Movers and Shakers:
Kinetic Energy Harvesting for the Internet of Things

Maria Gorlatova, John Sarik, Mina Cong, Ioannis Kymissis, Gil Zussman

Abstract—Numerous energy harvesting mobile and wireless devices that will serve as building blocks for the Internet of Things (IoT) are currently under development. However, there is still only limited understanding of the energy availability from various sources and its impact on energy harvesting-adaptive algorithms. Hence, we focus on characterizing the kinetic (motion) energy that can be harvested by a mobile device with an IoT form factor. We first discuss methods for estimating harvested energy from acceleration traces. We then briefly describe experiments with moving objects and provide insights into the suitability of different scenarios for harvesting. To characterize the energy availability associated with specific human activities (e.g., relaxing, walking, and cycling), we analyze a motion dataset with over 40 participants. Based on acceleration measurements that we collected for over 200 hours, we also study energy generation processes associated with day-long human routines. Finally, we use our measurement traces to evaluate the performance of energy harvesting-adaptive algorithms. Overall, the observations will provide insights into the design of networking algorithms and motion energy harvesters, which will be embedded in mobile devices.

Index Terms—Energy harvesting, motion energy, measurements, low-power networking, Internet of Things, energy harvesting-adaptive algorithms.

I. INTRODUCTION

Advances in the areas of solar, kinetic, piezoelectric, and thermal energy harvesting as well as low-power wireless communications and mobile computing will enable the realization of self-sustainable wireless devices [2], [9], [25]. These devices can compose rechargeable sensor networks [27], networks of Computational RFIDs [12], networks of mm$^2$-scale nodes [24], and Energy Harvesting Active Networked Tags [9]. Such networks will serve as building blocks for various Internet-of-Things (IoT) applications (e.g., supply chain management, smart buildings, and wearable computing).

Two promising energy sources for IoT nodes are light and motion. Accordingly, extensive effort has been dedicated to the design of solar cells and kinetic energy harvesters (e.g., [11], [16], [17], [20]). Moreover, the design of energy harvesting-adaptive communication and networking algorithms recently gained extensive attention [17], [8], [11], [15], [18], [22]. To complement these efforts, [11], [32], [33] collected traces and studied the impact of the energy sources dynamics on higher layer algorithms. However, there is still only limited understanding of motion energy availability and its impact on the design and evaluation of both hardware and algorithms. Hence, we focus on characterizing the kinetic (motion) energy that can be harvested by a mobile device with an IoT form factor and on the impact of these characteristics on energy harvesting-adaptive algorithms.

Everyday activities such as walking can generate significant power [26]. Therefore, several harvesters are under development, including shoe inserts that harvest energy from footfalls [16], mobile phone chargers integrated in backpacks [1] or phones [17]. While there are several ways of harvesting motion energy, we focus on inertial energy harvesters, since their form factor fits IoT applications. An inertial harvester suitable for a small wireless device (e.g., under 5cm x 5cm, and weighting less than 2 grams) can generate 100–200 $\mu$W from walking [13], [29], which is sufficient for many applications. However, the harvesting level changes dynamically as illustrated in Fig. 3 that includes an acceleration trace recorded by a device carried by a walking person and the corresponding power harvesting level.

In inertial harvesters, the output power is maximized when the harvester resonant frequency is “matched” to the motion frequency [21] (for more details, see Section V). Human motion is a combination of low frequency (<10 Hz) vibrations that vary from activity to activity and from person to person. Therefore, characterizing the properties of the harvested power requires an in-depth study of human motion (e.g., the frequencies associated with different types of motions) and human mobility patterns. Namely, characterizing kinetic energy harvesting is significantly more complex than characterizing light energy harvesting (e.g., [11]).

We first describe methods for collecting motion acceleration traces and for estimating harvested power from the traces. Our study is based on traces that we collected using SparkFun ADXL345 boards and traces collected in [31] using similar devices. While the traces in [31] were collected for activity recognition purposes, we use them to estimate the amount of energy that could potentially be harvested. Our approaches to estimating the power are based on methods developed in [20], [29], [34].

As the IoT will incorporate many objects, we briefly present

1 Note that the power available from RF harvesting is 100 times less than the power available from indoor light [22]. Moreover, although thermal gradients can provide substantial power for industrial applications, [19] they are currently impractical for the non-industrial IoT applications.

2 This is comparable to the power a solar cell of similar size can harvest from indoor light [11], [22].

3 Although smartphones include accelerometers, we use dedicated sensing units, since the phones’ accelerometers have a limited range, restricted sampling rate control, and high energy consumption (that hinders day-scale trace collection).
results regarding extensive measurements with a variety of moving objects. For example, we measured the power that can be harvested from activities such as writing with a pencil, reading a book, and opening a door. Moreover, we sent a FedEx box with a measurement unit across the U.S., had a unit in a checked-in luggage during a 3:13 hours flight, and carried units on cars and trains. Overall, our study demonstrates relatively low power availability levels for many of these activities. In particular, it highlights the need for periodic motion which is common in human motion but is uncommon for many objects.

We then examine the energy availability associated with specific human motions, such as walking, running, and cycling. Unlike previous studies that mainly focused on obtaining “rule-of-thumb” estimates based on small numbers of participants [6], [13], [29], we use a motion dataset with over 40 participants [31]. This allows us to obtain extensive and general kinetic energy characterization for common human motions. The study demonstrates the range of motion frequencies and harvested powers for different participants and activities, and shows the importance of human physical parameters for energy harvesting. For example, the taller half of the participants, can harvest on average 20% more power than the shorter half.

The short duration traces in [31] are for specific motions. In order to study the energy generation processes associated with day-scale human routines, we conducted an acceleration measurement campaign with 5 participants over a total of 25 days. We collected traces with over 200 hours of acceleration information for normal human routines. The traces provide important input for hardware design (e.g., for determining battery capacity and specifying transceiver power consumption) and for algorithm design (as will be discussed below). We analyze the traces to better understand motion energy availability and characteristics. We show that the power availability from normal routines and from indoor lights in enclosed environments are comparable. Moreover, we demonstrate that the power generation process associated with human motion is highly variable, with only brief intervals of high power levels.

