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Estimation of kinetic energy harvesting potential for self-powered wearable IoT devices with 67,000 participants from the UK Biobank

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***Abstract*— Energy harvesting from human motion can reduce reliance on battery recharging in wearable Internet of Things (IoT) devices. However, to date, studies estimating energy harvesting potential have largely focused on small scale, healthy, population groups in laboratory settings rather than free-living environments with population level participant numbers. Here, we present the largest ever investigation into energy harvesting potential by utilising the activity data collected in the UK Biobank from over 67,000 participants. This paper presents detailed stratification into how the day of the week and participant age affect harvesting potential, as well as how the presence of conditions (such as diabetes, which we investigate here) may affect the expected energy harvester output. We process accelerometery data using a kinetic energy harvester model to investigate power output at a high temporal resolution. Our results identify key differences between the times of day when the power is available and an inverse relationship between power output and participant age. We also identify that the presence of diabetes substantially reduces energy harvesting output, by over 21%. The results presented highlight a key challenge in IoT and wearable energy harvesting: that wearable devices aim to monitor health and wellness, and energy harvesting aims to make devices more energy autonomous, but the presence of medical conditions may lead to substantially lower energy harvesting potential. The findings indicate how it is challenging to meet the required power budget to monitor diseases when energy autonomy is a goal.**

***Index Terms*— Big data applications; energy harvesting**

I. INTRODUCTION

ENERGY harvesting promises to reduce reliance on battery charging for Internet of Things (IoT) and wearable devices, either wholly or in part, by scavenging ambient energy from the environment to power the device. Reducing reliance on battery recharging is essential as battery charging remains one of the main barriers to adoption of IoT and wearables, where battery lifetime is typically limited to a few days [1]–[3]. Moreover, wearable devices are often intended to benefit groups such as the elderly and those with cognitive impairments, meaning it is essential to make the IoT sensing automated and unobtrusive to the user [4]. Energy harvesting is a key method to help achieve this autonomy. Many different forms of energy harvesting are possible, for example using heat or motion as the energy input. For wearables, many energy harvesting papers (e.g. [5]–[7]) use *kinetic* energy harvesting which collects energy based upon the movement of a small proof mass.

While kinetic energy harvesting may be able to make IoT wearable sensing free from user-intervention, research into kinetic energy harvesting has to date focused on small-scale laboratory studies. As examples of recent works, [8] demonstrates the generation of 1.46 mW while walking, and [9] 2.1 mW during arm shaking. However these use extremely short testing durations. Only 60 s of movement was carried out in the case of [8]. Considering the wider literature, to date the majority of kinetic energy harvesting studies investigate power output from only one participant, with few investigating harvesting on over 10 participants [10]–[20]. Only a minority investigate energy harvesting in a free-living environment, and instead estimate the energy produced from periodic movements such as walking on a treadmill. These controlled experiments will overestimate harvesting potential against real-world usage, as the actual proportion of time spent undertaking periodic movements is relatively small. To our knowledge the largest study investigating energy harvesting potential in a free-living environment analyses 20 participants over 2 days [15]. Large-scale, free movement, investigations are now required to allow accurate modelling of energy harvesting output and stratification by a range of factors including age, time of day, and the presence of diseases in order to inform future harvester designs.

This paper aims to perform modelling work to allow real world energy harvesting potential to be evaluated across a wide range of confounding factors. We present a large-scale estimation of energy harvesting potential using data from the UK Biobank. We make use of data from >67,000 participants who wore an accelerometer device for a week. This dataset

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Software used to perform the analysis in this manuscript is available from: `https://doi.org/10.48420/14720964` and `https://github.com/Non-Invasive-Bioelectronics-Lab/UKBiobankKineticEnergyHarvesting`. The UK Biobank data utilised in the analysis in this publication is available by following the procedure described at `http://www.ukbiobank.ac.uk/using-the-resource/`.

allows the first, to our knowledge, energy harvesting estimation analysis at a population level, allowing the spread of energy values between many different individuals in everyday life to be investigated. The results presented in this paper represent the largest energy harvesting study in number of participants, by three orders of magnitude, and over the longest duration (seven days) allowing weekday and weekend variances to be observed. Further, this is combined with the large amount of metadata available in the UK Biobank, enabling a large number of sub-analyses to be performed. This paper analyses when energy is available throughout the day and stratifies this by age, gender and season, which has not been possible in previous, much smaller scale, energy harvesting modelling analyses. This paper also investigates how the amount of collected energy is affected when participants are diagnosed with a long term condition, looking at the effect of diabetes on energy harvesting output. The results allow far more detailed insights into the practicality of using kinetic energy harvesters in real-world situations. We do not present a new energy harvester device. Rather we focus on using established energy harvester models to inform how existing devices may actually perform if they were to be deployed at scale.

Our methods for estimating energy harvesting potential are based upon a widely used mass-spring-damper model [21] which takes measures of motion from a wrist worn accelerometer to estimate the movement of a proof mass and consequently the energy that could be collected by an energy harvester put in the same location. It builds upon our previous work optimising kinetic energy harvesters for wearables and IoT [22] where we demonstrated the optimum harvester parameters for various positioning on the body. Here, we utilise the model from [22] to analyse the output from non-repetitive movements in a free-living dataset.

The remainder of this paper is structured as follows. In Section II we introduce the UK Biobank dataset used in this study, our inclusion criteria, the steps for preparing the raw data for our model, and the statistical methods used to compare differences in harvested power between different groups. In Section III we present the results, showing both the modelled variation in harvested power against the time of day as well as the differences in power and total energy harvested for the different population groups. In Section IV we place the results in context, discussing the differences that are identified and whether the average power output seen here could power a typical wearable. In Section IV we also present the limitations of this work. A pre-print version of this article is available at [23] which contains the same results as this work. This article is based on Chapter 5 of the first author's PhD thesis [24].

II. Methods

A. Harvesting Methods

We model energy harvesting potential for a wrist worn wearable by processing three axis accelerometer data from a wearable device worn by participants. To give a large pool of data to use, participants are drawn from the UK Biobank as described in Section II-B.

