On Predicting the Battery Lifetime of IoT Devices: Experiences from the SPHERE Deployments

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ABSTRACT

One of the challenges of deploying IoT battery-powered sensing systems is managing the maintenance of batteries. To that end, practitioners often employ prediction techniques to approximate the battery lifetime of the deployed devices. Following a series of long-term residential deployments in the wild, this paper contrasts real-world battery lifetimes and discharge patterns against battery lifetime predictions that were conducted during the development of the deployed system. The comparison highlights the challenges of making battery lifetime predictions, in an attempt to motivate further research on the matter. Moreover, this paper summarises key lessons learned that could potentially accelerate future IoT deployments of similar scale and nature.

CCS CONCEPTS

• **Computer systems organization → Sensors and actuators**; *Sensor networks*; *Maintainability and maintenance*;

KEYWORDS

Battery-Powered Devices, Sensor Deployments, Internet of Things

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1 INTRODUCTION

An important requirement for successfully deploying networks of Internet-of-Things (IoT) devices is managing on-site maintenance visits. In case of battery-powered devices, in particular, on-site visits may be required for replacing or recharging depleted batteries. This paper focuses on predicting the lifetime of battery-powered IoT devices that are deployed *in the wild*. Our work is based on experiences from the SPHERE deployments. SPHERE is a sensing platform of non-medical sensors that are deployed in residential environments for personalised healthcare provision. The SPHERE system is currently being deployed into the houses of volunteering participants, as part of the *100 homes study*. The successful management of the on-site visits is vital for achieving a satisfactory deployment throughput and guaranteeing that the deployments will be completed with the limited resources of a research project. This goal was supported by attempts to estimate the battery lifetime of the deployed battery-powered sensing devices. However, monitoring data obtained from over 50 real-world deployments for up 12 months, indicate that battery lifetime estimation techniques that are widely used in academic papers, are insufficient for predicting the battery lifetime of IoT devices. Most interestingly, we have observed a very high variance in the actual battery lifetimes of the deployed devices: the same hardware design and the same firmware yielding very different lifetimes on different units.

In this paper, we share our experiences from the SPHERE deployments, and contrast predicted battery lifetimes against observed battery lifetimes obtained. We hope that our experiences will trigger interesting discussions and motivate further research that would accelerate future IoT deployments of similar scale and nature.

2 THE SPHERE DEPLOYMENTS

SPHERE is a sensing platform for healthcare in residential environments. It is composed of a series of non-medical IoT sensing devices, such as environmental sensors, wearable sensors and cameras. Unlike other home infrastructures for healthcare that are evaluated in laboratory or test-bed environments [16, 19], the SPHERE platform is currently being deployed in the houses of volunteering participants [1, 14]. At the time of writing, the platform has been deployed in over 50 residential properties.

The purpose of the SPHERE deployments is interdisciplinary: to enable research in the fields of networked embedded systems, activity recognition, as well as clinical research. Indeed, deploying IoT sensor networks in the wild and at large scale, enables us to evaluate state-of-the-art IoT technologies in real world settings (*e.g.*, interference, mobility patterns, deployment environments) [21], identify

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their current limitations, and ultimately make them more robust. Furthermore, real-world datasets would enable the development of robust machine learning frameworks that are able to operate robustly in real environments with imperfect data, *e.g.*, noise and missing data [2, 18]. Lastly, clinical researchers require data from large cohorts to derive to statistically significant conclusions.

The SPHERE platform incorporates two bespoke battery-powered IoT sensing devices: the SPHERE Environmental Sensor and the SPHERE Wearable Sensor. Detailed information on the low-power IoT sub-system of the SPHERE platform and its networking architecture is available in [6, 8].