Due to the high variability of energy obtained from human motion, IoT nodes will implement energy harvesting adaptive algorithms (e.g., [7], [8], [11], [15], [18], [22]). Hence, we evaluate the performance of a number of simple low-complexity policies [7], [8], [18], [22] using power inputs from our motion energy traces. The results highlight the need for policies that can accommodate the high dynamics of the motion energy harvesting process. Moreover, we compare the performance when using traces and when using i.i.d. and Markov harvesting processes. We observe discrepancies between the performance of the policies in those cases which emphasize the need to perform evaluations with real world traces.

To summarize, the main contributions of this report are: (i) insights into energy availability from human motion, based on a dataset a with large number of participants, (ii) collection of an extensive dataset of long-term human motion and a study of the related energy generation processes, and (iii) performance evaluation of energy harvesting-adaptive policies with real world traces. The report provides insights that are important for both system and algorithm design, and contributes to the understanding of motion energy harvesting availability and properties.

The report is organized as follows. Section II summarizes the related work and Section III describes the measurements and procedures for computing generated power. Section IV studies object motion. Section V focuses on common human motions and Section VI focuses on our measurement campaign and day-scale human motion measurements. Section VII evaluates the performance of harvesting adaptive policies with our traces. We conclude in Section VIII.

II. RELATED WORK

The importance of energy characterizations and measurements for networking energy harvesting wireless nodes is starting to be recognized. For example, light energy measurements for sensor networks were conducted in [11], [32]. This report focuses on energy of motion, which is assessed via examining recorded acceleration. Accelerometers are ubiquitous in consumer electronics, and the acceleration associated with human motion is widely used for user activity recognition [3] and physiology and population health studies [5], [28]. However, despite such wide use of acceleration information, few acceleration traces suitable for energy harvesting studies are publicly available. Moreover, only few kinetic energy harvesting characterizations have been attempted.

To the best of our knowledge, our experiments with object motion (Section IV) and with long-term activities (Section VI-A) are unique, and no similar studies have previously been conducted. Below we briefly summarize the related work for our other contributions.

Human activity characterization: To the best of our knowledge, the dataset [31] that we analyze in this report is the first publicly available acceleration dataset collected for a large number of participants. This dataset was not previously used for an energy harvesting study (only its features relevant to activity recognition studies, such as discrete cosine transform and autoregressive coefficients, were previously examined). Previous human motion energy harvesting studies had a limited number of participants (10 in [13] and 8 in [29], [33]) and mostly, with the notable exception of [33], examined short (10–60 seconds) intervals of walking and running on a treadmill at a constant pace. Due to the constrained motions, which differ from unrestricted human activities [23], the small sample sizes, and the small number of activities examined, these studies do not allow drawing general conclusions about the energy characteristics of general wireless and mobile nodes in wide scale deployments.

“Day-scale” human motion energy measurements: A set of day-scale human motion acceleration traces was previously collected for 8 participants over 3 days and examined in [33], which established energy budgets for wearable nodes using assumptions suitable for larger electronic devices. The data collected in [33] is not publicly available. We collect up to 9 days of traces for a single participant, examine the data under assumptions suitable for IoT nodes, and analyze the variability and properties of the corresponding energy generation process.
### Energy harvesting adaptive policy evaluations

A wide variety of energy harvesting adaptive policies are currently being developed [7], [8], [11], [15], [18], [22]. The policies are typically evaluated with artificial energy inputs, or with sunlight or wind energy traces. Our performance evaluations of motion energy harvesting traces are unique.

### III. MODEL & MEASUREMENT SETUP

Our motion energy study is based on recorded acceleration traces which are processed to determine the energy generated by an inertial harvester. In this section, we describe the harvester model, the collection of acceleration measurements, the procedure for obtaining the power generated by the harvester from the recorded traces, and the procedures for determining the harvester parameters. The notation is summarized in Table I.

#### A. Inertial Harvester Model

An inertial harvester can be modeled as a second-order mass-spring system with a harvester proof mass \( m \), proof mass displacement limit \( Z_L \), spring constant \( k \), and damping factor \( b \). Fig. 1(a) demonstrates such a harvester model.

Two important harvester design parameters are \( m \) and \( Z_L \). The harvester output power, \( P \), increases linearly with \( m \) [4], and is non-decreasing (but generally non-linear) in \( Z_L \). Yet, \( m \) and \( Z_L \) are limited by the harvester weight and size considerations, which ultimately depend on the application. We use the following values that are consistent with the mobile systems’ restrictions on the size and weight of the overall device, and correspond to one of the harvester configurations examined in [29]: (i) \( m = 1 \cdot 10^{-3} \) kg and (ii) \( Z_L = 10 \) mm.

The other two model parameters, \( k \) and \( b \), are tuned to optimize the energy harvested for given motion properties.

#### B. Collecting Motion Information

In Sections 4-6, we examine measurements that we collected and measurements provided in a triaxial acceleration dataset of common human motions [31]. Our measurements were obtained using sensing units based on SparkFun ADXL345 evaluation boards (see Fig. 2(a)). Each unit includes an ADXL345 tri-axis accelerometer, an Atmega328P microcontroller, and a microSD card for data logging. The sensing units record acceleration along the \( x \), \( y \), and \( z \) axes, \( a_x(t) \), \( a_y(t) \), \( a_z(t) \), with a 100 Hz sampling frequency. We conducted multiple experiments with multiple sensing unit placements, as described in Sections 4-6.

The dataset of [31] was obtained using an ADXL330 tri-axis accelerometers with a 100 Hz sampling frequency. The measurements of [31] were conducted with sensing unit placements corresponding to a shirt pocket, waist belt, and trouser pocket, as shown in Fig. 2(b). In all the measurements, the orientation of the sensing unit is not controlled. We examine the overall magnitude of acceleration, \( a(t) = \sqrt{a_x(t)^2 + a_y(t)^2 + a_z(t)^2} \). Due to the earth gravity of 9.8 m/s\(^2\) ("1g"), the measured acceleration includes a constant component that we filter out (similarly to [29], [33]) we use a 3rd order Butterworth high-pass filter with a 0.1 Hz cutoff frequency.