For estimating the energy that could be harvested at different times, each of the accelerometry files was processed with the steps that we have previously described in [22]. This process compromises of modelling the kinetic energy harvester as a second-order system with a proof mass, m, damper, b, and spring constant, k. The movement of the proof mass over time, $z(t)$, is described by (1),

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

where $d(s)$ is the external displacement acting on the frame of the harvester, s is the Laplace variable, and $\mathcal{L}^{-1}$ the inverse Laplace transform. The proof-mass movement is then converted into power at each time point, $P(t)$, using (2),

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

where $v(t)$ is the velocity of the proof-mass. We used the recommended parameters from [22] that we previously identified for a harvester placed on the wrist with a participant walking at 100 steps/min (taken as the lower end of a brisk walking pace [25]), and a physical harvester size of Z_L = 50 mm. These parameters were m = 0.11 g, b = 0.07 kg/s, k = 12.15 kg/s^2, which give a resonance frequency, f_r, of 0.71 Hz and Q of 0.55 for the second order system described by (1). As in [22], we calculate the maximum theoretical power output of an energy harvester, taking the efficiency as 100% for the majority of the analyses presented here. This allows us to investigate the maximum theoretical values of energy collectable in free-living environments, which can then be scaled as desired to a practical energy harvester implementation. We also compare the output of our energy harvester model to the power consumption of some commercial wearable devices. Here we assumed the efficiency of our harvester is 20%, based on the efficiency levels found in practical harvesters designed specifically for human motion and for the Internet of Things [10], [26]. It has been reported in other works that perfectly optimized energy harvesting systems have achieved efficiency values ranging between 30% and 90% [10].

The data output from the harvester power model was downsampled from 100 Hz to 1/60 Hz, equivalent to 1 sample per minute, to reduce the quantity of data and enable further analysis with manageable file sizes. The accelerometers record acceleration in 3-axes, while our energy harvesting model requires data of a single dimension. Only one axis of the data was analysed, taking the axis that produced the largest amount of power for the majority of participants, which was the x-axis (which aligns with the forward swinging motion of the arm). We add that in our model developed in [22], we noted that in physical realisations of an energy harvester the proof mass cannot travel further than its physical end-stop limits. In [22] we did not limit the movement of the proof mass in simulation, choosing instead to limit the values of m, b and k so that the proof-mass did not displace further than the end-stop limits of the frame, for the activities that we asked participants to undertake. Given the free-living dataset used here, it is possible that extremely large participant movements may cause the theoretical proof-mass to exceed the limits of the harvester frame. This is taken as a limitation of this work, but it is assumed that this only occurs in a minority of cases and does not have a substantial impact on the results presented. Similarly, we did not threshold the movement data and so any movement will contribute to energy generation, if only a very small amount for very small movements. In a practical implementation there may be friction and other factors which prevent small proof-mass movements, and any power conversion/storage circuitry present may require a minimum level of energy input to operate effectively. We account for these factors via the estimated 20% efficiency figure used when comparing to the power requirements of typical wearable devices in Section IV-B.

B. The UK Biobank Dataset

The UK Biobank dataset is a large prospective study with over 500,000 participants in total, aged 40–69 years and recruited between 2006 and 2010 [27]. The UK Biobank collected a wide range of data from participants including biological samples (such as blood, urine and saliva), questionnaires on lifestyle, socio-demographic factors, cognitive function, family history, and medical history (including the prevalence of non-communicable diseases such as diabetes, chronic kidney disease and mental illnesses) [28]. After the initial recruitment of participants to the study, further data was collected from subsets of participants including blood pressure, electrocardiograms (ECG), hand grip strength, eye measurements, hearing tests, and arterial stiffness [28]. In addition, the physical activity of just over 100,000 participants was measured by inviting them to wear a wrist-worn accelerometer for 24-hours a day, for a week, at some point between 2013 and 2015 [29]. For a small number of participants (2,500), repeated accelerometer measurements were undertaken over a year on a seasonal basis.

For these physical activity measurements, participants were asked to wear a 3-axis accelerometer (Axivity AX3) [30] on their dominant wrist. The sensor was designed to store data locally (rather than transmitting data in real-time) and was able to last for at least a week of continuous recording without requiring recharging. The device was designed to be comfortable and waterproof to allow for continuous 24-hour monitoring without the need for sensor removal. Each participant's accelerometer was programmed to start recording at 10:00 two days after the device was due to arrive in the post. Further references to the *UK Biobank* in this paper refer specifically to the activity monitoring data rather than any of the other samples collected as part of the study.

The activity monitoring dataset available to this study contains data for 103,651 participants wearing the device for a week each, with participants aged between 43–78. Other studies in the literature using UK Biobank data contain slightly different numbers of participants, such as 101,516 participants in [31], 103,712 participants in [29] and 103,702 participants in [32]. The exact pool of participants available to different researchers varies as participants are allowed to remove their consent after data collection, as well as differing inclusion criteria. This research has been conducted using the UK Biobank Resource under Application Number 33693. All access to data is in-line with GDPR and similar ethical requirements. The UK Biobank guidance on data privacy and related factors is available at [33].

C. Participant Selection from the UK Biobank

Not all of the 103,651 participants who were sent an accelerometer successfully, or correctly, wore the device for the entire week. As a result, only a subset of participants were included in this analysis to ensure valid and complete data were present in all cases. Firstly, not all participants wore the accelerometer for the requested continuous 24-hours each day, with many wearing the device for a substantially shorter time. To counter this, the UK Biobank accelerometer expert group [29] recommends excluding participants who wore the device for less than a cumulative total of three days, and who did not wear the device during each one-hour period in a day. [29] identified this as generating activity values within 10% of the values calculated from participants who wore the device continuously, for their particular analysis. Using these criteria gives 96,600 participants, excluding less than 10% of the total dataset. However, for the participant analysis we undertake here, this criteria would skew the results towards representing when the device was worn rather than the fundamental amount of energy that could be collected at different times of the day. Rather than only selecting participants who wore the accelerometer for the full 24-hours each day (20,100 participants, 20% of the data), we opted to only include participants who wore the device for a minimum of 20 hours each day, giving over 70,000 participants and temporal coverage across most of the day. Participants who remained in our data selection with periods of non-wear (of up to four total hours per day) did not have these specific non-wear periods excluded from the analysis. Further participants were excluded as follows.