The SPHERE Environmental Sensors [9] are wall-mounted sensing platforms that capture the environmental properties of a room. Each platform is equipped with temperature, humidity, light, air pressure and motion sensors. Some environmental sensors also host a custom water flow sensor [27]. The board is equipped with a CC2650 System-on-Chip (SoC) for processing and wireless communication. One environmental sensor is deployed per room. The device is powered by ER14505: a 3.6 V AA lithium-thionyl chloride non-rechargeable battery. The battery has a nominal capacity of 2.6 Ah at room temperature (25 ^{o}C) assuming a constant discharge at a rate of $\leq$ 2 mA, which drops to 1.9 Ah at 20 mA [7].

The SPHERE Environmental Sensor runs a fork of the Contiki operating system using its 6LoWPAN (IPv6 over Low-Power Wireless Personal Area Networks) over IEEE 802.15.4 TSCH (Time-Slotted, Channel Hopping) networking stack [5]. The operation is based on a TSCH schedule that is composed of a repeating frame of 99 time-slots. Two time-slots are allocated to each environmental sensor in each frame: one for transmitting and one for receiving data. The schedule also has one broadcast slot per frame. The remainder of the 96 time-slots, the system is in sleep mode. The average radio-on duration in an empty TSCH slot is 2 milliseconds, in a TSCH slot with a packet: 4 to 5 milliseconds. As a result, the radio duty cycle of the device is approximately 1.0 %. At the application layer, the temperature, humidity, light, and air pressure sensors are sampled at 0.2 Hz; yet, for energy-efficiency, the measurements are transmitted only if they are significantly different from the previously transmitted measurements, or every 5 samples. The motion sensor produces data at 1 Hz rate. Once every 20 seconds, 20 samples are packed into a bitmap and transmitted as a single value. In total, the system transmits one data packet per 20 s on the average. Finally, the system also generates monitoring data, such as statistics about the network performance: approximately one packet per minute.

The SPHERE Wearable Sensors [11] are wrist-word activity sensing platforms. They are equipped with an accelerometer that captures the mobility patterns of the user. In addition, they are used for room-level localisation within the SPHERE house. Each house resident is provided with one wearable sensor. The board is also based on the CC2650 SoC. The device is powered by the GMB261534: a 3.7 V lithium-ion polymer rechargeable battery. The battery has a nominal capacity of 100 mAh at room temperature (23 ^{o}C) assuming a constant discharge rate of 50 mA [20]. The board is equipped with a Qi inductive wireless charging circuit. The users are requested to periodically recharge the battery by placing it on top of a charging pad.

The firmware is based on the TI-RTOS operating system, running its Bluetooth Low Energy (BLE) stack. In particular, wireless communication is based on undirected non-connectable BLE advertisements, which is a form of broadcasting. The acceleration sensor operates at a fixed sampling frequency and the system transmits advertisements that contain 6 samples. In the first deployments, a sampling frequency of 12.5 Hz was used, which translates to approximately 2 transmissions per second. Later, the sampling frequency was doubled (25 Hz), and hence the frequency of transmissions doubled as well (4 per second). In parallel, the system collects monitoring data, which are piggy-backed on data packets. It is noted that the duty cycle of the wearable sensor (both the radio and CPU duty cycle) have no dependence on external triggers whatsoever. They fully depend on periodic events with constant periods.

3 BACKGROUND

3.1 Software-Based Estimation

The first step toward predicting the battery lifetime of an IoT device is identifying its long-term consumption profile. A common way to evaluate the consumption of embedded platforms platforms is software-based estimation (*e.g.*, [24, 28]). The technique is based on measuring in software, the time that the device is in various operating states. Each state is, in turn, associated with a fixed current consumption, which can be either derived from the datasheets of the respective component, or measured. The charge consumption over the measured period can be then calculated as the weighted sum of all state combinations. The Contiki OS incorporates a module for continuous monitoring of the consumed energy with software-based estimation [4].

