Inertial Kinetic Energy Harvesters for Wearables: The Benefits of Energy Harvesting at the Foot

CHRISTOPHER BEACH†, (Student Member, IEEE), AND ALEXANDER J. CASSON‡, (Senior Member, IEEE)
Department of Electrical and Electronic Engineering, The University of Manchester, Manchester M13 9PL, U.K.
Corresponding author: Christopher Beach (christopher.beach@manchester.ac.uk)

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ABSTRACT Wearable devices promise to reduce strain on the healthcare system and to improve quality of life for users. However, adoption in healthcare settings is limited due in part to the need for constant battery maintenance; which leads to reduced adherence, more complex operation and missing sections of data. Energy harvesting can reduce the reliance on batteries, but the harvesting potential varies substantially depending on where the harvester is placed. Few previous studies investigating placement have considered the foot as a harvesting site, despite the significant interest in smart-shoes and the intrinsic social discreteness of wearable devices at the foot. We investigate the amount of power that can be harvested from four sites on the human body (wrist, hip, ankle and foot), with 12 participants walking on a treadmill. We analyse the differences in the frequency spectrum at each of these sites and perform a sweep of inertial energy harvester parameters to identify the optimal parameters for each site on the body. By considering both performing the harvesting at the foot, and the frequency distribution of the input spectrum present for the first time, we identify that harvesting at the foot provides multiple benefits: more power is available in total; greater physical size is available (compared to the wrist); lower Q harvesters can provide better broadband response; and the foot is the least sensitive location for changes in frequency of walking rate. For harvesters sized at 100 mm, we find that there is 4.2, 6.4 and 25.7 times more power at the hip, ankle and foot respectively compared to the wrist. Foot based sensors thus provide a promising approach towards future fully battery-free wearable devices, motivating future work to investigate the sensing modalities that are feasible at the foot.

INDEX TERMS Battery charging, energy harvesting, wearable sensors.

I. INTRODUCTION
A key limitation of wearable devices is limited battery life [1]–[3], with devices often requiring recharging daily or every few days. This frequency increases for more complex devices that offer either greater sensing modalities, sampling rate or access to the raw data. In many target groups where wearables could offer the largest benefit, such as the elderly and those with cognitive impairments, sensing needs to be fully automated and completely unobtrusive to the end-user [4]. Recharging devices is reported as one of the most significant barriers to adoption in the elderly population [5], [6], where care needs to be taken to personalise devices to individual needs [7]. Further, having to remove a device for recharging causes gaps in the collected data, reducing the effectiveness of the technology [4]. Ideally, devices would be completely energy-autonomous allowing people to use them in a fit-and-forget fashion where there is no need for battery maintenance. The power consumption of recent commercial devices is a long way from realising this, necessitating improved batteries or approaches such as energy harvesting to be investigated.

A number of methods to harvest energy from the human body have been investigated, including harvesting from motion; electromagnetic radiation; light; and thermal gradients [8]. Harvesting from light is a well-researched field with solar panels being the most common transduction method. Although there is a need for a direct light source to maximise power output, there is work in the literature investigating their usage in implantable devices [9]. However, in the case of...
weareables, particularly when there is a need to place devices in discrete locations, shading is a particular concern, which considerably limits power output. Harvesting from electromagnetic radiation, most commonly from radio-frequency (RF) spectrum sources, are well researched [10], [11], and commercial products exist to take advantage of this, such as the Powercast [12]. Unfortunately, devices typically require large antennas to gain sufficient power and often require the source emitting the power to be near to the receiving electronics. While near-field communication (NFC) and Qi charging [13] are common on mobile devices, these have a very short range and therefore are not true energy harvesting technologies. Harvesting via heat using a thermal gradient has had limited success powering basic devices such as watches, with the Seiko Thermic [14] being a notable example. In practice, this requires a large temperature differential on the two sides of the device to be present. As thermal gradients on the body are typically small, the amount of energy that can be harvested is low. However, this topic is of some interest, with a recent review provided in [15].

The final method, motion, is the most common for powering devices placed on the human body as the predictable quasi-periodic movements during walking offer the most benefit for harvesting. Motion harvesting devices can be fabricated using micro-electromechanical systems (MEMS) techniques, making them very small and suitable for use in a wearable. Reviews of motion-driven energy harvesters, also known as kinetic energy harvesters, are provided in [16]–[18].

While there is considerable interest in inertial kinetic energy harvesting to reduce reliance on battery recharging, little work has been undertaken to model the energy harvesting potential at the foot. The foot is a location of particular interest as it not only offers a socially discrete location for wearable sensing, but devices placed here can also enable better monitoring of diabetic foot ulcers (DFUs), a life changing condition associated with diabetes [19]. Through continuous temperature [20] and pressure [21] monitoring smart devices at the foot may be able to reduce the incidence of DFUs [22]. Activity tracking via accelerometers can also be performed at the foot [23], with investigations on heart rate monitoring ongoing [24]. However, the need for battery recharging can be a particular barrier to adoption, reducing adherence and lowering the ability of the device to provide protection.

To demonstrate the potential benefits of foot based sensors for pairing with energy harvesting, this paper presents an investigation into kinetic energy harvester output and tuning at four sites on the human body (the wrist, hip, ankle and the foot) during the repetitive movements of walking on a treadmill. We have previously demonstrated how sites such as the foot and lower leg offer different performance and harmonic content for kinetic energy harvesters [25]. Here, we build on this work presenting a detailed investigation into not just how the power varies between sites on the body, but also how the frequency content varies at each of these sites and how this effects the tuning of an inertial energy harvester.