The AX3 accelerometer used in this study featured a USB port that was accessible to the participants, and numerous participants plugged the device into a computer when it was set to be recording. If a device was plugged in, recording would be paused and an *interrupt* would be logged. To account for these gaps in the data, participants who had large amounts of data missing ($>$ 1 minute) were removed from the analysis ($n = 300$).

The data collection of physical activity from participants in the UK Biobank was carried out continuously in batches across multiple years, recording groups of participants at different times throughout the year. As a result, some recording sessions occurred during a daylight savings crossover. Depending on the crossover (entering or leaving daylight savings), this causes either multiple records of data for an hour, or an hour of data missing. While this crossover occurs during the night, when harvested energy potential is likely to be the lowest, only a small number of participants ($n = 4,543$) were undergoing recording during a crossover, and therefore it was decided to remove all of the participants recorded during a daylight savings crossover in order to allow the power values from different times of day to be easily averaged together.

Participants in the UK Biobank were aged between 43 and 78 during accelerometry data collection (according to our age estimations—discussed later in Section II-D). However, only a small number ($n = 153$) were below the age of 45, an amount considerably lower than in any other age group, and therefore all of these participants were removed from the analysis. Finally, any participants that had removed consent between the downloading of the dataset from the UK Biobank repository and our data analysis had to be removed ($n = 15$).

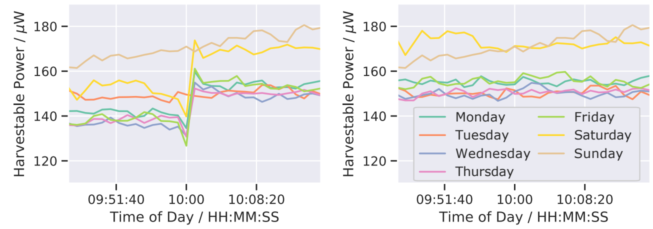
After these criteria, 67,024 participants were remaining, a number still substantially larger than the previous largest energy harvesting study on free-living data in the literature (20 participants) [15].

D. Data Extraction and Stratification

1) Accelerometer Data Extraction and Loading into Python: We downloaded the raw bulk accelerometer data from UK Biobank Data-Field 90001 in CWA (Continuous Wave Accelerometer) format, a compressed proprietary binary data format. The compressed dataset was approximately 20 TB in size, and we made use of high-performance computing facilities, the Computational Shared Facility 3 (CSF3) at the University of Manchester, to process this data. A complete analysis of the dataset took approximately two weeks to process across a large number of compute nodes.

For data pre-processing, we initially calibrated each participant's data to local gravity to account for variations in gravity in different locations (sensors are typically calibrated to set 1 g as the measurement of the acceleration due to gravity at their location of manufacture, but this does not necessarily correspond to the same value in the location where data recording takes place [34]). We then resampled the data to 100 Hz using linear interpolation, a process which is required as the AX3 accelerometer does not sample at precise intervals. The processing steps used here are based upon the protocol described by Doherty *et al.* [29] and their code available at [35]. Finally, each axis of the data was filtered with a sixth-order zero-phase high-pass Butterworth filter with a cutoff of 0.3 Hz to remove the gravity component. Although the gravity component is removed by low-pass filtering, we still correct for local gravity to remain consistent with pre-processing steps taken by other groups working on the UK Biobank accelerometer data. The data was processed in Python 3.7 using the Anaconda Distribution.

Initial analysis identified that at 10:00 on Monday, Wednesday, Thursday, Friday, and Saturday there was a large discontinuity in the estimated energy harvesting potential, where at 09:59 the power harvested was considerably lower than the power at 10:01, which is demonstrated in Fig. 1a. This effect was not was not present on Tuesday or Sunday. We also noted how no participants started the experiment on a Sunday and only a small number ($< 2\%$ of participants) started the experiment on a Tuesday, suggesting that the discontinuity is an artefact of the process of starting or stopping the experiment. As the data collection began and ended at 10:00 on the participant's particular day, we hypothesised that participants may have removed their wrist band early before the data



(a) (b)

Fig. 1: Power output from the energy harvester model for each day of the week. (a) Harvesting output before removing data discontinuity, (b) Harvesting output after removing discontinuity.

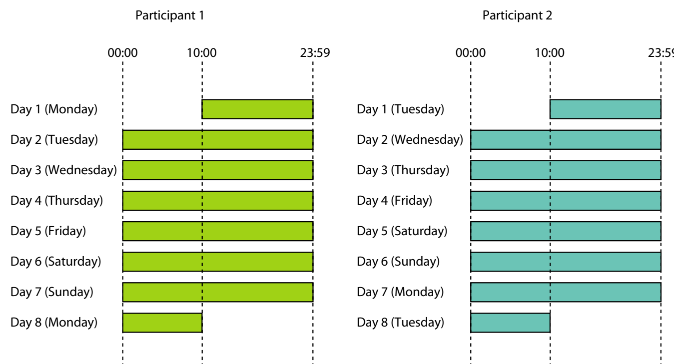


Fig. 2: Example of the recording routine for two participants in the UK Biobank.

collection had finished, which caused this discontinuity. As participants were told the data collection would last 7 days, they therefore assumed that data collection had ended by day eight. In actuality the device was still recording, and would not finish until 10:00 on the eighth day of data collection. This protocol is illustrated in Fig. 2. In UK Biobank Resource 141141, the participant instructions detail that they should wear the device *'continuously until the morning of [End Date] when it will switch itself off automatically'*, rather than explicitly specifying to only remove it after 10:00 when the device stopped recording.

To verify this, the energy harvester output between 08:00–10:00 on each day of the week was calculated (excluding Sunday as no participants started on this day), stratifying participants into the particular day of the week they started the experiment on. The first/last day for each participant was removed, with the resultant data shown in Fig. 1b. Here it can be seen that the discontinuity has been removed, and the data is continuous between 09:59–10:01. To correct for this, for all of the subsequent analyses in this paper the day of the week of the first day of wear was removed. Due to the recording starting at 10:00, this effectively results in the first and last day of wear, which sums to 24-hours, being removed for all participants. To our knowledge this discrepancy has not been previously reported or identified, as most studies have calculated their results at substantially lower temporal resolution than we do, so this effect is not noticeable. (Due to the size of the data set, studies (e.g. [29], [36]) plot one hour epochs of the accelerometry data, whereas we summarise results on a minute-by-minute basis.) Considering this limitation is important to create valid analyses and thus are important for future researchers to be aware of.