The main advantage of this approach is that long-term time measurements are practical. Yet, the process is as accurate as the state granularity and accepts several simplifications. To name a few: (i) the energy consumption of peripheral units is often considered negligible and, thus, not tracked; (ii) the transition between states, which accounts for approximately 3% inaccuracy in [15], is neglected; and (iii) the operating voltage is assumed constant. However, [15] shows that the technique can be very accurate if calibrated with current measurements. Moreover, [15] reports $\approx$ 2% variation in the current consumption between different instances of the same sensing platform. However, per-device calibration is impractical for large-scale deployments.

3.2 Current Measurements

The long-term current consumption of the system can also be approximated with short-term current measurements (*e.g.*, [10, 17]). This technique is typically based on placing a shunt resistor, R in series with the power supply (*i.e.*, the battery), and measuring the voltage drop across it over time, $V(t)$. The current profile, in turn, can be calculated by Ohm's Law as: $I(t) = V(t)/R$.

A typical challenge in measuring low-power IoT devices is the high dynamic range of the current. This challenge can be addressed by measuring the sleep current and the active current separately, using two different shunt resistors: a large shunt resistor for measuring the sleep current with high accuracy, and a small shunt resistor for measuring the active current without resetting the board. The key limitation of current measurements is that the device under test needs to be attached to the measurement device. Thus, unlike software-based estimation, it is impractical to continuously monitor deployed devices.

3.3 Battery Lifetime Estimation

Assuming that Q_h is the charge consumption per hour of operation, estimated with one of the aforementioned techniques, the next step is estimating the battery lifetime. Assuming a linear battery model [3], the lifetime of the device in hours, L_h, can be approximated by $L_h = C/Q_h$ where C is the nominal capacity of the battery.

Such a simple battery model has several limitations [3, 12, 13, 23]. To summarise, it does *not* take into account: (i) non-linear effects of the battery, such as the relaxation effect; (ii) the resistance that builds inside the battery over time and alters the supply voltage; (iii) the dependence of the discharge rate on current draw; and (v) the fact that not all the stored energy stored in the battery is usable. In [3], the authors propose a battery model that captures these effects and show that a linear battery model overestimates the battery lifetime by up to approximately 40%. It is highlighted that this error is an order of magnitude higher than the error introduced in the prediction of the consumption.

Lastly, it should be noted that there is also variation among different battery brands [22] and among individual batteries subject to the same load: approximately 10% observed in [13].

4 RESULTS

4.1 Environmental Sensors

4.1.1 Predicted Battery Lifetime. First, we measured the charge consumption of the Environmental Sensor using the RocketLogger [26], and used these measurements to calibrate the Contiki software-based energy estimator (*Energest*). We additionally developed a separate software-based model to quantify the energy of TSCH timeslots based on packet size. The system charge consumption was estimated by combining these two models (the regular *Energest* is turned off in TSCH slots). Then, we verified that the charge consumption as calculated by the *Energest* matches RocketLogger measurement results obtained simultaneously on the same node. These two sets of results indeed showed a good match, *i.e.*, less than 10 % absolute difference.

As the next step, we used the nominal capacity of the ER14505 datasheet [7] to convert the charge consumption to the number of days. We assumed that 90 % of the nominal capacity can be extracted from the battery. Since the ER14505 datasheet claimed to provide stable voltage until the very end of the battery life (see Fig. 1 in [7]), any potential energy savings due to undervolting the battery were discounted. The results [9] showed a predicted lifetime well above 12 months. Furthermore, the breakdown of the charge consumption (Fig. 3a) suggested that operation in TSCH reception slots consume almost half of the total system's energy, therefore providing a focus point for future improvements.