This paper focuses on signals collected in a controlled laboratory environment, rather than analysing a natural free-living environment. Previous estimates have shown that lower body locations are more energy-dense for energy harvesting in an absolute sense [26], [27], however, to our knowledge no studies have compared the actual energy harvested from the foot with other locations on the body. (Some studies have used the ankle as a proxy for the foot, which we demonstrate is not valid.) Additionally, previous works have not given a detailed investigation into how the frequency content of the collected waveforms differ at each site of the body and how this affects the optimum harvester parameters and harvester output. This paper details how not only is the foot the best location on the body for harvesting power because more energy can be collected in an absolute sense, but the frequency content at the foot allows for lower Q harvesters that give a better broadband response, and for more efficient harvesters that are less susceptible to changes in walking rate.

The remainder of this paper is structured as follows. Section II discusses the methods used, including the implementation of the harvester model to estimate harvestable power from an accelerometer, the methods for identifying the optimum harvester parameters, and the experimental protocol undertaken with 12 participants. Section III presents how the frequency content differs at each of the sites on the body by analysing the frequency spectrum. Section III also presents how the optimum harvester parameters vary at different sites of the body for different physical sizes of harvester. Following on from this, the average power that can be harvested at each location for a variety of harvester sizes is presented. Next, the variation in power output with changes in walking rate for each of the sites is shown, allowing investigation into how sensitive each location on the body is to changes in walking cadence. Section IV places these results in context, discussing whether the typical range of harvestable energy from the body can power some common wearables.

II. HARVESTER MODEL AND EXPERIMENTAL METHODOLOGY

A. HARVESTER MODEL

In this work we focus on inertial kinetic energy harvesters, the energy output from which can be modelled with a mass-spring-damper system, as shown in Figure 1, based upon the model presented by Bürer et al. [26]. Physical realisations of these harvesters exist [28]–[33], but the work here focuses on the modelling of a harvester operating in the ideal case to investigate the maximum theoretical energy that can be harvested and how this compares between body sites. The model presented in this paper is based upon the work introduced in [16], [26], [34], of which Berdy et al. [28] found gave accuracy within 14.4% compared to a practical device.

The harvester is modelled as a second-order system with a proof mass, \(m\), damper, \(b\), and spring constant, \(k\). When the proof mass has a force exerted on it by an external displacement, the proof mass itself is displaced, the movement of which is controlled by the harvester parameters.
The combination of $m$, $b$ and $k$ form a second-order system that can be represented by the transfer function shown in (1),

$$Z(t) = \mathcal{L}^{-1}\left\{ \frac{d(s)}{ms^2 + bs + k} \right\}.$$  

(1)

Here the inverse Laplace transform of the external displacement acting on the device ($d(s)$) is taken to find the relative movement of the proof mass inside the harvester ($Z(t)$). The system takes the form of a second-order low pass filter, and therefore the system can be represented in the standard form as shown in (2),

$$Z(t) = \mathcal{L}^{-1}\left\{ d(s) \frac{K_0(2\pi f_r)^2}{s^2 + 2\pi f_r s + (2\pi f_r)^2} \right\}.$$  

(2)

where,

$$K_0 = \frac{1}{k} f_r = \frac{\sqrt{k/m}}{2\pi}$$  

and $K_0$ is steady-state gain, $f_r$ is the resonant frequency and $Q$ is the quality factor.

Due to the physical size limitations of the harvester, the proof mass cannot travel further than its end-stop limits. Rather than limiting the movement of the proof mass in simulation, we only consider values for $m$, $b$ and $k$ that do not cause the mass to displace further than the end-stop limits of the harvester frame, similar to the methods by Büren et al. [26].

To find the instantaneous power, the displacement of the proof mass is converted into velocity, by differentiating the movement of the mass. This value is then squared and multiplied by the damping coefficient. Here, we assume that the damper in the system is able to convert all the energy absorbed into it into electrical energy, with no losses. The equation to convert the displacement of the proof mass to instantaneous power is shown in (3),

$$P(t) = b \left( \frac{dz(t)}{dt} \right)^2 = b (v(t))^2.$$  

(3)

A linear efficiency factor can then be applied to account for losses in converting mechanical energy to electrical energy. However in this paper, to identify the theoretical maximum energy that can be harvested, this efficiency factor is assumed to be 100%. The steps of the harvesting process are summarised in Figure 2.

Changing the $Q$ of the harvester changes the frequency response and thus the gain (and therefore power) harvested at the resonant frequency ($f_r$). With $Q > 1$ there is a resonant peak in the frequency response, which causes amplification at the resonant point of the filter (harvester), with higher $Q$ factors increasing this amplification. However, higher $Q$ factors also correspond to more selective harvesters with a narrower bandwidth. A very narrow bandwidth corresponds to a single walking rate (cadence), which is unlikely to be desirable as the harvester will generate a substantially larger amount of power only when the user walks at this cadence, and very little when deviating from this cadence. Further, given that the harvester parameters, $m$, $b$ and $k$, interact with one another to change the properties of the harvester it is not possible to configure the harvester to a set $Q$ without changing another parameter of the system. For example, decreasing $b$ would increase the $Q$ of the harvester (leading to higher gain and therefore power at $f_r$), but (3) shows how decreasing $b$ would reduce the collected power. Other work has fixed the $m$ of the harvester and swept $b$ and $k$ to maximise power [26], [35], but none have discussed what the optimum $Q$ and $f_r$ harvester parameters were, nor how these differ at different sites on the body where the collected frequency content may differ at different sites.

The process detailed in Figure 2 requires an input of the relative displacement of the harvester. However, recording the absolute position of a device is challenging, whereas recording acceleration is easy and widely available with accelerometers. Thus accelerometers are used to estimate energy harvesting generation output. This acceleration measured in gravitational force equivalents (g) needs to be converted into a displacement experienced by the harvester in meters.