We examine two motion properties of the measurements: the average absolute deviation of the acceleration, \( D \), and the dominant frequency of motion, \( f_m \). \( D \) quantifies the variability in the \( a(t) \) value and is a measure of the "amount of motion". It

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**TABLE I**

**NOMENCLATURE**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( m )</td>
<td>Harvester proof mass [ kg ]</td>
</tr>
<tr>
<td>( Z_L )</td>
<td>Harvester proof mass displacement limit [ m ]</td>
</tr>
<tr>
<td>( k )</td>
<td>Harvester spring constant [ kg/s(^2) ]</td>
</tr>
<tr>
<td>( b )</td>
<td>Harvester damping factor [ kg/s ]</td>
</tr>
<tr>
<td>( f_r )</td>
<td>Harvester resonant frequency [ Hz ]</td>
</tr>
<tr>
<td>( f_m )</td>
<td>Dominant motion frequency [ Hz ]</td>
</tr>
<tr>
<td>( a(t) )</td>
<td>Acceleration [ m/s(^2) ]</td>
</tr>
<tr>
<td>( D )</td>
<td>Absolute deviation of acceleration [ m/s(^2) ]</td>
</tr>
<tr>
<td>( P(t) )</td>
<td>Power [ W ]</td>
</tr>
<tr>
<td>( z(t) )</td>
<td>Proof mass displacement [ m ]</td>
</tr>
<tr>
<td>( r )</td>
<td>Data rate [ Kb/s ]</td>
</tr>
<tr>
<td>( \eta )</td>
<td>Energy conversion efficiency [ dimensionless ]</td>
</tr>
</tbody>
</table>

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Fig. 1. (a) A second-order mass-spring system model of a harvester with proof mass \( m \), proof mass displacement limit \( Z_L \), spring constant \( k \), and damping factor \( b \), and (b) the frequency response magnitude for two different harvesters, \( H_1 \) and \( H_2 \).
Laplace-domain transfer function is denoted by \( P(s) \), based on the approaches developed in [33], [34]. We first implement this procedure in MATLAB and Simulink.

To characterize the performance of wireless mobile systems, we calculate the data rates, \( r \), that a node would be able to maintain when harvesting the generated \( P(t) \). We assume, similar to [33], that the harvester energy conversion efficiency, \( \eta \), is 20%, and similar to [11], that the communication cost is \( c_{\text{tx}} = 1 \) nJ/bit for ultra low power transceivers appropriate for IoT nodes. Hence, \( r = \eta P / c_{\text{tx}} = 2 \times 10^5 P \) (Kb/s).

C. Harvesting Rates and Data Rates

We calculate the power generated by a harvester, \( P(t) \), subjected to acceleration \( a(t) \), using the following procedure based on the approaches developed in [33], [34]. We first convert \( a(t) \) to proof mass displacement, \( z(t) \), using the Laplace-domain transfer function:

\[
z(t) = L^{-1}\{z(s)\} = \frac{a(s)}{s^2 + (2\pi f_r/Q)s + (2\pi f_r)^2}
\]

Next, to account for \( Z_L \), we limit \( z(t) \) using a Simulink limiter block. The power \( P(t) \) generated by the harvester is then determined as \( P(t) = b(az(t)/dt)^2 \). The average of the \( P(t) \) is denoted by \( \overline{P} \).

We implemented this procedure in MATLAB and Simulink. Fig. 3 shows an example of obtaining \( P(t) \) for a particular \( a(t) \). The \( a(t) \) values were recorded by a sensing unit carried by a walking person (Fig. 3(a)), and the \( z(t) \) and \( P(t) \) values were obtained using the procedure described above for the harvester \( H1 \).

To characterize the performance of wireless mobile systems, we calculate the data rates, \( r \), that a node would be able to maintain when harvesting the generated \( P(t) \). We assume, similar to [33], that the harvester energy conversion efficiency, \( \eta \), is 20%, and similar to [11], that the communication cost is \( c_{\text{tx}} = 1 \) nJ/bit for ultra low power transceivers appropriate for IoT nodes. Hence, \( r = \eta P / c_{\text{tx}} = 2 \times 10^5 P \) (Kb/s).

D. Optimizing the Harvester Parameters

Finding the optimal harvester parameters \( k \) and \( b \) is difficult, since it requires optimizing over a multi-dimensional surface of unknown geometry [29]. For example, Fig. 4 shows the average power \( \overline{P} \) values calculated from one set of \( a(t) \) measurements (corresponding to 20 seconds of a person running) for different \( f_r \) and \( b \) combinations. To determine the optimal harvester parameters for short \( a(t) \) samples, we implemented an exhaustive search algorithm. This algorithm considers a large number of \( k \) and \( b \) combinations, obtains the corresponding \( \overline{P} \) (using the procedure described in Section III-C), and chooses the \( k \) and \( b \) combination that maximizes \( \overline{P} \).

The exhaustive search algorithm is time-consuming even for relatively short \( a(t) \) samples. For longer \( a(t) \) samples, in Section III-C we implemented a simplified procedure developed in [33]. The procedure first determines the \( k \) value that matches the harvester’s \( f_r \) to the dominant frequency in the \( a(t) \) sample, \( f_m \). Specifically, the procedure selects \( k \) such that \( k = m f_r^2/(2\pi)^2 = (m f_m^2)/(2\pi)^2 \). It then considers a relatively large number of \( b \) values and selects the \( b \) that maximizes \( \overline{P} \).

IV. OBJECT MOTION ENERGY

Everyday motions generate large amounts of energy, but not all of that energy can be harvested by an inertial harvester. While Sections V, VI focus on human motion, in this section we provide some brief observations regarding the energy availability associated with the motion of objects. We conducted extensive experiments, recording \( a(t) \) and calculating \( \overline{P} \) for a wide range of motions. Our experiments included performing everyday activities with a variety of everyday objects (see Table II), shipping a FedEx box with a sensing unit in it from Houston, TX to New York, NY, transporting sensing units in carry-on and checked airport luggage, and taking sensing units on cars, subways, and trains.

Below, we present observations based on our measurements. To put the \( \overline{P} \) values in perspective, we note that human walking typically corresponds to \( 120 \leq \overline{P} \leq 280 \) \( \mu \text{W} \), as we will show in Section VII shortly.