2) Age Estimation: To protect participant anonymity, the UK Biobank does not make available to researchers the exact date of birth of participants, instead only providing their year and month of birth. The exact date on which the accelerometer recording was started is known and made available. To estimate the participant's age from these fields, we assumed that each participant was born on the 15^{th} of the month, making the estimate of the participant's age potentially out by a maximum of 16 days. Further, if the participant's *birthday estimate* occurs during the week-long data collection period, the age is taken as that when they started data collection. This increases the potential maximum error in age estimation to 22 days if their birthday was at the start of the data collection period. This slight *fuzziness* in grouping participants is accepted as a limitation of the study. Participants are also grouped into seasons of the year during data collection, calculated by taking the month when they started the data collection as the season, categorising March–May as spring, June–August as summer, September–November as autumn, and December–February as winter. Again, if the season changed during the data collection, the record was not split into two parts, but categorised as the season the data collection started in. The sex of participants was identified using UK Biobank Data-Field 31.

3) Diabetes Diagnosis: After analysing all participants together, we also investigate the effects of the presence of a long term condition on energy harvesting potential. This requires the generation of a dataset with this condition and a matched control dataset to reference against. The UK Biobank dataset contains participants who reported having a diagnosis of diabetes during the initial questionnaire stage of the study, which is of interest due to the potential to use IoT wearables to monitor conditions of diabetes, such as diabetic foot ulcers [37]. The UK Biobank Data-Field 2443 asked participants if they have ever had diabetes diagnosed by a doctor. This gave a total of 2,389 participants with diabetes as the experimental group (using the same exclusion criteria detailed in Section II-C).

To generate a set of control group of participants with no diagnosis of diabetes, theoretically all the remaining participants in the UK Biobank could be used. However, this would result in an unbalanced comparison as the control group would have an order of magnitude more participants [38]. Instead, a control group was randomly selected to match the number of participants in the diabetic group, matching them on both the number in each of the four age groups in our study, and the number of each sex within those age groups. Further, for generating a matched control data set, it is important to note that Data-Field 2443 on diabetes diagnosis was collected at recruitment to the study (for some participants as early as 2006). Some participants started the activity monitoring stage of the study as late as 2015, a potential maximum difference of 9 years. Based on an estimated 0.17% of the general population being diagnosed with diabetes each year (based off 300 people being diagnosed per day with diabetes in 2011 [39]), it was assumed that around 1% of the control group could have developed diabetes by the time they carried out the accelerometry data collection. This is an amount which we assume will have a negligible effect on the results presented but should be noted as a potential limitation.

TABLE I: Number of participants in each of the analysed groups from the full UK Biobank accelerometer records.

Stratification		Female	Male	Total
		Number of Participants		
Age Groups	45–54	7749	5085	12 834
	55–64	13 812	9387	23 199
	65–74	15 208	14 128	29 336
	74–78	743	912	1655
Season	Spring	8397	6451	14 848
	Summer	10 334	8093	18 427
	Autumn	10 651	8368	19 019
	Winter	8130	6600	14 730
Total		37 512	29 512	67 024
Age (Mean ± SD)		61.8 ± 7.6	63.2 ± 7.7	62.4 ± 7.6

TABLE II: Number of participants in the sub-set with diabetes and the control group used for comparison.

Sex	Number of Participants Control	Diabetes
Female	892	892
Male	1497	1497
Age (Mean ± SD)	64.7 ± 7.0	65.1 ± 7.0

Given the discrepancy between the date of metadata collection and accelerometer data collection, we identified the time lag between these two elements of data. The time lag was 2087 ± 406 days (5.7 years) and 2064 ± 402 days (5.7 years) between metadata and accelerometer data collection for the control (declaring they had *no* diagnosis of diabetes) and the group with diabetes (declaring they had a diagnosis of diabetes) respectively. As it is relatively uncommon for diabetes to go into remission [40], even when well controlled, it was assumed that in the diabetes group, diabetes was still present during data collection. Additionally, given the random selection of control group participants, this group may also have a variety of other diseases despite not having diabetes. This was not controlled for as it was assumed that most younger participants had no other conditions while many of the older group had a variety of comorbidities, which would be representative of the actual population that the energy harvesting output is to be compared against.

E. Dataset Statistics

Full statistical information on the analysed participants in the subset of the UK Biobank used in this paper is shown in Table I, and the subset of participants with diabetes (and associated control participants) is shown in Table II. Values of participants age are mean ± SD (standard deviation). Participants were grouped into four age groups, which were not all of equal sizes in order to match the age groupings used in [29].

F. Selection of Data

Both the power output throughout the day, and differences in average power harvested per groups of participants, were analysed. To compare the average power harvested between groups, the period from 07:00 to 20:00 was analysed, defined here as *daytime hours*, chosen as the point where the harvested power level is over 50% of the maximum, rounded to the nearest hour. This is to ensure that differences between groups are not biased by the very small amount of power that is harvested during the night (i.e. when most participants were asleep), under-reporting the differences between the groups. We also expect the maximum allowed non-wear time (four hours total per day) to occur mainly during the night period.

G. Statistical Methods

To analyse the differences between groups statistical methods were applied using the SciPy library in Python. The Student's t-test [41] was used for comparisons of two groups with the significance level (α) set as $p < 0.05$. For comparisons between multiple groups, the one-way analysis of variance (ANOVA) [42] was calculated again with α set as $p < 0.05$. An ANOVA identifies if one or more sample distributions are not equal, but not where these differences occur. The ANOVA is also considered as robust to non-normal data [43]. To identify where (if any) differences occur, post-hoc tests were run to identify which groups had differences. Here the Bonferroni correction was used to account for multiple comparisons. Multiple comparisons are made between the four age groups and four seasons, of which there are a total of six comparisons in each, so the adjusted α value is corrected to $p < 0.0083$. Effect sizes were calculated using Cohen's d with small, medium and large effect sizes of >0.2, >0.5 and >0.8 respectively [44]. 95% confidence intervals (CIs) were also calculated for the variations in power output throughout the day.