Here, the output data in g is first converted into m/s$^2$, by multiplying the signal by 9.81 m/s$^2$, the average value for the nominal gravity at the surface of the earth. As [26] discusses, the accelerometer records data with respect to a moving reference frame, and as there is not a gyroscope recording alongside the accelerometer, it is not possible to identify the
orientation of the device. However, it is possible to find the relative motion (displacement) of the body motion at the location of the accelerometer (which will correspond to the displacement experienced by the generator proof mass), by double integrating the acceleration signal. Therefore, we perform a double integration of the data with respect to time to convert the acceleration signal into a value of displacement, using the trapezoidal rule with the `integrate.cumtrapz` function from SciPy. After performing the double integration it was found that the data contains a downwards baseline trend. This is a result of small amounts of sensor drift accumulating and cumulatively being added when performing the double integration. To remove this, the double integrated data is filtered with a sixth-order zero-phase high-pass Butterworth filter with a cutoff of 0.3 Hz, selected as it is low enough to remove the drift, while not overlapping with the frequency content from walking. The output of these steps gives a signal representing the relative displacement of the accelerometer in meters which can be used to estimate the amount of power that can be generated from an energy harvester. These steps are summarised in Figure 3.

![Figure 3. Steps to convert the data from an accelerometer to displacement.](image)

**B. EXPERIMENTAL PROTOCOL**

While there are numerous studies estimating energy harvesting output from accelerometer data, and many of these datasets available online [36], [37] for participants walking on a treadmill and performing various other activities, none of these are suitable here as they do not look at placing the sensors at the foot. Therefore new data collection was required for this study.

A total of 12 participants were recruited to take part, 4 female and 8 male. Age, height, weight and BMI (mean ± SD): 39.25 ± 13.84 years, 171.79 ± 7.92 cm, 71.79 ± 17.05 kg, 24.09 ± 4.04 kg/m². Participants were excluded from the experiment if they were unable to undertake light exercise for 20 minutes, ever had a fainting spell or syncope, were pregnant or had any damaged skin tissue or a skin condition such as severe eczema, skin allergies or sensitive skin. All procedures used in this study were reviewed and approved by the University of Manchester Research Ethics Committee, application number 2019-6498-9910. Written informed consent was obtained from all individual participants included in the study, and participants were not remunerated.

Participants were fitted with a three-axis accelerometer (Axivity AX3, Newcastle-upon-Tyne, UK) [38], with sensors mounted on different locations on the body at the same time: the wrist, the hip, the ankle and the foot. Sensors were mounted on both the right and left side of the body to provide redundancy, in the event one sensor contained artefacts from poor sensor adhesion to the body or excessive additional arm movements. The wrist was chosen to allow direct comparison with previous works for validation purposes, and represent the location where most wearables are worn today. The hip was chosen to represent the location where many people keep a mobile phone. The sensor at the ankle is used to provide a comparison with where others have mounted sensors in similar work [26], [35], [39] as well as a location where some wearable electronics have been fitted (such as in the Siren Smart Socks [40]). Finally, the sensors were placed at the foot to consider insole type devices such as the SurroSense Rx (a pressure sensing insole developed to monitor DFUs). Of note is that the foot is likely a desirable location for an energy harvester as the large cavity of a shoe may be able to fit larger generators compared to other locations on the body. Little work in the literature considers the foot location for kinetic energy harvesters, with many using the ankle or lower leg as a proxy location for the foot [35], [39], [41]. Figure 4 shows the locations of each of the sensors on the body with the orientation of the sensors. The orientations were selected for mounting convenience, as opposed to mounting each sensor in the same orientation.

![Figure 4. Locations of each of the accelerometer sensors on the body in the experiment. Arrows denote the orientation of the axes for each sensor. Note the arrows angled at 45 °, \( \Rightarrow \), \( \Rightarrow \), \( \Rightarrow \) denote a vector going into the page or out of the page respectively. Image edited from [42] (CC BY-SA license).](image)

The accelerometers used in this experiment were 3-axis sensors, which recorded acceleration in three axes, \( x \), \( y \), and \( z \). However, the model presented in Section II-A suggests an input signal of a single dimension. To tackle this, Gorlatova et al. [34] analysed the magnitude of the three axes. However, taking the magnitude requires taking the square root of the sum of squares of each axis, which is a non-linear operation and therefore will introduce non-linearities...
The sensors at the ankle and hip were held in place using hypoallergenic medical tape (Hypafix, BSN Medical Ltd., Hull, UK) attaching them directly to the skin. The sensors at the wrist were held in place using the supplied Axivity wrist band. For the sensors placed at the foot, a custom 3D-printed insole was created for a variety of shoe sizes (EU 37 – 47). The insole was printed out of a flexible thermoplastic polyurethane (TPU) material (Ninjaflex Semiflex, Fenner Drives, Inc., Pennsylvania, USA), with a slot to allow the accelerometer to fit underneath the arch of the foot, shaped to match the contours of a typical foot. The equipment used in this study is shown in Figure 5, showing the AX3 sensor, the wrist strap, custom sensor insole mount and running shoe. All sensors were securely fastened to the body to minimise any relative movement between the sensor and the body. Before the sensors were fitted to each participant the sensors underwent a synchronisation procedure, synchronising all sensors in time with each other to within a few samples.