**Only periodic motion is energy-rich:** Due to the filter properties of inertial harvesters (see Section III-A), a motion needs to be periodic to be “harvestable”. The vast majority of common object motion is not periodic, and hence the corresponding energy availability is low. For example, we
attached a sensing unit to a book and observed that when the book is being taken off the shelf, read, or put back on the shelf, $P < 10 \mu W$. For a sensing unit attached to a pencil used by a student to write homework, $10 \leq P \leq 15 \mu W$. Even high-acceleration non-periodic motions, such as a plane landing and taking off, and an accelerating or decelerating car, correspond to only limited energy availability ($P < 5 \mu W$). For example, when a unit was placed in a bag checked in on a 3:13 hour flight the recorded $a(t)$ showed that the luggage was subjected to varying high-acceleration motions, but the $P$ did not exceed $5 \mu W$ even during the most turbulent intervals of the flight.

**Damped (softened) object motion is energy-poor:** The motion of many objects in our environment is damped for human comfort (e.g., by door dampers, cabinet drawer dampers, and springs in swirling chairs). In such cases, most of the motion energy is absorbed in the dampers and only small amounts can be harvested (e.g. sticker form factor harvesters \[9\]). Opening and closing a drawer, spinning a swivel chair, and opening and closing a building door corresponded to $10 \leq P \leq 30 \mu W$, $1 \leq P \leq 6.5 \mu W$, and $P < 1 \mu W$, respectively. This suggest that wireless nodes embedded in objects such as doors and drawers should integrate motion energy harvesters with the mechanical dampers.

**Purposeful object motion can be extremely energy rich:** Periodic shaking of objects can generate a relatively large amount of energy in a short time (as demonstrated by “shake” flashlights). In our experiments, purposeful shaking corresponded to $P$ of up to $3,500 \mu W$, that is, 12–29 times more than the power for walking. In IoT applications with mobile nodes, this can be useful for quickly recharging battery-depleted nodes.

### V. Human Motion

We now examine a dataset with over 40 participants performing 7 common human motions in unconstrained environments. It was collected in \[31\] and used for activity recognition rather than energy characterization. We first introduce the study. Then, we characterize the energy availability for different motions, the variability in motion properties among sensing unit placements and participants, and the dependence of energy availability on the participant’s physical parameters.

#### A. Study Summary

The dataset we examine \[31\] contains motion samples for 7 common human activities – relaxing, walking, fast walking, running, cycling, going upstairs, and going downstairs, – performed by over 40 different participants and recorded from the 3 sensing unit placements, shown in Fig. 2(b). For each 20-second motion sample, we use the acceleration, $a(t)$ trace to calculate $D$, $f_m$, $P$, and $r$. To obtain $P$, we use the exhaustive search harvester optimization algorithm, described in Section IV-D. By determining the best harvester for each motion, we can offer important insights into the harvester design.

To validate the data from \[31\], we replicated the measurements with our sensing units. The results of our measurements were consistent with the provided data. We note that the $f_m$ values calculated for the different motions in the dataset are consistent with the physiology of human motion.

The statistics of the calculated $D$, $f_m$, and $P$ are summarized in the boxplots in Fig. 5. For each of the 7 motions the leftmost (black), middle (red), and rightmost (blue) boxes correspond to shirt pocket, waist belt, and trouser pocket sensing unit placements, respectively. For each motion and sensing unit placement, the number of participants that had $a(t)$ samples appears on the top of Fig. 5(a). At each box, the central mark is the median, the edges are the 25th and 75th percentiles, the “whiskers” extend to cover $2.7\sigma$ of the data, and the outliers are plotted individually. In Table III we separately summarize the results and the data rates for 4 important motions.

#### B. Energy for Different Activities

**Relaxing:** As expected, almost no energy can be harvested when a person is not moving ($P < 5 \mu W$).
TABLE III
ENERGY BUDGETS AND DATA RATES BASED ON MEASUREMENTS OF COMMON HUMAN ACTIVITIES.

<table>
<thead>
<tr>
<th>Activity</th>
<th>Sensing unit placement</th>
<th># subjects (N/A)</th>
<th>Median $f_m$ ($Hz$)</th>
<th>25th percentile</th>
<th>Median</th>
<th>75th percentile</th>
<th>Median $r$ ($Kb/s$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relaxing</td>
<td>Trouser pocket</td>
<td>42</td>
<td>1.9</td>
<td>0.3</td>
<td>2.4</td>
<td>4.8</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Waist belt</td>
<td>42</td>
<td>N/A</td>
<td>0.2</td>
<td>1.4</td>
<td>5.9</td>
<td>0.3</td>
</tr>
<tr>
<td>Walking</td>
<td>Trouser pocket</td>
<td>42</td>
<td>2.0</td>
<td>151.8</td>
<td>180.3</td>
<td>200.3</td>
<td>36.0</td>
</tr>
<tr>
<td></td>
<td>Waist belt</td>
<td>42</td>
<td>N/A</td>
<td>0.2</td>
<td>1.4</td>
<td>5.9</td>
<td>0.3</td>
</tr>
<tr>
<td>Running</td>
<td>Shirt pocket</td>
<td>42</td>
<td>2.8</td>
<td>724.2</td>
<td>813.3</td>
<td>910.0</td>
<td>162.6</td>
</tr>
<tr>
<td></td>
<td>Waist belt</td>
<td>41</td>
<td>2.8</td>
<td>623.5</td>
<td>678.3</td>
<td>752.8</td>
<td>135.6</td>
</tr>
<tr>
<td>Cycling</td>
<td>Shirt pocket</td>
<td>42</td>
<td>3.5</td>
<td>37.4</td>
<td>52.0</td>
<td>72.3</td>
<td>10.4</td>
</tr>
<tr>
<td></td>
<td>Waist belt</td>
<td>29</td>
<td>3.8</td>
<td>36.3</td>
<td>45.4</td>
<td>59.2</td>
<td>9.1</td>
</tr>
<tr>
<td></td>
<td>Trouser pocket</td>
<td>30</td>
<td>1.1</td>
<td>35.6</td>
<td>41.3</td>
<td>59.5</td>
<td>8.3</td>
</tr>
</tbody>
</table>

Walking and fast walking: Walking is the predominant periodic motion in normal human lives and thus particularly important for motion energy harvesting. For walking, the median $P$ is 155 $\mu$W for shirt pocket sensing unit placement, 180 $\mu$W for waist belt placement, and 202 $\mu$W for trouser pocket placement. These $P$ values are in agreement with previous, smaller-scale, studies of motion energy harvesting for human walking [13],[29]. In comparison, indoor light energy availability is on the order of 50–100 $\mu$W/cm². Considering harvester energy conversion efficiency estimates [11],[33], a similarly sized harvester would harvest more energy from walking than from indoor light. Fast walking (which was identified as “fast” by the participants themselves) has higher $P$ for the trouser placement is different from the upstairs. Because the body is in a sitting position, the stresses experienced by the legs and the torso are different and $f_m$ differs for the different placements.

