these modes is needed to guarantee quality of application. Further work on auto generation of energy driven test cases is also proposed. Once realized, these tools and techniques will allow intermittently powered devices, even the smallest and most energy constrained, to be deployed confidently, enable long maintenance free lifetimes, and finally allow for large scale deployments in new and critical applications ranging from healthcare to infrastructure monitoring.

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