H. Analysis Overview

Following the data processing steps described above, the estimated energy harvested from each of the 67,000 participants was calculated by processing the complete accelerometer trace from the entire wear period. We present the results of the analysis by stratifying it in several ways:

Firstly, the variations in power output throughout the 24-hour period of the day are analysed. This gives new insights into how the harvested power varies as the day progresses, compared to other studies looking at free-living energy harvesting which have presented the average power available throughout the day rather than how this varies with time [15], or over shorter periods up to 11 hours in [10]. Within our analysis, the power output across the day is stratified by:

- Variations by day of the week
- Variations by age group
- Variations by presence of diabetes.

Secondly, the variations in power output during *daytime hours* (07:00–20:00) are presented, allowing comparison between a range of groups that have not previously been considered, including the presence of a diabetes diagnosis and how the energy harvesting potential varies at different times of the year. For this analysis, participants are stratified by:

- Variations by sex
- Variations by age
- Variations by season
- Variations by presence of diabetes.

Finally, we consider the percentage of a day where the energy harvester power output is above set power thresholds, for the entire dataset. This analysis allows designers to identify the likelihood that a given energy budget will be met when using a harvester in an average population.

III. Results

A. Energy Harvester Output Throughout the Day

1) Variations by Day of the Week: First, the variation in power harvested across the day for each day of the week is shown in Fig. 3, with the shaded areas showing 95% confidence intervals. The confidence intervals are relatively narrow and are therefore covered by the mean trend line, suggesting that the mean offers a good estimate of the true data. In Fig. 3 it can be seen that each weekday (Monday–Friday) follows a similar pattern. Between the hours of 00:00–06:00 the average power harvested is < 25 μW, while the vast majority of people are asleep. After 06:00 the harvested power begins a steady increase, reaching the maximum value of around 150 μW at 09:00. The average power output begins a steady decline until around 13:30, where it remains around 120 μW until 19:00. Beyond this, the power follows a generally decreasing trend with large peaks, around 10 μW high. It can be seen that these peaks often fall on the hour (for example at 21:00 and 22:00), corresponding to larger amounts of activity taking place on the hour. There are also multiple smaller peaks between 18:00–23:00 corresponding to increasing activity taking place not only on the hour but also on the half, quarter past and quarter to the hour.

The weekend shows different patterns to the weekdays. Saturday shows a later time of day where the harvested power begins to *ramp up* after the night, starting to increase at around an hour later (07:00 compared to 06:00 in the week), the data on Sunday shows this later increase in the morning as well, but starts to increase slightly later again (by around 15 minutes). The weekend has a higher maximum power, reaching over 180 μW in the morning, and remaining higher than the weekdays until around 17:00 by at least a 10 μW margin. Into the evening (18:00–21:00), the weekend has lower power output than the weekdays. In the early hours of the morning at the weekend (00:00–02:00) the harvested power is higher than during the week. The peaks of power seen on the hour between 18:00–22:00 are much less prominent on Saturday, but are still relatively visible on Sunday. There are also small differences in the total energy harvested for each day of the week, with Sunday having the smallest total energy. The total energy harvested for each day was 7.09 J, 7.10 J, 7.09 J, 7.10 J, 7.05 J, 7.22 J and 6.95 J for Monday, Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday respectively.

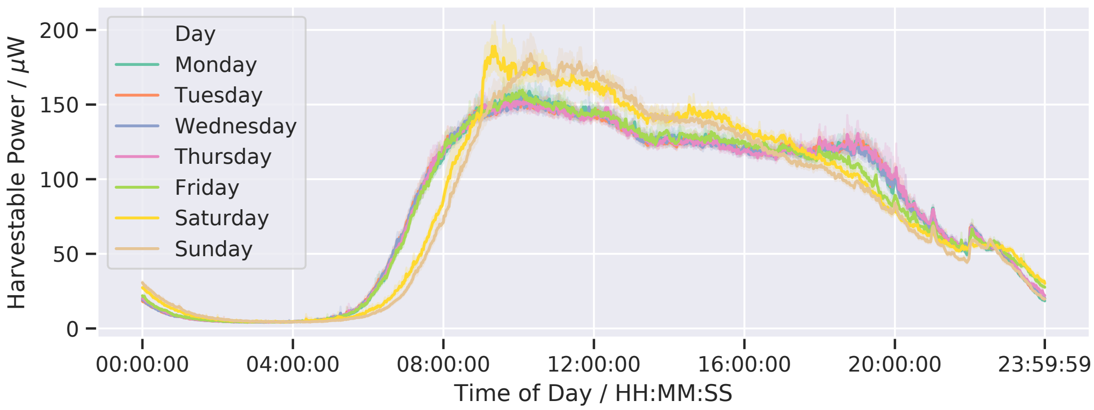


Fig. 3: Average power harvested per day across all participants by day of the week. Shaded areas show 95% confidence intervals.

2) Variations by Age Group: Fig. 4 shows the variations in harvested power throughout the day for each of the four age groups detailed in Section II, again with shaded areas showing 95% confidence intervals. Between the hours of 00:00–05:00 there are very few differences between the groups, with all groups harvesting ≤ 25 μW. As in Fig. 3, the power begins to increase after 06:00, with the youngest age group (45–54) being the first to increase, followed by the second oldest (55–64), with the oldest two groups (65–74 and 75–79) following a similar pattern to each other until 10:00. For a brief period in the morning (09:00–10:30) three groups, 45–54, 55–64, and 65–74, display similar levels of power at just over 150 μW. For the majority of the day, the power output is inversely proportional to the age of the participant.

Comparing with Fig. 3, where the power output decreases as the afternoon progresses, the 45–54 age group sees an increase in power output between 16:45–18:45. From 19:15 onwards all groups see a sharp decrease in power output with time, with small differences between groups after 23:00. As in Fig. 3, there are peaks of power occurring on the hour from 19:00–22:00, which are prominent in each of the age groups. The total energy harvested across the 24-hour period for each of the age groups decreases with age, with values of 8.21 J, 7.40 J, 6.43 J and 5.42 J for the 45–54, 55–64, 65–74 and 74–78 age groups respectively.