Participants were instructed to walk on a treadmill (LifeSpan TR1200i, LifeSpan, Staffordshire, UK) as close as possible to how they would normally walk, while the speed of the treadmill was controlled by the experimenter. The treadmill was started at 2.4 km/h and the speed increased every 60 s by 0.1 km/h until the treadmill reached 4.3 km/h. These speeds were chosen to maximise the number of participants meeting the walking rate of 95, 100 and 105 steps/minute (see Section II-C), while keeping all participants at a walking (opposed to running) gait. After 20 minutes the treadmill was stopped and the participant was instructed to leave the treadmill and remove the sensors. The data from the sensors was then downloaded and saved to a PC. The sensors sampled at 100 Hz with considerable sampling jitter, as a result the data was re-sampled to 100 Hz using the provided OmGUI software from Axivity.

C. ANALYSIS METHODS

Data was analysed using Python 3.7 from the Anaconda Distribution v2019.03. Each axis of the data was filtered with a sixth-order zero-phase high-pass Butterworth filter with a cutoff of 0.1 Hz removing the gravity component as in [34]. The filtered data was split into 60 s segments corresponding to each increment in the treadmill speeds between 2.4 km/h – 4.3 km/h. The first and last 10 s of each record was then removed to leave a 40 s window of the participant walking at a fixed speed, to remove any transient effects as the treadmill stabilised its speed and the participant reacted to the speed change, as well as compensating for any timing errors between the treadmill and the accelerometer.

The cadence of the participant (numbers of steps taken in a minute) at each speed was calculated using peak detection on both of the sensors at the feet. Then, for each participant, the treadmill speed at which each participant was closest to walking at three cadences (of 95, 100 and 105 steps/minute) were found. These cadences were selected to provide a range which the majority of participants met when walking between 2.4 km/h – 4.3 km/h. In this work we normalised by cadence rather than speed to allow more accurate comparisons between participants. When normalising by cadence the fundamental frequency will be approximately the same as footfalls occur at the same frequency. In contrast, when normalising by speed, the fundamental frequency will be determined by the stride length (dominated by their leg length) of the participant. Using cadence allows the variations in stride lengths between participants to be removed.

Each participant was fitted with two sensors at each location, one on each side of the body, to provide redundancy. By default, the left sensor was chosen as the analysis sensor, but if a sensor at a particular location was found to have a large number of artefacts (e.g. due to high arm movements or a sensor becoming unmounted) at a particular cadence, the alternative sensor on the right side of the body was selected.

D. HARVESTER PARAMETER SWEEP

We then processed the data using the harvester model presented in Section II-A. To identify suitable values for the harvester parameters \((m, b, \text{and } k)\), we swept these parameters
while using the data from each participant at each sensing location at 100 steps/minute as the input, while calculating the average power as the output. The harvester parameters were swept according to common values found in the literature [35], \( m: 0.01–5 \) g, \( b: 0.001–2 \) kg/s, \( k: 0.1–400 \) kg/s\(^2\), while ensuring that the resultant \( f_r \) of the harvester remained below 10 Hz. Each of the values were swept in equal steps, with 100 values for \( m \) and \( b \), and 800 values for \( k \), generating a total of eight million combinations, for which we make use of a high-performance computing system to process. We considered physical harvester sizes (\( Z_L \)) between 5–100 mm, by discarding combinations of \( m \), \( b \), and \( k \) that caused the proof-mass to exceed each physical harvester size. The values of \( Z_L \) considered here correspond to harvesters fabricated using precision engineering techniques, rather than MEMS type devices [26], [28]. In the case of placing a device at the foot, it is possible to imagine physically larger harvesters could be placed inside a shoe cavity compared to being placed at the wrist, although this is not discussed further here. We then identified the optimum parameters for each configuration (\( Z_L \) and physical position on the body) by considering the parameters that generated the highest mean power for the largest number of participants.

E. EXTRACTED ANALYSES

From the collected accelerometer data and the optimum value for the harvester parameters, we will consider the following analyses:

- The frequency spectrum for a single participant’s record and a composite spectrum representing an average participant.
- The variation in optimal harvester parameters (and their corresponding \( f_r \) and \( Q \)) across the body and for different harvester \( Z_L \) values.
- The variation in power output with \( Z_L \).
- The variation in harvester output with walking cadence.

III. RESULTS

A. SAMPLE WAVEFORMS

A total of four participant’s records were switched from the left wrist to the right wrist to remove records that contained excessive arm movements, but no participants had to be removed from the analysis. We found that while all participants walked at the cadence of 100 steps/minute, not all participants walked at 95 or 105 steps/minute. This was due to a combination of speed control on the treadmill (which could only be controlled in 0.1 km/h steps), variances in walking pattern between participants, and differences in stride lengths between participants that were not predictable in advance. For the participants that did not walk at these cadences, their record was discarded when analysing the power output at this cadence. A total of four participants did not walk at 95 steps/minute (giving eight participants walking at this rate) and one participant did not walk at 105 steps/minute (giving 11 participants walking at this rate).

Figure 6 shows an example of the signals collected during this experiment, with a participant walking on the treadmill at 100 steps/minute. Figure 6 shows an example of the acceleration signals (after filtering and converting to m/s\(^2\)), as well as the velocity (after the first integration step), and the displacement (after the double integration and filtering). At each of the locations, the displacement waveform in Figure 6c, f, i, l, shows a clear peak each time a footstep is taken. At the ankle and foot, this is very clear to see, while records at the wrist and hip also show a component of at double the frequency than seen at the ankle and foot. The wrist and hip also appear to be noisier as they are subject to additional high-frequency components from random movements of the arm and the shank as the person walks.

B. FREQUENCY SPECTRUM ACROSS THE BODY

To analyse how the frequency content varies across the body we analyse the frequency spectrum of the velocity signal, rather than the displacement. This is because, as in Section II-A we showed that while the harvester model input is the displacement of the harvester frame, the movement of the resultant proof mass is then differentiated (which is the velocity). The operations in the harvester model are commutative (order is not important), and therefore the velocity components of the input signal can be analysed as this is what affects the power generated.

