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Impact of shift working on the potential for self-powering via kinetic energy harvesting in wearable devices

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***Abstract*— Wearable devices are having a transformative impact on personalised monitoring and care. However, they frequently have limited battery life, requiring charging every few days; a major source of user frustration. Kinetic energy harvesting may help overcome this, collecting energy from the user's motion to allow the device to self-charge. While there are many works which have investigated wearable energy harvesting potential, none have incorporated socio-economic factors which affect activity, such as occupation type, on energy harvesting potential. We use the UK Biobank free-living accelerometer dataset to investigate the impact of occupational patterns on energy harvesting potential for the first time. We identify that those following shift patterns have a different distribution of when power is available, with those who work shifts having the most power intense period spread over a longer period of the day compared to controls. When stratifying into day or night shift work, we identify that those who work night shifts have a large variation between participants, as their most energy dense period is spread over the entire 24-hour period. This is compared to day shift workers who have the most power concentrated within a substantially smaller window, typically in the morning. Considering these socio-economic factors may affect system design of wearable energy harvesters.**

I. INTRODUCTION

Energy harvesting promises to reduce reliance on battery maintenance for wearable devices, which may increase compliance and increase use in medical settings [1]. Scavenging energy from the ambient environment, known as kinetic energy harvesting, where semi-predictable levels of power can be harvested from quasi-periodic movements such as walking and running, is a potential energy source for wearable energy harvesters [2]. There is considerable literature on developing kinetic energy harvesters in non free-living environments, that is, in the lab, including walking, running and cycling [2]. However, it is challenging to provide actual estimates of the true amount of energy that can be scavenged from free-living movements, as levels of activity, and therefore energy harvester output, vary greatly between population groups.

To investigate this, we have utilized the >100,000 accelerometry datasets in the UK Biobank to generate estimations of energy harvesting potential across different population groups, including differences in harvester output across the day, days of the week, seasons, age groups and presence of diseases [3]. It is important to understand when power is available from an energy harvester so that operations that consume large amounts of power, such as the wireless transmission of data, can be scheduled to match the time period when the energy harvester is likely to have the greatest power output. However, different socio-economic factors, which affect daily routines, may lead to changes in the expected times when power is available.

In this work, we build upon our previous analysis to consider for the first time the impact of socio-economic factors on the output of a wearable kinetic energy harvester. We consider the impact of a participant's occupation, particularly whether their job involved taking part in shift work, to investigate changes in energy harvester output. Others have previously investigated accelerometer measurements on shift-workers, including hospital shift workers [4], differences between activity and sleeping time [5] and physical activity/sedentary periods at work [6]. In this work, we build upon this, but focus on energy harvesting potential as a key step towards deploying energy harvesters in real devices to be used by a diverse population.

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II. METHODS

A. The UK Biobank dataset

As part of the UK Biobank study, physical activity was collected from over 100,000 participants aged 43–78, by instructing participants to wear a wrist worn accelerometer (Axivity AX3) on their dominant wrist for 24-hours a day for a week [7]. The sensor collected continuous 3-axis accelerometry without the need for sensor removal over the 7-day period while sampling at 100 Hz. We make use of this accelerometry data in this paper, alongside the detailed work environment data collected as part of an online follow-up with participants. This research has been conducted using the UK Biobank Resource under Application Number 33693.

B. Participant selection

Prior to participant selection, we exclude participants from the study based upon criteria laid out in [3]. This briefly compromises of excluding participants who wore the accelerometer for less than 20-hours a day, were under the age of 45, had large gaps in recorded data, crossed a daylight savings crossover, or removed their consent prior to our analysis being undertaken. Due to our previously reported discrepancies on the first day of data collection [3], we also discard the first day of data collection for each participant.

Given the large-scale and prospective nature of the UK Biobank study, data was collected over multiple dates both within the same category of data and across data types. This necessitates care to obtain a valid analysis, in particular

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ensuring the metadata is correct for the period when the main data collection (the physical activity accelerometery in this manuscript) took place, especially when some measures were repeated. To account for this, we only include participants that we can reasonably assume were employed at the time of data collection, by excluding all participants who entered their metadata over 100 days *before* carrying out their accelerometer data collection, as a reasonable assumption that their occupation had not changed during this period.