3) Variations by Presence of a Disease: The data in Fig. 5 shows the variations in harvester power throughout the day for the group of participants with diabetes and the age/sex matched control group used as a reference. From 00:00–06:00 the diabetic group generates more power compared to the control group, with small differences of around 10 μW. After 07:00 this crosses over and the power output from the control group is larger than the diabetic group by 30 μW between 10:00–18:00. Into the evening the differences between the two groups decrease with little difference from around 21:00 onwards. Again, the peaks of power that occur on the hour in Fig. 3 and Fig. 4 are visible in both of the groups, with both showing very similar trends, just offset by different amounts throughout the day. There is a difference of over 1 J between the total energy harvested across the day between the control participants and participants with diabetes, with values of 6.93 J and 5.56 J respectively. Further investigation into the differences in power harvested between these two groups during daytime hours of the day is given in Section III-B.

B. Average Power Harvested During Daytime Hours

1) Variations by Sex: Female participants generated a marginally larger average harvested power during *daytime hours* compared to males, with medians of 118 μW for female participants compared with 113 μW for male participants. Interquartile ranges (IQRs) were 58.9 μW and 66.2 μW for females and males respectively. Differences were not significant ($p = 0.104$).

2) Variations by Age: During *daytime hours* differences between each of the age groups again followed the pattern shown for the majority of the day in Fig. 3, where power was inversely proportional to age. The median power harvested for each of the groups was 128 μW, 121 μW, 109 μW and 91.5 μW for the 45–54, 55–64, 65–74 and 75–79 age groups respectively. IQRs were 68.0 μW, 62.1 μW, 58.0 μW and 49.3 μW for each age group respectively. Significant differences between groups were found ($p < 0.000001$). The post-hoc tests identified significant differences between all combinations of age groups ($p < 0.000001$), all differences between age groups corresponded to a *small* effect, except for differences between groups 45–54 and 55–64, which corresponded to *no effect*. No effect size highlights how these differences may be statistically significant (as is often the case with very large sample sizes [45]), but the actual differences are very small.

3) Variations by Season: Differences in average harvested power during *daytime hours* were small between each of the four seasons. Median harvester power was 120 μW, 118 μW, 115 μW and 112 μW in Spring, Summer, Autumn and Winter respectively. IQRs were 65.0 μW, 62.5 μW, 61.3 μW and 59.6 μW respectively. Significant differences between groups were found ($p < 0.000001$). The post-hoc tests found significant differences between all combinations of seasons (except for Spring–Summer), and in all these cases these differences corresponded to *no effect*.

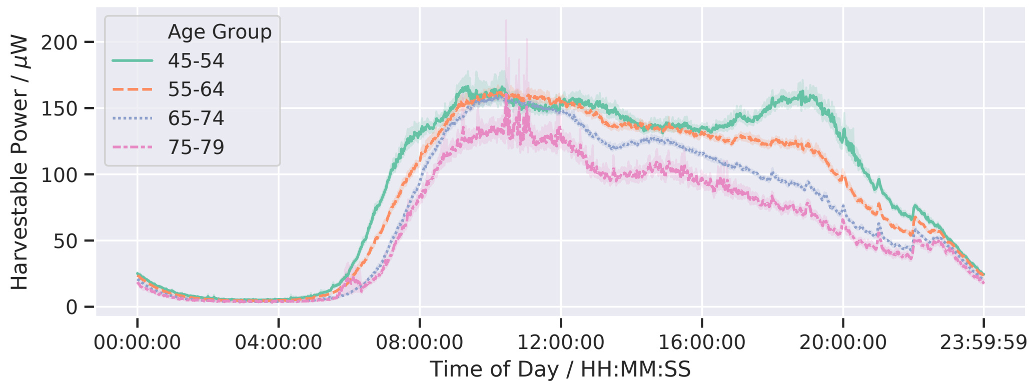


Fig. 4: Average power harvested across the day for each of the age groups of participants. Shaded areas show 95% confidence intervals.

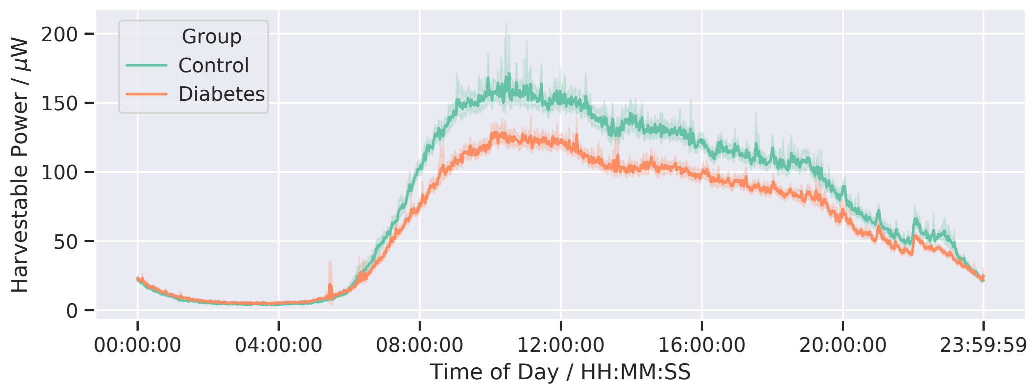


Fig. 5: Average power harvested across the day for control participants and participants with diabetes. Shaded areas show 95% confidence intervals.

4) Variations by Presence of a Disease: We consider again the impact of a diabetes on harvesting power, this time comparing average power during *daytime hours*. Here, the median power was 114 μW and 90 μW for control and participants with diabetes respectively, a difference of over 21%. IQRs were 63.1 μW and 55.6 μW respectively. Differences were again significant ($p < 0.000001$) with a small effect size.

C. Time Spent in Harvesting Zones

Finally, the percentage of the day where the energy harvester is collecting power over specific energy thresholds is considered. The analysis includes all 67,024 participants from this study, and allows designers insight into the required duty cycling of their device. If a device has a specific known average power consumption, the amount of the day the device will be able to operate at for that power level can be found. In Fig. 6, the x-axis shows a range of minimum harvesting levels and the y-axis shows the percentage of the day that the energy harvester output is above this threshold. Importantly, outliers are present for all of the minimum energy harvesting levels, which will always be the case in real-world scenarios. Even with an extremely small power budget of around 1–2 μW for a particular device, there will be some users who we cannot get this power from. It is important that designs or usage patterns reflect this.