4.1.2 Observed Battery Lifetimes. Nevertheless, during the first year of the SPHERE's deployments it became clear that the devices discharge their batteries much faster than predicted (Fig. 1). Overall, we observed these problems: (i) median lifetime of 6 months or less, rather than the predicted lifetime of over a year; (ii) large variance in battery lifetime between the deployed houses (Fig. 1); (iii) large

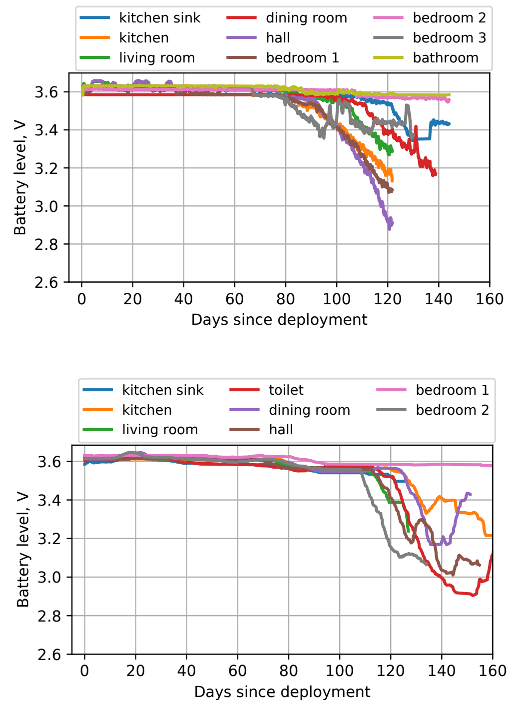


Figure 1: Battery discharge curves in two SPHERE deployments, House 2680 (top) and House 3610 (bottom).

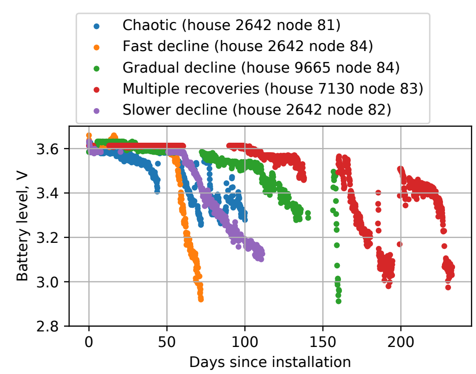
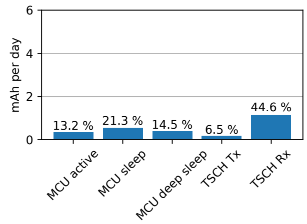


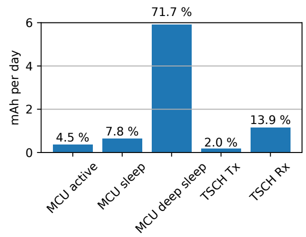
Figure 2: Categories of ER14505 battery discharge patterns.

variance in battery lifetime between nodes in a single house (Fig. 1); (iv) battery voltage that is unstable (Fig. 2), not always strongly correlated with the remaining battery lifetime, and not matching the discharge characteristics of the ER14505 battery (see Fig. 1 in [7]); (v) lack of correlation between the estimated charge consumption (Fig. 3a) and the lifetime of the batteries.

4.1.3 Discussion. **TSCH coordinator issues.** The initial evidence pointed towards a problematic system design, rather than problems with the estimation of the energy consumption. By design, TSCH nodes that are trying to join the network consume significantly



(a) Pre-deployment estimate



(b) Post-deployment estimate

Figure 3: Breakdown of the daily charge consumption.

Table 1: Daily consumption on Environmental Sensors

Parameter	Value
Average daily charge consumption	8.7 mAh
Max. abs. deviation between nodes	4.8 % (STD=0.251)
Max. abs. deviation between time periods on a single node	1.8 % (STD=0.085)

Table 2: Lifetime of Environmental Sensors

Description	Value
Average lifetime, prediction before deployments	780 days
Average lifetime, prediction after deployments	275 days
Median lifetime in House 2680	≈ 130 days (Fig. 1a)
Median lifetime in House 3619	≈ 150 days (Fig. 1b)

more energy as compared to normal operation. As a result, having an active coordinator node in the network is critical to ensure that the energy consumption remains low. In SPHERE's networks, a single physical coordinator node is present; it is attached to a Linux host device (the SPHERE Home Gateway, SHG). Originally, the TSCH coordinator was powered only when the SHG was turned on. However, the SPHERE participants in several cases turned off the SPHERE Home Gateway for extended periods of time (a month or more). This problem was ameliorated in subsequent deployments (starting from January, 2018), which made sure that the coordinator node remained powered on even when the SHG was turned off.