Running: Running, an intense repetitive activity, is associated with high $D$ and $f_m$ (Fig. 5(a,b)), and hence results in $612 \leq P \leq 813 \mu$W. Cycling: For the examined unit placements, cycling generates relatively little energy – the median $P$ values are 41–52 $\mu$W, 3.7–3.9 times less than the $P$ for walking. For the lower legs and lower arms. However, for the sensing unit placements examined in this section (shirt, waist, and trousers), the same motion resulted in similar $f_m$ values, as can be seen in Fig. 5(b). These placements are on or near the torso, and are subjected to similar stresses. Cycling is an exception; the $f_m$ for the trouser placement is different from the other placements. Because the body is in a sitting position, the stresses experienced by the legs and the torso are different and $f_m$ differs for the different placements.

Walking upstairs and downstairs: Our examination demonstrates that human exertion (perceived effort and energy expenditure) does not necessarily correspond to higher motion energy harvesting rates. While people exert themselves more going upstairs, the $P$ for going downstairs is substantially higher than for going upstairs. Specifically, for the downstairs motion, the median $P$ is 1.78 times higher than the upstairs motion for shirt unit placement, 2.1 times higher for waist placement, and 1.65 times higher for trouser placement. Although counterintuitive, going downstairs is associated with higher magnitudes of motion and higher motion frequencies (Fig. 5(a,b)), which leads to the higher $P$. We observed the disconnect between perceived human effort and energy harvesting rates in our own measurements as well, where we noted that highly strenuous activities, such as push-ups and sit-ups, resulted in lower $P$ than non-strenuous walking at a normal pace.

C. Consistency of Dominant Motion Frequency

To maximize power output, the resonant frequency of a harvester, $f_r$, should “match” the dominant frequency of motion, $f_m$. In this section we comment on the variability in $f_m$ and provide important observations for harvester design.

Consistency among sensing unit placements: The same motion will result in a different $f_m$ depending on the sensing unit’s placement on the human body [13],[33]. We observed this in measurements that we conducted, especially for sensing units attached to the lower legs and lower arms. However, for the sensing unit placements examined in this section (shirt, waist, and trousers), the same motion resulted in similar $f_m$ values, as can be seen in Fig. 5(b). These placements are on or near the torso, and are subjected to similar stresses. Cycling is an exception; the $f_m$ for the trouser placement is different from the other placements. Because the body is in a sitting position, the stresses experienced by the legs and the torso are different and $f_m$ differs for the different placements.

The uniformity of $f_m$ offers valuable hints for energy harvesting node designers. People are likely to keep many objects that will become IoT nodes (keys, wallets, and cell phones) in pockets located in places that correspond to the placements we examine. This suggests that a harvester will perform well regardless of where a person chooses to carry such an object.

Inter-participant consistency: For common periodic motions, such as walking and running, the $f_m$ values are relatively consistent among the different participants. The 25th and 75th percentiles of the participants’ $f_m$ values are separated by only 0.15 Hz for walking and by only 0.3 Hz for running. For less commonly practiced motions (cycling, going upstairs, going downstairs), the values of $f_m$ are less consistent, but are still somewhat similar. This consistency indicates that an all-purpose harvester designed for human walking or running will work well for a large number of different people. The next section examines whether harvesters can be tuned to particular human parameters.

D. Dependency on Human Height and Weight

We examine the dependency of energy availability on human physiological parameters. We correlate $D$, $f_m$, and $P$ obtained for different motions and different participants with
their height and weight data from [31]². The participants’ heights range was 155–182 cm, and their weights range was 44–65 kg. We verified that, in agreement with general human physiology studies, the participants’ height and weight are strongly positively correlated (ρ = 0.7, p < 0.001).

As indicated in the previous subsection, for many activities \( f_m \) is consistent among different participants. Yet, we additionally observed \( f_n \) dependencies on human physiology. For many of the activities we examined, we determined negative correlations of \( f_m \) with the participants’ height and weight. When walking, running, and going upstairs and downstairs, heavier and taller people took fewer steps per time interval than lighter and shorter people.

For example, for going upstairs with waist unit placement, \( f_m \) and the participant’s height are correlated as \( ρ = −0.34 \) (\( p = 0.03, n = 39 \)). When going upstairs, the taller half of the participants made, on average, 9 fewer steps per minute (0.15 Hz) than the shorter half (\( f_m = 1.85 \) and 2.05 Hz, correspondingly). For running, with trouser unit placement, \( f_m \) and the participant’s weight are correlated as \( ρ = −0.46 \) (\( p < 0.01, n = 39 \)). When running, the heavier half of the participants made, on average, 18 fewer steps per minute (0.3 Hz) than the lighter half. This suggests that future harvester designs may benefit from targeting harvesters with different \( f_r \) values for human groups with different physiological parameters. For example, different harvesters may be integrated in clothing of different sizes.

Generally, motion energy availability increases as \( f_m \) increases [20]. However, in human motion, other dependencies may additionally come into play. In our study, for running with trouser unit placement, we determined a positive correlation between \( D \) and participants’ height (\( ρ = 0.35, p = 0.03, n = 38 \)) and a positive correlation between \( T \) and participants’ height (\( ρ = 0.38, p = 0.01, n = 38 \)). For the taller half of the participants, the average \( T \) is 20% higher than for the shorter half (704 and 582 \( \mu W \), respectively). Studies with larger number of participants, wider participant demographics, and wider range of participant parameters will most likely identify several additional dependencies. This will allow harvester designers to develop harvesters for different demographics, as well as to provide guarantees on the performance of different harvesters based on different human parameters.

VI. LONG-TERM HUMAN MOBILITY

The results presented in the previous section are based on short motion samples from an activity recognition dataset. In this section, we present results of our own, longer-term, motion measurements. We describe our set of day-long human mobility measurements and discuss energy budgets and generation process properties.