Initially, Figure 7 shows the frequency spectrum of the velocity for a single participant walking at 100 steps/minute for each of the locations on the body. The frequency spectrum was calculated by taking the magnitude of the fast Fourier transform (FFT) using the \texttt{fft} function in SciPy with a rectangular window (with no overlap) and 4,000 points, corresponding to a frequency resolution of 0.025 Hz. The location of each of the peaks shown in Figure 7 in the FFT were identified with the \texttt{find_peaks} function. As the treadmill speed was kept constant for each record, the gait frequency is constant (and thus the collected waveforms are stationary) making the use of the Fourier transform appropriate, rather than requiring the use multiple overlapping windows or techniques such as Welch’s method.

A walking cadence of 100 steps/minute corresponds to a cadence frequency of 1.67 Hz, while the gait frequency is half of this (two steps per gait cycle), at 0.83 Hz. The peaks in the waveform demonstrate this, with the two largest peaks at each of the locations corresponding to the gait and cadence frequency at 0.83 and 1.67 Hz respectively.

The locations of the other peaks highlighted in Figure 7 correspond to the harmonics in the signal, which are integer multiples of the gait frequency. The weightings of these harmonics vary at each location, with the 2\(^{nd}\) harmonic being the dominant at the two upper body locations (the wrist and hip) and the 1\(^{st}\) harmonic the dominant at the two lower body locations (the ankle and foot).

To obtain a composite of the frequency spectrum for all participants we analyse the magnitude of each of the harmonics in the velocity spectrum for each participant and
normalise to the largest magnitude at each location. This was repeated for each of the participants and averaged together to create Figure 8. It is not possible to simply average together each frequency spectrum created by each participant as variations between participants (such as small variations in their cadence (jitter) and the force exerted with each step) cause small variations in the spectrum peak locations as well as different absolute values of peak heights. Therefore, normalising by the largest peak height and by harmonic number rather than frequency allows a more accurate representation of a composite frequency spectrum. Figure 8 shows the contribution of each harmonic in the waveform to the overall velocity signal, for an average participant. In Figure 8a it can be seen that the relative weighting of the 2nd harmonic is nearly 1, but not exactly. This is a result of having at least one record where the 2nd harmonic was not the dominant peak, therefore bringing down the average from 1.

In Figure 8, the distribution of the frequency content across the body can be seen. Of note is that at the wrist, (in Figure 8a), the majority of the content is present in the even harmonics, with the largest contribution from the 2nd harmonic. Again in Figure 8b, at the hip, the largest contribution comes from the 2nd harmonic. However, here we do not see the same pattern as the wrist (where the majority of the contribution was from the even harmonics), instead at the hip the contributions decrease as the harmonic number is increased. The ankle and foot in Figure 8c and d, show a different pattern. The harmonic with the largest contribution is

**FIGURE 6.** Example of signals collected from a single participant walking at 100 steps/minute. Showing an example of the acceleration, velocity and displacement waveforms for each location on the body.
TABLE 1. Optimum harvester configurations for each location for a variety of physical sizes ($Z_L$), tuned for the participants walking at 100 steps/minute. Units of $m$ are g, $b$ are kg/s, and $k$ are kg/s$^2$.

| $Z_L$ / mm | Wrist | | Hip | | Harvester Location | | Ankle | | Foot |
|-----------|-------|-------|-------|-------|-------|-------|-------|-------|
|           | $m$   | $b$   | $k$   | $m$   | $b$   | $k$   | $m$   | $b$   | $k$   |
| 5         | 0.64  | 0.67  | 69.88 | 1.09  | 0.53  | 117.57| 2.64  | 1.37  | 191.98|
| 50        | 0.11  | 0.07  | 12.15 | 0.11  | 0.31  | 9.64  | 0.29  | 0.93  | 11.65 |
| 100       | 0.06  | 0.03  | 6.63  | 0.04  | 0.04  | 4.12  | 0.39  | 0.39  | 10.64 |

FIGURE 7. Frequency components of the velocity signal from each of the sensors with a single participant walking at 100 steps/minute. Here the locations of each of the harmonics are highlighted with a black circle. Note y-axis scale is not identical between sub-figures.

FIGURE 8. Weighting of each of the harmonic components at each location for all participants relative to the largest peak in each FFT. Each harmonic weight for each location and participant has been normalised to the largest harmonic in each case. Error bars show 95% confidence intervals.

C. OPTIMAL HARVESTER PARAMETERS ACROSS THE BODY

Table 1 details the optimum values of $m$, $b$ and $k$ for each location and value of $Z_L$. In Table 2, the values of $f_r$ and $Q$ corresponding to the values of $m$, $b$ and $k$ in Table 1 are shown. Table 2 also highlights which harmonic from Figure 8 $f_r$ corresponds to. In Table 2 it can be seen that at the ankle and foot, as the physical size, $Z_L$, increases, the optimum $f_r$ decreases. That is, with a larger physical size it becomes more optimal to use a lower harmonic for tuning the energy harvester to, and vice versa. As can be seen in Figure 8, higher harmonics typically have lower weighting, therefore choosing a higher harmonic as the resonant frequency will give smaller proof mass displacements — which is desirable when the 1st harmonic, with the contributions dropping off, approximately halving with each increase in harmonic number for the first four harmonics.

The dominant harmonics in Figure 8 are not necessarily surprising. Sensors at the wrist and hip are placed on the upper half of the body and see both footfalls (unlike a sensor on the leg which predominately sees one foot hit the ground). It would, therefore, be expected for the two upper body sensors (wrist and hip), that the dominant frequency will correspond to the cadence frequency (1.67 Hz). At the ankle and foot, the dominant frequency will correspond to half the cadence frequency (0.83 Hz), as it takes two footsteps to complete a gait cycle. The wrist sees the most contribution from even harmonics, at even multiples of the cadence frequency, as this part of the body will move at multiples of the cadence frequency with the contributions from half the cadence frequency being smaller.