Current leakage issues. After the initial deployments were finished, we re-measured the energy consumption on some of the problematic devices and noticed that they have much higher deep sleep current than anticipated: instead of the predicted 16 μA, they have 254 μA on the average. This leads to much higher daily charge consumption than anticipated (Table 1). The consumption also follows an unexpected pattern (Fig. 3b). The energy leakage was traced to the GPIO pins. The GPIO pins are initialised by the water flow sensor driver [27]. This is a software component that was merged in the system at a quite late stage: after our thorough pre-deployment evaluation was finished, after the two pilot deployments had taken place, and more than half a year after the previously agreed-upon feature-freeze deadline. Furthermore, sensor nodes that did not have the water flow sensor physically attached were leaking *more* current than nodes which had the sensor connected. Since only a few nodes per deployment employ the water flow sensor, the problem turned out to be trivial to fix: by disabling this sensor driver on nodes that do not need it.

Battery lifetime variance and voltage instability issues. After fixing these first two problems, we arrived at the current state. The charge consumption and the energy consumption from the software-based energy estimator is now accurate, with less than 10 % error when validated with a RocketLogger. However, the results show that despite accurately predicting the charge consumption (as far as we can tell), it is *still not possible to accurately predict the lifetime of individual batteries.* The variance of the individual batteries (Fig. 1) in a single house remains high. These differences are not explained by the variance of the load on the individual devices: the software-estimated charge consumption is very stable and similar across different devices and different deployments. They are also not explained by the hardware variations of the individual devices: as shown in Table 1, the differences in charge consumption between different devices is less than 5 %. The variance in battery lifetime between the different houses is higher than the variance in a single house; however, this additional inter-house variance is at least partially explained by the SHG being turned off for long periods in House 2680, but not in House 4954.

Moving forward, it seems that the best strategy would be to use these empirical results to estimate the lower bound of the battery lifetime, and plan the system design accordingly.

Networking and environmental effects. Our results provide an interesting counterpoint to the conventional wisdom that the battery lifetime is primarily determined by the network environment (interference levels, link quality, etc.) or by the physical environment (temperature, humidity, etc.). All devices share similar environments, which as characterised by stable temperature in the $20-30\ ^{o}$C range. Furthermore, despite the fact that the nodes experience varied radio link qualities and interference levels, TSCH provides a predictable schedule that can be used to predict the energy consumption before the deployment reasonably well.

4.2 Wearable Sensors

4.2.1 Predicted Battery Lifetime. In the case of the Wearable Sensors, we employed current profile measurements to approximate its battery lifetime at various design stages. These current measurements and battery lifetime approximations are described in detail in [11]. In a nutshell, we first measured the current profile of various operation states and events. Then, we combined this measurements and developed a parametric formula that estimates the battery lifetime depending on various configurations, such as the sampling frequency and the bit-resolution of the accelerometer. The formula is based on a linear battery model.