A. Prolonged Activities

To study motion energy properties over time, we collected a set of measurements of longer activity durations (over 20 minutes). We considered long walks, bike rides, runs, and other activities, performed in normal environments (i.e., not on a treadmill or a stationary bike). To the best of our knowledge, such long samples of particular motions have not been analyzed before.

The measurements demonstrate that for prolonged activities, \( D, f_m, \) and \( P(t) \) vary substantially over time. This variability is related to physiological parameters, such as changes in cadence or posture over time due to fatigue, and changes in the surrounding environment, such as traffic lights, terrain changes, or pedestrian traffic. For example, Fig. 6 shows \( D, f_m, \) and \( P(t) \) corresponding to a 3 hour run, calculated for 1-second \( a(t) \) intervals. In this trace, the average \( D \) changes subtly over time (Fig. 6(a)), and \( f_m \) varies continuously in the 2.6–3.4 Hz range (Fig. 6(b)). Consequently, while the mean \( P(t) \) is 550 \( \mu W \), the 10th–90th percentiles of \( P(t) \) span the range of 459–710 \( \mu W \) (Fig. 6(c)).

The variability of \( P(t) \) throughout an activity suggests that node energy management policies are essential even for specifically targeted IoT applications, such as nodes for fitness runners or cyclists. In the following sections we demonstrate even more variability in \( P(t) \) for the regular everyday human mobility patterns.

B. Day-Long Human Mobility

1) Collected Data: To determine the daily energy available to a mobile node with an inertial harvester, we collected
acceleration traces from different participants during their normal daily routines. Our results are based on over 200 hours of acceleration information we obtained for 5 participants for a total of 25 days. Some information about the participants is provided in Table IV. The participants were instructed to carry a sensing unit in any convenient way. Thus, the measurements correspond to the motion that a participant’s keys, mobile phone, or wallet would experience.

Fig. 7 shows $a(t)$ for a day-long trace of participant M5, and the corresponding $P(t)$. For all the collected traces, the dominant motion frequency, $f_m$, range is 1.92–2.8 Hz, corresponding to human walking.

The calculated energy budgets are summarized in Table IV. We calculated $\bar{P}$, the average power a harvester would generate over the length of the trace, as well as $\bar{P}_d$, the average power a harvester would generate over a 24-hour interval. To calculate $\bar{P}_d$ we assumed that when the sensing unit did not record data (e.g., before the participants got dressed for school or work), it was stationary and that a harvester would not generate energy during these intervals. Specifically, for a $T$-hour-long measurement trace, $\bar{P}_d = \bar{P} \cdot T/24$. For each of the participants, Table IV summarizes the minimum, average, and maximum $\bar{P}$ and $\bar{P}_d$ over the different measurement days, and the data rate $r_d$ that a node would be able to maintain continuously throughout a day when powered by the harvested $\bar{P}_d$. For completeness, for all participants we additionally calculate $\bar{P}_d^{on}$, the average power a particular harvester, same for all participants (in this case, the harvester calculated based on the traces for participant M4), would harvest. An extensive examination of the sensitivity of power harvested to different harvester design parameters is subject of ongoing work.

2) Power Budgets: For most participants, an inertial harvester can provide sufficient power to continuously maintain a data rate of at least 1 Kb/s (i.e., $\bar{P}_d > 5$ $\mu$W). This is comparable with the data rates estimated in [11] for nodes (not exposed to outdoor light).

The majority of inter-participant and inter-day differences seem to relate to the participants’ amount of walking. For example, participant M2, whose $\bar{P}$ and $\bar{P}_d$ values are higher than the others, has a relatively long walk to the office, and walks frequently between two different offices in the same building. Other factors (unit placement, amount of daily activity as perceived by the participants) appear to be only of secondary importance. We note that the majority of traces that correspond to $\bar{P}_d < 5$ $\mu$W (and thus $r_d < 1$ Kb/s) correspond to participants working from home. Overall, daily routines that involve a lot of walking correspond to relatively high levels of energy availability.

3) Harvesting Process Variability & Properties: The amount of energy that can be harvested varies widely throughout the day. As shown in Section V, walking generates substantial amounts of energy, while being stationary generates little. Physiological studies (e.g., [23]) have shown that the people are at rest a majority of the time. Correspondingly, in our measurements, $P(t)$ is low for most of the day and over 95% of the total energy is collected during only 4–7% of a day. For example, Fig. 8 shows, for participant M1, the percentage of the total energy that would be harvested over different ranges of $P(t)$ and the percentage of the time the harvester would generate these $P(t)$ values. For this participant, the harvester would generate $P(t) < 15$ $\mu$W 91% of the time, but only 6.1% of the total energy would be harvested during this time.

Consider an ON/OFF representation of the energy harvesting process, $P_{onoff}(t)$, where $P_{onoff}(t) ← 1$ (“ON”) if $P(t) > THR$, and $P_{onoff}(t) ← 0$ (“OFF”) otherwise. For the analysis below, we empirically set $THR = 10$ $\mu$W. The results are similar for $10 \leq THR \leq 40$ $\mu$W. For all participants,