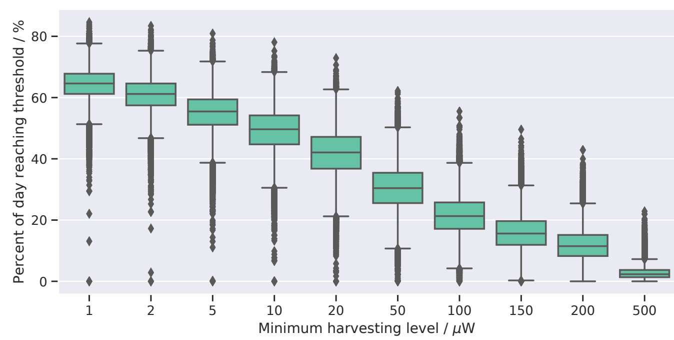


Fig. 6: Percentage of the day that minimum harvesting levels are reached. The central line in the box plot represents the median percentage of participants reaching that threshold, ♦ denotes outliers.

IV. Discussion

A. Implications of Results

1) Variations in Power Across the Day: We demonstrated in Fig. 3 how, on average across participants, large peaks of power are available on the hour (with smaller peaks at the half-hour, quarter past and quarter to the hour) in the afternoon and evening. These peaks likely correspond to large groups of people moving at a similar time, and this being fixed to events that happen on the hour. The cause for this may be potentially driven by broadcast television, where programmes are often set to start and finish on the hour. Therefore, as a programme is starting or finishing a large number of the participants are moving to watch television or getting up after the programme has finished. This effect is widely known for affecting the UK's National Grid [46], where it is known as *TV pickup*; as large proportions of the population operate devices during commercial breaks in transmission, causing high electrical demand and noticeable strain on the UK electricity generation network. This finding introduces the possibility of scheduling power intensive device operations with when there is large amounts of power available. Previously, we have discussed the possibility of timing operations with the power that is available from each footstep [47].

In the population level data in this paper, the peaks of power from individual footsteps are not visible, but the larger-scale movements are visible (typically on a minute by minute basis rather than a few second basis as would be the case with timing with footsteps). The peaks of power highlighted in Fig. 3 increase in height by around 10 μW over the baseline. This potentially could be used in opportunistic transmission [48] as the device can predict that there is a high probability of there being more power available on the hour and wait to do its power-hungry operations (such as wireless transmission [49]) at this point. Comparing this figure to an average of 135 μW over 3.5 ms that is required to transmit a single byte of data on the Bluetooth Low Energy (BLE) Nordic Semiconductor nRF52832 device [50] (assuming V_{cc} = 3.0 V), the energy required for full opportunistic transmissions is some way from being directly realizable. Fitting BLE packets directly into these peaks is out of reach by around 10 times, but given that these peaks of power last for multiple minutes, and it only takes 2.5 ms to send a byte of data, it is possible that combining with an energy storage element could allow devices to have sufficient power to transmit using this known peak. However, this effect may potentially diminish or decrease in prominence in the future as younger groups move away from broadcast television and towards streaming services [51], where the effect of the *TV pickup* seen by the UK's National Grid is already starting to decrease in prominence [52].

The data shown in the line plots in Fig. 3, Fig. 4 and Fig. 5 all show a similar shape, representing a typical pattern as someone active from approximately 09:00–19:00, sleeping between approximately 23:00–07:00, and fairly sedentary in the evenings. There do not seem to be sufficient participants who work night shifts in the UK Biobank to show any bimodal patterns in the overall average. There is not a clear second group of people who work shifts and sleep at odd patterns or during the day. This would be seen as a bimodal distribution around the mean, which is not present in the shown confidence intervals in these plots. The UK Biobank does record participants who work shifts and night shifts (under UK-Biobank Data-Fields 826 and 3426 respectively). Further work could involve an investigation into how this changes the pattern of power generation and how it introduces uncertainties into the estimations as discussed in [53].

2) Variations Between Groups: Patterns in age differences shown in Fig. 4 are not necessarily what might be expected. The youngest group in this study is 45–54, whom are all of working age and therefore likely to be at work, with most UK workers spending their time stationary [54] particularly for office workers [55], [56]. It could be expected that this group would generate the least power, as they spend a majority of the time sitting at a desk with little periodic movement and therefore little energy generation. This trend is not present, with all age groups up to 75 producing similar levels of energy in the morning (between approximately 8:00–12:00). In the afternoon the energy produced decreases as the age group increases. We start to see more potentially expected differences in the late afternoon and evening where the 45–54 group finishes work and commute home, perhaps undertaking activities with family or exercise while the older group undertakes less activity. Further, the peaks in the evening on the hour are likely attributed to the fact that older people are more likely to watch broadcast TV than the younger group [57]. Moving in to the future, the *commute home* peak may be smaller if people continue to work from home after the COVID19 pandemic.

3) Variations by Presence of a Disease: The group of participants with diabetes showed significant differences in energy harvesting output compared to the healthy control group. The diabetes group harvested 21% less power, a statistically significant difference. These differences were also visualised across the time series in Fig. 5, where we could see how differences in power output were small at night and largest during the morning. These differences are possibly due to those with diabetes being less active than the general population as they struggle to carry out physical activity [58]. This highlights a key challenge in IoT and wearable energy harvesting—wearable devices aim to monitor people's health and wellness, and energy harvesting aims to make devices energy-autonomous and *fit-and-forget*—but in populations with a disease there is potentially less power available to harvest and therefore it is harder to meet the required power budget and do the desired health and wellness monitoring. Future work would be beneficial to investigate how the trend seen for people with diabetes applies to other conditions and people with co-morbidities.

B. Meeting IoT and Wearable Power Requirements

During daytime hours the average power harvested was around 105 μW. Using the approximation of 20% conversion efficiency as introduced in Section II-A, this gives around 21 μW of available power during the day. Even ignoring conversion efficiency, there is still a substantial gap between the power required and that which can be generated. This suggests that fully autonomous operation in free-living environments may not be feasible with current kinetic energy harvester approaches, and some form of battery backup will always be required.