In Figure 8b, the first harmonic has a weight of 0.65, while doubling the frequency, and therefore looking at third harmonic, the weight is 0.34, approximately half. Therefore, for a harvester tuned exactly to align with these harmonics, the average power generated will be a quarter of the amount when tuned to the third harmonic compared to the first harmonic for a person walking at 100 steps/minute with a harvester placed on the hip. In general, the wrist has a narrow bandwidth with all of the energy contained in only a few harmonics. Therefore, if the harvester is not well-tuned to these harmonics very little energy will be collected. In contrast, the other sites, and particularly the hip, have a broader spectrum allowing some energy to be collected even if the harvester is not well-tuned to any single harmonic (recalling that Figure 8) is normalised and so this does not account for the absolute amount of energy available at each site. Comparing with Figure 7, the magnitudes at the hip are larger than the wrist, giving two opportunities for greater harvester output.
TABLE 2. Optimum harvester configurations for each location for a variety of physical sizes ($Z_L$), tuned for the participants walking at 100 steps/minute. Units of $f_r$ are Hz, values in brackets show the harmonic number corresponding to this resonant frequency.

| $Z_L$ / mm | Wrist | Harvester Location | Hip | Ankle | Foot |
|------------|-------|--------------------|-----|-------|------|
|            | $f_r$ | $Q$                | $f_r$ | $Q$    | $f_r$ |
| 5          | 1.67(2) | 9.90              | 1.65(2) | 21.21 | 1.36(2) | 16.48 | 2.60(3) | 12.17 |
| 50         | 1.67(2) | 16.23              | 1.49(2) | 3.30   | 1.02(1) | 1.97  | 0.83(1) | 6.20  |
| 100        | 1.67(2) | 20.28              | 1.72(2) | 9.23   | 0.84(1) | 5.16  | 0.83(1) | 5.80  |

TABLE 3. Average harvested power at each location for a range of harvester sizes. Values are Means ± SD.

| $Z_L$ / mm | Wrist | Average Power / mW | Hip | Ankle | Foot |
|------------|-------|--------------------|-----|-------|------|
|            | $f_r$ |                     | $Q$ |       |      |
| 5          | 0.051 ± 0.011 | 0.103 ± 0.029 | 0.013 ± 0.002 | 0.094 ± 0.014 |
| 50         | 0.371 ± 0.044 | 0.390 ± 0.042 | 1.669 ± 0.581 | 9.254 ± 0.547 |
| 100        | 0.731 ± 0.098 | 3.043 ± 0.778 | 4.683 ± 0.876 | 18.777 ± 1.066 |

...the harvester dimensions are constrained — as this again reduces the likelihood of the proof mass reaching the end stops of its movement, introducing non-linearities and reducing the energy that can be harvested. This effect is not seen at the wrist and hip as the displacements at these locations are smaller (see Figure 6), therefore it is not necessary to tune to a higher frequency harmonic to avoid reaching the limits of proof-mass displacement, at the values of $Z_L$ investigated here. We can also identify that the wrist and hip generally have values of $f_r$ that correspond to even harmonics, while the ankle and foot generally correspond to odd harmonics. This follows the expected trend from the frequency spectrum in Figure 8.

There is a less clear trend with the optimum $Q$ value shown in Table 2 for increasing values of $Z_L$. Generally, at the hip, ankle and foot $Q$ decreases for larger values of $Z_L$, and at the wrist $Q$ increases for larger values of $Z_L$. When moving from the wrist to the ankle or foot, there is a decrease in the optimum $Q$ of the harvester, except for when $Z_L = 5$ mm. A larger value of $Q$ represents a more selective harvester with higher gain at around $f_r$, while a lower $Q$ is less selective and therefore less sensitive to changes in input frequency and therefore cadence. In Section III-E we will look further at how changes in cadence affect the output of the harvester.

D. VARIATIONS IN POWER HARVESTED WITH HARVESTER PHYSICAL SIZE

In Table 3 the average power that can be harvested as the physical size of the harvester ($Z_L$) is increased is shown for each location on the body. Here, the harvester parameters are tuned to maximise average power for each size increase and location, as in Table 1. The data in Table 3 allows an analysis of how the power output varies from each location. It can be seen that, for $Z_L ≥ 50$ mm, the power output increases when moving down the body, for a given harvester size. The increases in average power relative to the wrist are 1.1, 5.5 and 24.9 times at the hip, ankle and foot respectively when $Z_L = 50$ mm. When $Z_L = 100$ mm the increase relative to the wrist is 4.2, 6.4 and 25.7 times at the hip, ankle and foot respectively. When $Z_L = 5$ mm, the trend is less clear, with increases of 2.0, 0.3, 1.8 times at the hip, ankle and foot respectively compared to the wrist.

E. VARIATION OF HARVESTED ENERGY WITH CHANGES IN CADENCE

Walking at a faster rate will typically increase output power, as more energy is available to be harvested. However, the parameters of the harvesters considered in this paper are not tuneable in real-time. That is, these harvester devices have a fixed resonance frequency ($f_r$) and quality factor ($Q$), and therefore will perform at their optimum when walking at the cadence they are tuned for. However, as suggested previously, harvesters with a smaller $Q$ are less selective and are therefore will be less sensitive to changes in cadence. Table 2 showed how harvesters lower down the body generally have lower optimum $Q$, suggesting that a harvester placed on the lower body may be less sensitive to changes in cadence compared to one at the wrist, assuming they are both tuned to their optimum parameters.