It is noted that the measurements reported in [11] were conducted on a modified unit. Indeed, this batch of wearable sensors had hardware faults that resulted into a ≈ 12 μA current leak. Aiming to evaluate the design rather than the implementation, in [11] we used a patched device for the measurements. However, the deployed wearable units have the unfortunate current leak. Fig. 4 plots the predicted battery lifetime of the device for various sampling frequencies, considering the deployed firmware. The numbers are based on the measurements and formulas provided in [11], yet

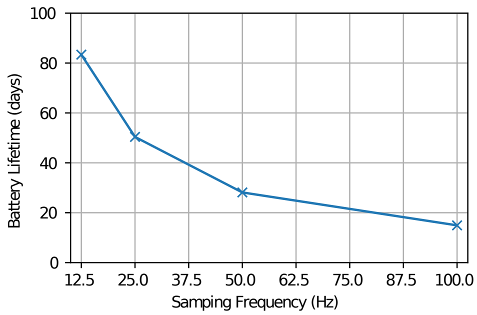


Figure 4: Predicted battery lifetime of the wearable device. The predictions are based on [11], corrected for a 12 μA current leak in the deployed devices.

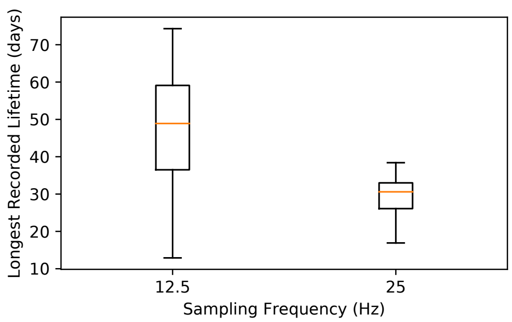


Figure 5: The longest recorded battery lifetime with a single charge for 65 wearable sensors, summarised in box plots.

the sleep current is adjusted to account for the current leak in the deployed units. The predicted battery lifetime of the device is approximately 83 days at $f_s = 12.5$ Hz, and 50 days at $f_s = 25$ Hz.

4.2.2 Observed Battery Lifetimes. Fig. 5 plots the longest recorded battery lifetime with a single battery charge for 65 wearable sensors in box plots. It is noted that this figure does not necessarily reflect the maximum achievable battery lifetime because certain devices may be recharged by their user more frequently than needed. The median longest recorded battery lifetime is approximately 50 days and 30 days for an acceleration sampling frequency of 12.5 Hz and 25 Hz respectively. Both medians are approximately 40% less than the predictions shown in Fig. 4. This offset is, indeed, close to the difference between using an ideal and a realistic battery model, as reported in [3]. Moreover, the empirical data from the deployments are characterised by a very high variance, which cannot be attributed to the battery model. This variance is also much higher than what [15] attributes to manufacturing differences in the electronics among instances of the same platform, and what [13] attributes to battery capacity variations.

A closer look into the discharge profiles of the wearable sensors further illustrates this high variance in the observed battery lifetimes. Fig. 6 shows the battery discharge profile of two characteristic cases for a period of 12 months. As shown in the Fig. 6 (top), some devices have a very rapid discharge rate at installation;