We select all the participants who met the inclusion criteria above, and then select all participants who indicated whether their job involved shift work (see Data-Field 22620 in the UK Biobank for definitions of shift work). From this we generate our first cohort to analyze, including a comparison control dataset of participants who are employed but whose job did not involve shift work. The control dataset is generated by randomly selecting an equivalent number of participants, matching them on sex and age. We refer to this cohort as cohort 1, with 1295 participants per group (2590 total), 626/669 female/male respectively per group, and ages of 55.9 $\pm$ 6.1 and 55.7 $\pm$ 6.0 (mean $\pm$ SD), for the control and shift working group respectively. We also generate a second cohort, cohort 2, as a subset of cohort 1. In this second cohort, we stratify participants further by breaking down the dataset to identify whether their job involved *only* day or *only* night shift work patterns respectively (Data-Fields 22630 and 22650). In this cohort participant numbers were substantially smaller than cohort 1, particularly in the group who reported they *only* worked a night-shift pattern. We therefore follow the same procedure as in cohort 1, selecting control and day shift participants to match the demographics of the night shift pattern participants. Cohort 2 has 51 participants per group (153 total), 25/26 female/male respectively, and ages of 57.6 $\pm$ 6.3, 56.9 $\pm$ 5.8 and 57.9 $\pm$ 5.2 for the control, day shift workers and night shift workers respectively.

C. Energy harvesting model

The energy harvesting model is based upon a second-order mass-spring-damper from [8]. Here, we use the parameters previously identified as optimal for a harvester placed on the wrist and sized at 50 mm. These parameters are m = 0.11 g, b = 0.07 kg/s, k = 12.15 kg/s^2 (using the notation from [8]). In this paper we identify the theoretical maximum output from the energy harvester and thus use an efficiency factor of 100%, which can be scaled as appropriate to match a desired practical harvester implementation.

We process each of the raw accelerometer files using the pre-processing steps in [3], based upon those by the UK Biobank expert group [7]. These steps briefly compromise of: calibrating each record to local gravity, resampling to 100 Hz, and filtering with a sixth-order zero-phase high-pass Butterworth filter, f_h = 0.3 Hz, to remove the gravity component. After pre-processing, each participant's record is processed by our harvester model, generating power output against time for the seven-day record. We down-sample the output from 100 Hz to one sample a minute (0.0167 Hz), to reduce storage and processing requirements.

D. Analyses

We explore multiple representations of energy harvester output to compare the difference our two cohorts. These are:

- Cohort 1: Variations in mean harvested power across 24-hours for an average day.
- Cohort 1: Location of the most power dense ten minute period across the weekdays, Saturday and Sunday.
- Cohort 2: Differences in the total average harvested power across 07:00 to 20:00, defined as *daytime hours*.
- Cohort 2: Location of the most power dense ten minute period across the weekdays, Saturday and Sunday.

III. RESULTS

A. Comparisons on cohort 1

In Fig. 1 we compare the harvestable power across an average day in cohort 1. In Fig. 1 the lines represent the mean value at each time point, while the shaded regions denote 95% confidence intervals. Here we can see how the two groups follow a similar profile; low power output ($<$ 30 μW) during the night, with the shift worker group generating slightly more ($\sim$10 μW) than the control group. Both groups begin to increase in power output at around 05:00, with the power output from the control group rising faster than the shift worker group, whom take around 1 hour longer to plateau. At around 09:00 for the control and 10:00 for the shift worker group, power output plateaus between 140–160 μW, with a slight dip of around 20 μW in the afternoon (13:00–17:00), which is more prominent in the control group. The shift group has peaks around 30 μW high at 9:20 and 12:30, possibly corresponding to shift change over times. Between 16:40–17:20 the control group has spikes of power around 20–30 μW high, corresponding with commuting times, an effect not present on the shift working group. Both groups remain around 120–150 μW until 19:00, when both groups begin to roll-off, both following a close pattern to each other. The total energy harvested across an average day was 7.62 J for the control group and 7.92 J in the shift worker group. In Fig. 1 some of the differences in lifestyle are starting to become evident, and there is the expected pattern of the shift working group being more active in the night. Interesting for wearable designers is the slower morning increase of power, meaning that compensation may need to be made, as the time for power output to plateau is later in the day in shift workers.

To provide more insight into the spread of data values, we compare the location of the ten minute window across a 24-hour period which contains the largest amount of power generated. For compactness we make comparisons on the ten minute window for participants stratified by: weekday, Saturday and Sunday; with only minor differences present between weekdays. In Fig. 2, a raincloud plot of the location of the ten minute window that contains the highest power over weekdays, Saturdays and Sundays is shown. In Fig. 2, the top part shows a kernel density estimation (KDE), the central part a box plot and the *rain* denotes the individual data points with added jitter to improve visibility. In Fig. 2