<table>
<thead>
<tr>
<th>Participant</th>
<th>Occupation and commute on campus</th>
<th># Days</th>
<th>Total dur.(h)</th>
<th>$\bar{P}$ min/avg/max $(\mu$W$)$</th>
<th>$\bar{P}_d$ min/avg/max $(\mu$W$)$</th>
<th>$r_d$ avg $(\text{Kb/s})$</th>
<th>$E(%)$</th>
<th>$T/\mu$W</th>
<th>$P(t)$ $(\mu$W$)$</th>
<th>% ON, min/avg/max</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>Undergraduate student, living on campus</td>
<td>5</td>
<td>60.4</td>
<td>6.9/13.8/17.3</td>
<td>4.8/6.5/8.1</td>
<td>1.3</td>
<td>5.0/8.5/10.9</td>
<td>5.4/9.9/12.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M2</td>
<td>Undergraduate student, commuting to campus</td>
<td>3</td>
<td>27.7</td>
<td>23.3/29.0/38.2</td>
<td>8.4/11.5/17.7</td>
<td>2.3</td>
<td>17.1/19.6/24.5</td>
<td>13.6/16.1/18.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M3</td>
<td>Undergraduate student, living on campus</td>
<td>9</td>
<td>62.0</td>
<td>2.4/7.16/13.4</td>
<td>0.6/2.02/3.6</td>
<td>0.4</td>
<td>2.0/5.8/12.2</td>
<td>3.6/6.0/9.95</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M4</td>
<td>Graduate student, commuting to campus</td>
<td>7</td>
<td>80.1</td>
<td>1.4/11.98/25.3</td>
<td>0.6/5.6/10.7</td>
<td>1.1</td>
<td>1.4/11.98/25.3</td>
<td>2.8/12.7/18.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M5</td>
<td>Software developer, commuting to office</td>
<td>1</td>
<td>11.0</td>
<td>16.3</td>
<td>7.3</td>
<td>1.5</td>
<td>15.9</td>
<td>11.5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 8. Motion energy harvesting process variability for participant M1: (a) the percentage of the total energy harvested at each of the demonstrated power levels, $P(t)$, and (b) percentage of time the power is harvested at each of the demonstrated $P(t)$ (notice that for $0 \leq P(t) \leq 15$, the value is 91%).
it can be seen that the process is ON for less than 20% of the time (Table IV). Note that the participants do not lead sedentary lifestyles; their activity patterns are well in line with general health guidelines. However, the recommend 30 minutes of physical activity per day correspond to only 9% of an 11-hour measurement trace. Additionally, the typical duration of ON intervals is short – on the order of seconds. While some of the ON intervals are long (over 200 seconds), the vast majority of ON intervals (78.5–89.0%) are shorter than 30 seconds; the median ON intervals are 5–9.5 seconds. The longer ON intervals correspond to commuting (e.g., walking from a subway station to a campus building), and represent only 1–3% of the ON intervals.

In summary, \( P(t) \) is low for the majority of the time, and when it does become high, it stays high for only a brief period of time. This emphasizes the need for energy harvesting-adaptive policies.

VII. Harvesting Adaptive Policies

In this section, we study the performance of energy harvesting-adaptive policies. We describe the model, the policies, and the evaluation metrics. Then, we evaluate the performance using the motion traces and discuss the performance differences when using the traces and using random processes.

A. Model and Policies Examined

We follow the model of energy harvesting wireless systems used in several recent works (e.g., [7], [11], [15], [18]). We assume that time is slotted and denote the time index by \( i \) and the number of time slots by \( K \). Energy harvesting adaptive policies control the node energy spending rates, \( s(i) \), based on the energy harvesting rates, \( e(i) \), and the node battery levels, \( B(i) \). For a node with a battery capacity \( C \), the battery level evolution is \( B(i) = \min[B(i-1) + e(i-1) - s(i-1), C] \). The length of a time slot is \( T_{int} \). We use \( T_{int} = 1 \) second and set \( B(1) = 0.5C \).

To determine \( e(i) \) based on the \( P(t) \), we determine \( P_{\text{meas}}(i) \) by obtaining the average value of the \( P(t) \) for each \( T_{int} \). We calculate \( e(i) \) as \( e(i) \leftarrow \eta P_{\text{meas}}(i) T_{int} \), where \( \eta \) is the conversion efficiency (assumed to be 20% [33]). Some of the examined policies keep track of the running average of \( e(i) \), \( \tilde{e}(i) \leftarrow \sum_{j=0}^{i-1} e(j)/i \).

We examine the following node energy harvesting-adaptive policies, which are suitable for low power nodes, due to their low complexity:

- **Spend-what-you-get (SG)**: \( s(i) \leftarrow e(i) \).
- **Storage-linear (SL)**: \( s(i) \leftarrow 2\tilde{e}(i)B(i)/C \).
- **Scheme-LB**: \( s(i) \leftarrow (1 - \epsilon)\tilde{e}(i) \) if \( B(i) + e(i) \geq (1 - \epsilon)\tilde{e}(i) \), and \( s(i) \leftarrow B(i) + e(i) \) otherwise, where \( \epsilon \) is a small constant (we use \( \epsilon = 0.01 \)).

The SG policies were examined in [8], [13]. The SL policies are common-sense heuristics examined in [22]. The Scheme-LB policies were proposed and examined in [7]. For all policies, the data rate, \( r(i) = s(i)/c_{tx} \).

To the best of our knowledge, there are currently no testbeds for wireless nodes equipped with inertial energy harvesters. Thus, we evaluate the performance of the policies via simulations, performed in MATLAB. Some of the policies described above have been previously evaluated in a testbed of wireless nodes equipped with light energy harvesters [10], and the experimental results closely matched the simulation results. Thus, we expect our simulations to closely correspond to the behavior of nodes equipped with inertial harvesters.

Examples of realizations of the SG, SL, and Scheme-LB policies are shown in Fig. 9. These realizations use the \( P_{\text{meas}} \) values for participant M5 (Table IV), whose \( P(t) \) was previously shown in Fig. 7(b). For these realizations, we used \( C = 0.5 \sum_i P_{\text{meas}}(i) \). Fig. 9(a) shows the instantaneous data rates, \( r \) while Fig. 9(b) shows the battery levels, \( B \). The average data rate, \( \overline{r} \), is 3.27 Kb/s under the SG policy, 2.95 Kb/s under the SL policy, and 3.07 Kb/s under the Scheme-LB policy. We evaluate policy performance using metrics appropriate for energy harvesting nodes. Nodes should achieve “energy neutrality” (use all of the harvested energy, but not overuse it) and maintain consistent communication over time [15]. As an objective function value, we use \( Z = \sum_i \log(1 + r(i))/K \). Maximizing such an objective guarantees energy allocation consistency [11]. We compare the \( Z \) values for each policy to the maximal possible objective function value \( Z_{\text{max}} = \log[1 + (\sum_i e(i))/c_{tx}]/K \). To measure the policies’ energy neutrality, we consider the percentage of energy misused, \( E_{\text{md}} \), which we define as \( E_{\text{md}} = 100(\sum_i s(i)/\sum_i e(i) - 1) \). A positive \( E_{\text{md}} \) represents overspending of the available energy and using some of the energy originally stored in the battery, and a negative \( E_{\text{md}} \) represents underspending the energy. We also consider the node ON time. For a time slot \( i \), a node is ON if \( r(i) > 500 \) b/s and OFF otherwise.