From Fig. 6, it can be seen that if a device had an average power consumption of 1 μW, the device would be able to operate for over 60% of the day, for an *average* user. To compare this to practical examples, the Axivity AX3 wearable accelerometer, used by the UK Biobank and in this study, has a battery capacity of 150 mAh and 14 days of battery life (when sampling at 100 Hz). Assuming a nominal Lithium Polymer battery voltage of 3.7 V, this corresponds to an average power draw of 1.7 mW. The Fitbit Versa 2 has a battery capacity of 165 mAh and a rated 5 days of battery life, corresponding to an average power draw of 5 mW (assuming 3.7 V battery voltage). These figures are an order of magnitude beyond the potential harvesting levels shown in Fig. 6.

Closing the power gap, particularly for devices that have to operate overnight, will be a significant challenge. Nevertheless. there are many emerging approaches to tacking this. Firstly via improving the design of harvester devices themselves, through better energy harvester design using conventional approaches such as [8], [9], through novel energy harvesting approaches such as nano-generators [59], and through using multi-modal harvesting to collect energy from multiple sources simultaneously and improved energy storage and conversion. Secondly, improved low power electronics will continue to emerge, and also improved electronic architectures dedicated to energy harvesting. For example, dynamic task scheduling for optimal run-time allocation of harvested energy is a growing area of research [47], [60]–[62]. This could make use of the results demonstrated here as prior information, showing when during the day peaks of energy are likely to be present for different user groups to enable Bayesian optimisation. Improved communications strategies will also likely be important. Given the size of the power gap between small scale in-lab experiments, and our estimations for large scale real-world use, it is likely that innovations will be needed in all of these areas.

C. Limitations

The results presented in this paper are for a fixed harvester configuration, using the optimum parameters for a participant walking at 100 steps/minute sized at Z_L = 50 mm as determined in [22]. It also assumes a fixed 20% efficiency factor. The walking cadence that this harvester is optimised for may not correspond to the optimum harvester parameters for a harvester on a free-living group (rather than a group in laboratory conditions walking on a treadmill), and it is possible that other combinations could improve power output. However, even with different harvester configurations we would expect to see similar trends across the groups analysed in this paper, with a much greater impact on the absolute values of power. To identify optimum values, the harvester parameters would have to be swept on a large number of the UK Biobank records, which would be very computationally intensive (the records in this manuscript are 7 days long, compared with 40 s in [22]). Alternatively, records could be analysed to find their dominant frequency and a harvester designed with a resonant frequency f_r centred on this. However, as was shown in [22] this does not always produce the optimum combination. Such design approaches still only optimise the harvester based on periodic walking movements. Other activities may have a drastically different frequency spectrum to walking and optimising for these spectrums may improve power output. This may however also increase variation between participants, as some may generate lots of harvestable energy from non-periodic movements, but others very little. Given the scale of data and results, inevitability this paper has presented only one harvester configuration. Our code is openly available, with the details provided at the start of this paper, and the data openly available on application to the UK Biobank, to allow the investigation of other harvester configurations.

There are also some limitations in the data extraction methods used, including having to estimate the participant's age (which could be incorrect by up to 22 days). However, this is likely to have little impact on the results as changes in activity are not likely to occur as soon as participants cross an age threshold. Further, given the time-lag between metadata collection and data collection, participants in the comparison control group (in the diabetes analysis) could have received a diagnosis diabetes in the interim. We assumed this was a negligible number of people.

Datasets such as the UK Biobank are intended to represent the average population, but are known to be skewed by *healthy volunteer* bias. In particular in the UK Biobank, participants have been found to be more likely to be older, female, and to live in less socioeconomically deprived areas than the general UK population [63].

In addition, the age range of participants is from 43–78, and so our results lack information from younger participants who might be more familiar with IoT technologies. This is a clear gap in our dataset, but at the same time a common criticism of healthcare IoT technologies is that they tend to be designed for people who are young and healthy and so not necessarily representative of the end user group [64] and our work does not have this limitation. The average age of the population worldwide is increasing, and the challenge of healthy ageing is a major driver for the creation of healthcare IoT technologies [65]. Our results are most relevant to energy harvesting situations from older adults who may have a range of health related conditions, affecting their behaviours, movements, and levels of harvest-able energy.

Further, we do not have any information available around holidays, and which festivals and similar may or may not have been observed by participants. As a large, free-living dataset, the results intrinsically capture a wide range of different behaviours around holidays. The majority of our results presented are averages across many people, and the exact figures for any one person may vary from these averages, and the person's own personal average, if they have a *non-typical* day for any given reason such as holidays and festivals.

While these dataset related factors may have an impact on the results presented here (particularly those in Fig. 6 where the data is intended to represent the average UK population), there are no other datasets available of the size and scale of the UK Biobank to generate an analysis such as the one presented in this paper. It provides an insight into the potential for using energy harvesting to power wearable devices in free-living environments at a scale that has not previously been possible.

V. Conclusions

We processed free-living accelerometer data from 67,024 UK Biobank participants to identify their energy harvesting potential and how this varies between different population groups. This work represents the largest modelling of energy harvesting potential on free-living data, in terms of participant numbers, by three orders of magnitude. By utilising the UK Biobank we have been able to stratify energy harvester output by day of the week, age, sex, season and a presence of a disease (diabetes). These factors have not previously been investigated in energy harvesting studies as datasets were too small to allow detailed stratification. They provide detailed insights into how real world factors may affect energy harvester performance.

On average female users were modelled as generating more energy than males, although the difference was not statistically significant. The average harvested energy was statistically significantly different between age groups, and between different seasons of the year (although the effect size was negligible for the latter). Future energy harvester design, implementation, and evaluation works should take these factors into account when designing their experimental methodology in order to avoid potential sources of bias. We have also shown that energy generation times vary during the day, with rise times in the morning being later on weekend days. Task scheduling algorithms for the optimal run-time allocation of harvested energy may make use of this prior information for guiding their decisions. Finally, we have demonstrated that the presence of a disease, specifically diabetes, can statistically significantly affect the amount of energy harvested.

Our findings demonstrate a key challenge in IoT and wearable energy harvesting—wearable devices aim to monitor people's health and wellness, and energy harvesting aims to make devices energy-autonomous—but in populations with a disease there is potentially less power available to harvest and therefore it is harder to meet the required power budget and do the desired health and wellness monitoring. To our knowledge, the small scale testing of harvester devices considered previously has not allowed such effects to be seen, and we quantify them for the first time.

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