To test for this, the average power output was investigated with the optimum parameters for a harvester with $Z_L = 100$ mm, and the data from the participants walking at 95, 100 and 105 steps/minute, but the harvester was tuned at 100 steps/minute. First, Figure 9 shows the absolute changes in average power with changes in cadence, using the optimal configuration parameters for each location. As expected, as the cadence is increased the mean power increases (except at the wrist), as more energy is exerted by the participant to walk faster. The opposite effect is also seen as the participant walks slower. However, the amount at which these change with cadence varies between locations on the body.

To identify how sensitive each of the locations is to changes in walking rate, the percentage changes in power output with changes in cadence (compared against 100 steps/minute as a reference) are shown in Table 4. Here, both the
TABLE 4. Percentage changes in mean harvested power at different cadence rates for optimal harvester configurations for each location with $Z_L = 100$ mm.

| Harvester Location | Percentage Change in Mean Harvested Power | Mean Absolute Percent Change |
|-------------------|------------------------------------------|-----------------------------|
|                   | 95 steps/minute                           | 105 steps/minute            |
| Wrist             | $-13.99$                                  | $-17.50$                    | 15.75 |
| Hip               | $-18.90$                                  | $27.88$                     | 23.39 |
| Ankle             | $-14.17$                                  | $23.83$                     | 19.00 |
| Foot              | $-7.21$                                   | $1.14$                      | 4.18  |

TABLE 5. Percentage changes in mean harvested power for a fixed harvester configuration (optimised for the foot) with $Z_L = 100$ mm.

| Harvester Location | Percent Change in Mean Harvested Power | Mean Absolute Percent Change |
|-------------------|---------------------------------------|-----------------------------|
|                   | 95 steps/minute                        | 105 steps/minute            |
| Wrist             | $-11.43$                               | 13.06                       | 12.24 |
| Hip               | $-7.68$                                | $-18.31$                    | 12.99 |
| Ankle             | $-12.64$                               | 18.42                       | 15.53 |
| Foot              | $-7.21$                                | $1.14$                      | 4.18  |

percentage change in mean harvested energy for each cadence (95 and 105 steps respectively) are considered, as well as the mean absolute percentage change in harvested power. Here, the hip is the location most sensitive to changes in cadence, followed by the ankle and wrist, with the foot as the least sensitive location.

The results presented in Table 4 were gathered using the optimum harvester configuration for each location on the body. It has already been shown how lower body locations have lower (less selective) optimum values of $Q$, and therefore it is expected that a harvester at the foot will be the least sensitive to changes in cadence, as this is how it was tuned. To consider how cadence variation affects the energy harvested while removing the effect of changing the harvester parameters, the change in average power with cadence is now considered with fixed harvester parameters at each location (i.e. the $Q$ of the harvester is kept the same across sites). The results of this are presented in Table 4, using the optimal parameters again for a harvester with $Z_L = 100$ mm, but optimised only for a harvester at the foot. Here despite the harvester parameters remaining constant (and therefore the $Q$ remaining constant), the foot still remains the location least sensitive to changes in cadence. For the other locations, the ankle is now the most sensitive to changes in cadence, followed by the hip and wrist for this harvester configuration. Even with removing the bias of changing the harvester $Q$, the foot remains the least sensitive to changes in cadence.

IV. DISCUSSION

A. MEETING WEARABLE ENERGY REQUIREMENTS

This work has considered harvesters that operate with 100% efficiency. Here, we aim to make some brief comparisons to how much actual energy is harvested and whether this is in the range of some commercial devices. For this, a linear conversion efficiency factor of 20% is applied, as in [34], which is similar to the performance of practical harvesters such as those demonstrated in [28]. With the largest physical harvesters ($Z_L = 100$ mm), the average power generated (with the efficiency factor of 20%) was 0.2 mW, 0.6 mW, 0.9 mW and 3.8 mW at the wrist, hip, ankle and foot respectively.

The average power harvested can be compared against some typical commercial and research-grade wearable devices. The average power consumption of these devices has been estimated based on the limited publicly available information, presented in Table 6. First, considering devices at the wrist, three commercial devices are considered: the Fitbit Charge 3, the Fitbit Sense, and the Apple Watch Series 6. These have an average power consumption of 1.6 mW, 6.8 mW & 62.3 mW respectively. The lowest power consumption of these devices, the Fitbit Charge 3, draws around eight times more power than can be harvested on average from the wrist. If the same sensing electronics were placed at the foot or ankle, the power generated is in the same range of the current draw of the Fitbit Charge 3 device, suggesting it would be possible to put a device with similar sensing modalities at this location (heart rate and accelerometer), although the motion artefacts present at the foot make heart rate sensing difficult [24], [43]. The devices with more features, such as the Fitbit Sense and Apple Watch Series 6, are out of the range of the power generated at all harvesting locations. These devices offer more functionality than standard
fitness tracking, with more sensing modalities including ECG (electrocardiogram), SpO2 (blood oxygen saturation), larger displays and the ability to sync with smartphones for notification alerts. This requires continuous wireless communication, which often dominates power draw on a wearable device [25]. This, therefore, puts these devices out of reach of energy harvesting. (Although at the foot such a screen is unlikely to be necessary.) The research-grade device, the Empatica E4, is also considered. This device has no display but as a research-grade device prioritises continuous sampling, opposed to commercial devices that prioritise longer battery life. Therefore, this device has higher power draw at 48.1 mW as a result of featuring many more sensing modalities (PPG (photoplethysmography), accelerometer, temperature, EDA (electrodermal activity)) and faster and continuous sampling for the sensors, compared to commercial devices which often duty cycle sensor sampling to save battery life. Again, this device is out of the range of the power levels harvested in this work.