B. Policy Performance with Traces

We examine the performance of the SL, Scheme-LB, and SG policies using our traces. The SL and the Scheme-LB policies perform well, particularly for large \( C \). For example, Fig. 10 shows the performance under the Scheme-LB, SL,
and SG policies for a trace of participant M2. Fig. 10(a-d) show $\tau$, $Z$ (as a fraction of $Z_{\text{max}}$), ON time percentages, and $E_{\text{md}}$, respectively. These performance metrics are evaluated for different values of $C$, which are shown as a percentage of the total daily energy harvested, $E_d$. Each data point in Fig. 10(a-d) corresponds to a full policy realization, such as the one illustrated in Fig. 9.

For relatively large $C$ values (e.g., $C > 0.7E_d$), the SL and Scheme-LB policies perform well – $\tau$ is high (Fig. 10(a)), $Z$ is close to $Z_{\text{max}}$ (Fig. 10(b)), and ON times reach 100% (Fig. 10(c)). Both the SL and Scheme-LB policies slightly overspend the harvested energy (Fig. 10(d)), but the overspend does not exceed 5% of $E_d$.

Both the SL and the Scheme-LB policies dramatically outperform the SG policy. The SG policy achieves high $\tau$ (Fig. 10(a)) and fully uses the harvested energy (Fig. 10(d)), but performs poorly in terms of both objective function values and node ON times. Specifically, under the SG policy, $Z/Z_{\text{max}}$ values are up to 2 times smaller than under the SL and the Scheme-LB policies (Fig. 10(b)), and the ON times are up to 4 times smaller (Fig. 10(c)). The poor performance under the SG policy emphasizes the need for energy management policies that consider motion energy variability and do not base spending rates directly on harvesting rates.

While the SL and Scheme-LB policies perform well, the performance differs from trace to trace. For example, Fig. 11 shows the performance of the SL policy with traces for participants M1, M2, and M5. Fig. 11(a,b) show the ON times and $E_{\text{md}}$ values, correspondingly. It can be seen that in terms of both metrics, the SL policy performs better for M2 than for M1 and M5.

### C. i.i.d. and Markov Processes

Several energy harvesting adaptive policies have been developed under the assumption that the energy harvesting process has independent identically distributed (i.i.d.) per-slot energy inputs or is a Markov process (e.g., [11], [14]). Such simplifications allow for analytical tractability, and are realistic in certain scenarios [11]. However, the assumptions do not hold for the motions energy traces we examine: for these traces, $P_{\text{meas}}$ is clearly not i.i.d. or Markov. For example, for the $P_{\text{meas}}$ for participant M1 and for $THR = 10 \mu W$, $p(P_{\text{meas}}(i) > THR | P_{\text{meas}}(i-2) > THR) = 0.91$, while $p(P_{\text{meas}}(i) > THR | P_{\text{meas}}(i-1) > THR, P_{\text{meas}}(i-2) < THR) = 0.54$.

To assess the difference in performance between policies evaluated using real traces and i.i.d. and Markov processes, we use a different representation of the same energy harvesting process. Specifically, for a process $P_{\text{meas}}$ calculated from our measurements, we generate an i.i.d. process, $P_{\text{id}}$, by randomly permuting the values of $P_{\text{meas}}$. To generate a Markov process, $P_{\text{markov}}$, we first calculate the empirical state transition probabilities of the $P_{\text{onoff}}$ process (defined in Section VI-B3), $p_{0,1} = p(P_{\text{onoff}}(i) = 0 | P_{\text{onoff}}(i-1) = 1$) and $p_{1,0} = p(P_{\text{onoff}}(i) = 1 | P_{\text{onoff}}(i-1) = 0$. Then, we generate a Markov process with states $\{0, 1\}$ and transition probabilities $p_{0,1}, p_{1,0}$. We set the $P_{\text{markov}}$ values to states 0 and 1 to the average values of $P_{\text{meas}}$ for which $P_{\text{onoff}}(i) = 0$, and for which $P_{\text{onoff}}(i) = 1$, respectively. This ensures that the processes have the same first-order statistics.

The policy performance evaluated using i.i.d. and Markov processes differs dramatically from the policy performance using the traces. For example, Fig. 12 shows $\tau$ and ON times obtained under the Scheme-LB policy for different processes based on a trace of participant M2. Using the process $P_{\text{onoff}}$, the performance is similar to the performance obtained using $P_{\text{meas}} = \tau$ values differ by at most 17% (0.23 Kb/s), and the ON times differ by at most 7%. However,
the performance evaluated using $P_{\text{markov}}$ and $P_{\text{iid}}$ differs greatly from the performance using $P_{\text{meas}}$. The differences in $\tau$ values reach over 105% (1.35 Kbps), and the differences in ON times reach 63%.

Moreover, using Markov and i.i.d. processes results in different performance trends. Using $P_{\text{meas}}(i)$, the performance strongly depends on $C$, with $\tau$ for the different values of $C$ differing by over 2.3 times, and with the ON percentages differing by over 45%. However, using $P_{\text{iid}}$ and $P_{\text{markov}}$, both $\tau$ and ON times are nearly independent of $C$. Additionally, evaluating policy performance using $P_{\text{meas}}$ demonstrates than ON times are an important metric – they can be relatively low for small values of $C$ (Fig. 12b)). However, when evaluating using $P_{\text{iid}}$ and $P_{\text{markov}}$, the ON times are nearly 100% for all values of $C$, including values as low as 15% of the $E_d$. These results emphasize the need to evaluate energy harvesting-adaptive policies for wireless nodes equipped with an inertial harvester using real traces.

VIII. CONCLUSIONS

This report considers motion (kinetic) energy availability for Internet of Things applications. We provide observations regarding object motion and thoroughly study human motion. For human motion, we use the results of our measurement campaign that include 200 hours of acceleration traces from day-long human activities. Moreover, we use a dataset of 7 common human motions performed by over 40 participants [31]. Based on our dataset, we evaluate the performance of energy harvesting adaptive algorithms with motion energy traces. Our study can provide insights into the design and evaluation of motion energy harvesters, mobile devices, and energy harvesting adaptive algorithms.

REFERENCES