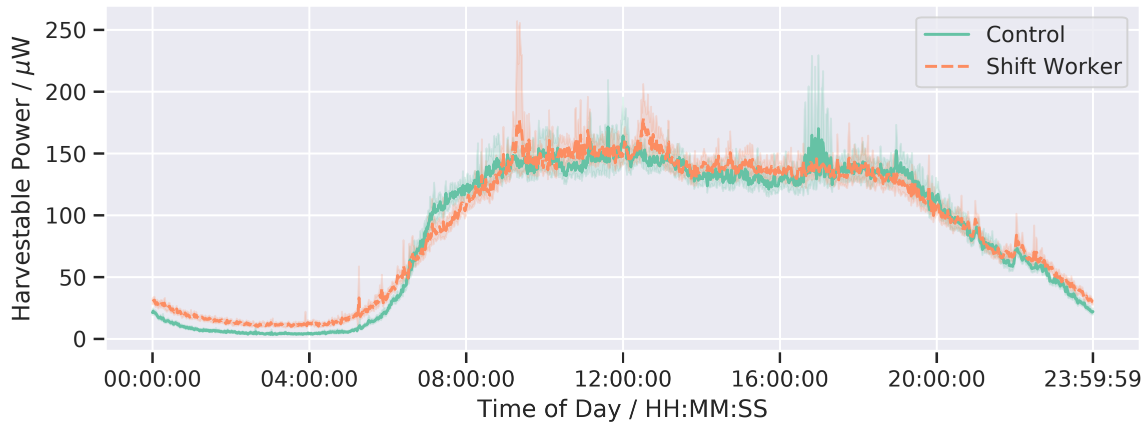

Fig. 1. Comparison of the mean power output across the day, for an average day, for cohort 1. Shaded regions denote 95% confidence intervals.

we can identify more details in the power profile between shift workers and the control group than in Fig. 1. Looking at the KDE for the weekday data, we see how the control group is approximately grouped into two; with one group whom have the most power dense period in the morning, around 08:00, and the second who have a peak in the evening, around 18:30. In the shift worker group, this split is less clear, with the most energy dense period being spread across 08:00–18:00. The differences in distribution can also be highlighted by comparing the Inter Quartile Range (IQR), with the shift working group having a narrower range; 1 hour and 22 minutes smaller than the control group. Comparing the differences between the two groups on Saturday and Sunday, these are substantially smaller, with very similar distributions on Saturday, small differences in the median time (13:15 vs. 13:14 control and shift respectively) and the IQR (6 hours 27 minutes vs 6 hours 51 minutes for control and shift respectively). Sunday again shows similar patterns, with a slightly larger skew to the left of the distribution in the control group representing more participants with their most energy dense period in the morning, compared to a slightly more even spread for the shift workers. These differences highlight how, particularly on the weekdays, there is less of guarantee that the best time for powering energy harvesting devices is in the morning, as the time with the maximum power is spread over a longer time period with shift working participants.

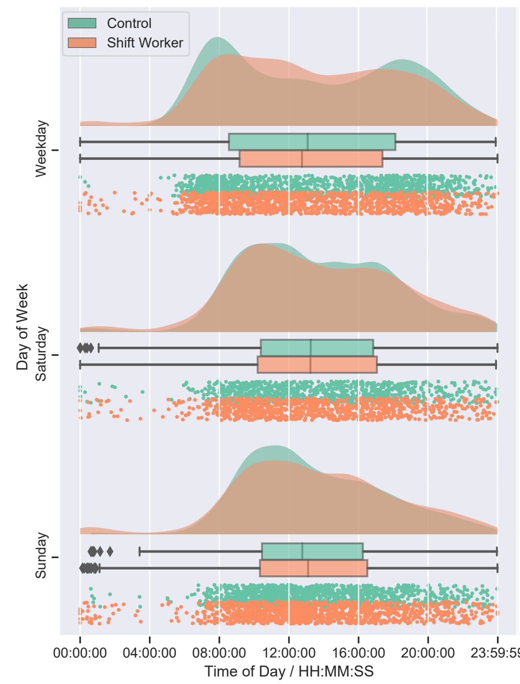

Fig. 2. Location of the ten minute window across a 24-hour period where average energy harvester output is the greatest, for cohort 1. Note the y-axis of the kernel density estimate (KDE) represents the probability of a data point occurring at this time, the total area of each KDE sums to 1.

B. Comparisons on cohort 2

The total energy harvested during an average day was 8.04 J, 7.41 J and 8.18 J for the control, day shift and night shift workers respectively. Due to the smaller size of cohort 2, it is not possible to create a meaningful plot of cross-subject average power output over time with the high temporal resolution as in Fig. 1. Instead, we compare the mean power output between groups during *daytime hours* (07:00–20:00). Fig. 3 demonstrates this as a violin plot, with the white dot as the median, the thick black bar the IQR and the thin line the limits of the distribution (excluding outliers). Dots indicate individual data points, with added jitter. The outer *violin* is a KDE of the distribution. The control and day shift group have a similar median power during the day (at 127 μW and 121 μW respectively), while the night shift group have a marginally lower median power at 107 μW. Further, the IQR of average power is greater in the control group compared with the day shift group, with 75 μW compared with 61 μW. The night shift group has an IQR of 48 μW. The smaller IQR in the shift working groups suggest that participants working shifts generate a more predictable power output, i.e. they are likely to undertake a set level of activity, whereas the control group has more people who are both less and more active. The small differences between the night shift group and the control are surprising, as we expect the night shift group to be inactive during this daytime period.