One of the few commercial wearable devices based at the foot is the SurroSense Rx [48], which is a plantar pressure sensing insole designed for monitoring the condition of feet in those who are at risk of diabetic foot ulcers. This device has an average current draw of 1.8 mW, which is within the power levels of a harvester at the foot. This device is able to reduce power consumption by duty cycling data transmission, saving data locally on the device and only performing the power-intensive wireless communication periodically, when there is relevant data to transmit. Further, as this device samples only pressure, it can sample at a low rate. For example, acceleration is often sampled at higher frequencies, typically around 100 Hz, while the SurroSense Rx device samples at 8 Hz. This presents a trade-off of higher sample rate for potentially better performance compared with lower sampling rate saving battery life (while also additionally reducing the rate required for costly wireless transmissions).

Only some of the commercial devices presented here are within the range of the levels of power that can be harvested from the body. These are typically the devices that either reduce the amount of data collected from a sensor (by duty cycling or reducing sample rate) or by reducing the number of features/sensing modalities on the device. This highlights the need that if a device needs to be powered by energy harvesting alone, care must be taken to design the device around the limitations this presents — the average power draw of this device will have to be considerably (typically around an order or less) lower than the average power draw if the device was expected to be powered from a typical rechargeable cell.

While it has been noted that some current wearable devices could theoretically be powered by energy harvesting alone, the values of average power from energy harvesting considered in this work are from participants continuously walking on a treadmill. In real-world environments, participants spend only a small amount of time walking and therefore the amount of energy generated will be considerably lower. In real-world environments the majority of the time will likely be sedentary, or undertaking an activity that has non-periodic movements, unlike the dataset considered in this paper.

### B. RELEVANCE OF RESULTS

We have demonstrated that a harvester placed at the foot is the least sensitive to changes in cadence. This suggests that the foot is the best location for an kinetic energy harvester if the designer wants to ensure that they are cadence invariant (or as close as is reasonably possible). This will have impacts on designing for a large population, as not everyone has the same natural walking speed, nor do they walk at the same speed throughout the day. Therefore having a harvester that minimises the sensitivity to cadence changes is desirable.

Further, we have demonstrated that each location on the body gives very different output in terms of spectral content, optimum harvester parameters and the average power output from an energy harvester. We have shown that locations such as the ankle cannot be used as an accurate proxy for the amount of power that can be generated from the foot, and results from the actual foot compared to other locations on the body are presented here for the first time. This has not only shown the expected result that more power is available lower down the body, which is known from previous works, but a suite of other benefits of device placement at the foot. As previous works have only focused on the average power this full range of benefits and optimisations have not been demonstrated previously.

### C. LIMITATIONS

While the desired rate for participants to walk on the treadmill was 95, 100 and 105 steps/minute, the treadmill only provided speed control in 0.1 km/h increments. As a result, not all participants walked exactly at the desired cadences, and the closest record to this cadence was instead selected. At 100 steps/minute the maximum deviation in cadence was 1–2 steps/minute, moving the fundamental frequency by a maximum of 0.02 Hz (which is smaller than the frequency resolution of the FFT, 0.025 Hz), a small change which is considered to have a negligible impact on the results here.

Further, the harvesting methods here consider a harvester operating in the best case. Apart from the discussion (Section IV) the transduction efficiency is ignored, and it is assumed that the mechanical damper is able to convert all the energy that is absorbed into it. Practical harvesters are likely to have two effective dampers, the parasitic mechanical
damping of the device and the damping from the electrical transducer. The damping provided by the transducer will depend on the electrical load on the harvester, which will, in turn, move the resonant frequency and damping of the system, and introduce non-linearities. This was ignored in this work as the aim was to consider the maximum theoretical output rather than considering all practical realisation aspects.

Finally, the results discuss the average power generated, assuming that all power generated can be stored without losses. All energy storage elements have some degree of self-discharge [49], which reduce the stored energy in them even when no energy is removed from the terminals. High rates of self-discharge are a particular problem for supercapacitors, with rates much higher than conventional lithium-based rechargeable cells [50]. Supercapacitors are of particular interest for wearables as they can be made fully flexible and from textile substrates [51]. As devices are not able to store all the energy in them for an indefinite period of time, it cannot necessarily be assumed that all the energy generated by the harvester can be stored and extracted when it is required by the connected electronics. This self-discharge effect may become significant in reducing the total amount of energy available. Reducing self-discharge may be possible with energy-driven communication, timing data transmissions with when the most energy is available in the gait cycle [25].

V. CONCLUSION
We have presented a methodology for investigating the amount of energy that can be harvested from different locations on the body from an inertial kinetic energy harvester. 12 participants were recruited and walked on a treadmill at 95, 100 and 105 steps/minute while wearing accelerometers on their wrist, hip, ankle and foot. It was identified that the largest amount of power comes from the second harmonic in the wrist and hip, while the ankle and foot have the largest amount of power in the fundamental. The optimum harvester values varied depending on harvester size and location, with harvesters further down the body typically benefiting from smaller $Q$ factors. Harvesters placed at the foot are the least sensitive to changes in cadence, which may prove beneficial to energy harvester designers.

We have demonstrated that the foot offers multiple advantages for energy harvesting that have previously not been reported. By analysing the time series and frequency content of collected waveforms from different locations of the body there are multiple benefits from harvesting at the foot: more power available in total; more physical size available; lower $Q$ harvesters providing better broadband response; and less sensitive to changes in frequency of walking motion. All of these factors increase the potential for getting usable amounts of power from a harvester. As previous works have focused on the average power, this full range of benefits has not been previously demonstrated. It was found that the average powers harvested in this work were theoretically sufficient to meet the demands on some low-power commercial wearables.

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