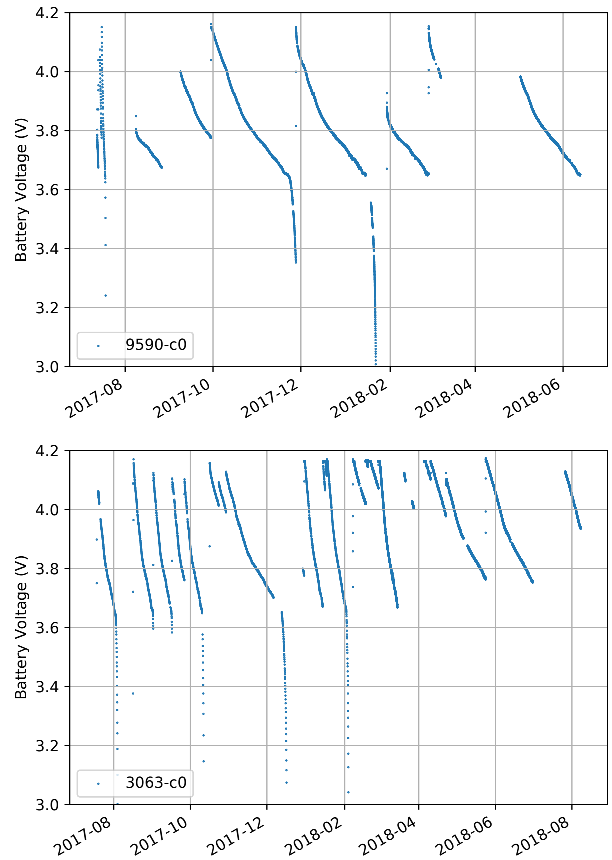


Figure 6: Two distinct discharge patterns: `9590-c0` discharges very rapidly, yet continues with normal discharge rate after a power-cycle (top); `3063-c0` alternates between rapid and normal discharge rates (bottom).

yet this is fixed after a power-cycle. (It is noted that the wearable sensors do not have a power switch; thus, a flat battery is the only cause of a power-cycle.) Indeed, `9590-c0` discharges after only 3 days initially, but after a power-cycle the discharge rate drops to normal levels, yielding approximately 2 months of battery lifetime. Other devices, such as the `3063-c0`, alternate between rapid and normal discharge rates. As shown in Fig. 6 (middle), the device is characterised by a rapid discharge rate for the first months of the deployment (*i.e.*, battery lifetime at approximately 15 days), yet later it recovers yielding 55 days battery lifetime between November and December 2017. The device continues to alternate between rapid and normal discharge rates throughout 2018.

4.2.3 Discussion. A first potential cause of this unexpected behaviour is that the wearable sensor may be in an erroneous state that draws more current that during the normal operation. For instance, a known issue with the wearable sensor is that the accelerometer of the wearable sensor occasionally fails to boot on power-up, and can only recover from this failure with a power-cycle. Secondly, the occasional rapid discharge rates that discharge the battery in 15 days may be caused by failures with the wireless charging process. In fact, the Qi inductive charging standard assumes larger devices, and the modifications that we did to reduce the circuit's form factor have side-effects in the charging procedure. As a result, it is possible that the Qi charging circuit occasionally fails to charge the battery to 100%, resulting in rapid discharge rates. Lastly, the very rapid discharge rates (2 – 5 days) can be attributed to potential short-circuits. Indeed, the deployment technicians have reported that the connection of the battery to the board has been broken after several months of operation in few wearable devices. This indicates that the battery wires are moving inside the enclosure. These movements may be the cause of intermittent short-circuits.

5 CONCLUSIONS

Following a large-scale deployment of IoT sensing devices in over 50 residential properties for up to 12 months, in this paper we present real-world battery lifetimes and battery discharge patterns, and we contrast them against battery lifetime predictions, conducted during the design of the platform. The results confirm and highlight the importance of previous works that advocate the use of realistic models and calibration with hardware measurements for accurate predictions. Yet, our results demonstrate that, although state-of-the-art techniques for measuring the current consumption are pretty accurate, converting the consumption to a accurate battery lifetime is not a trivial problem. Indeed, we experienced unusual battery discharge patterns and a very high degree of variation among devices that run the same firmware. In conclusion, we summarise some key lessons for practitioners:

- An IoT device may not necessarily operate as intended when deployed; when characterising the consumption of a device, it is important to profile potential failed states as well.
- High variance between different batteries of the same model may be present. Looking at the average or median discharge time may not be sufficient.
- As also shown in the literature [8, 25], datasheets are not always accurate or complete, so must be treated with caution.
- For lithium-thionyl chloride batteries, the remaining voltage is not a good indicator of the remaining lifetime.
- The system's energy consumption needs to be re-evaluated after adding any new components to it, even if the components are not actively used. It is important to follow good engineering practices, such as integration testing and pilots.
- TDMA networking protocols such as TSCH allow to predict the energy consumption of the deployed systems better than the conventional wisdom suggests.
- Successful prediction of energy consumption does not directly translate into successful prediction of battery lifetime.

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