Finally, we compare the location of the ten minute window with the highest power generated across a 24-hour period for cohort 2, shown in Fig. 4. Initially, the KDEs demonstrate how the night shift group has the greatest spread of values,

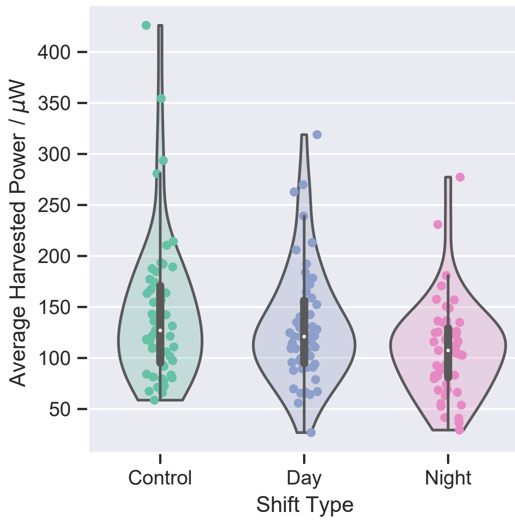

Fig. 3. Mean power during *daytime hours* (07:00 – 20:00), for cohort 2.

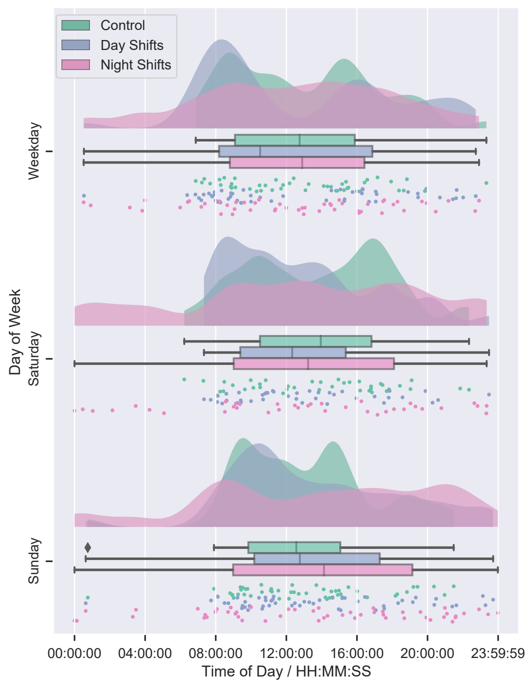

Fig. 4. Location of the ten minute window across a 24-hour period where average energy harvester output is the greatest, for cohort 2.

with the most energy dense period occurring across the entire 24-hours, compared with the substantially narrower distributions of the control and day shift workers. This effect is prominent on all days of the week, although Sunday has fewer participants located in the early hours of the morning. In the control group, the majority of participants fit into two groups, the morning and afternoon, with the exact timings of these differing between weekdays and weekends and two groups being considerably closer in time on Sunday. In the day shift group, participants are largely centered around the morning hours 06:00–10:00, with this moving around an hour later on Saturday and an several hours later again on Sunday. Compared to the night shift group, with the exception of outliers, both the control and the day shift group have the most power dense period after 06:00. Of note, the largest difference between the spread of groups occurs on Sunday, where the control group has an IQR of over 5 hours, compared with the night shift group with an IQR of over 10 hours. This has a significant implication for designers, who will need to know the times when the most energy is available from an energy harvester, but for those who work night shifts, particularly on Sunday, this is spread over long time period and it is not possible to assume power will be available in a narrow window.

IV. CONCLUSIONS

We have compared how the output of a wearable kinetic energy harvester changes both in amount of power and the times of day that the power is available, stratified by whether their occupation involved shift work. We have identified that, within the UK Biobank dataset, participants who worked shifts showed similar patterns in the typical profile of power availability throughout the day, while the location of the most energy dense period was spread over a larger time period in those who worked shift work. We also identified that the type of shift work undertaken by participants had a large impact on the time of day when the most power is available, with night shift workers having values spread over 24-hours, compared to day shift workers where the majority were situated in the morning. These results have substantial impacts for designers of wearable energy harvester devices, where energy intense operations need to be timed with the time where power is most available.

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