Understanding Human-Smartphone Concerns: A Study of Battery Life

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Abstract. This paper presents a large, 4-week study of more than 4000 people to assess their smartphone charging habits to identify timeslots suitable for opportunistic data uploading and power intensive operations on such devices, as well as opportunities to provide interventions to support better charging behavior. The paper provides an overview of our study and how it was conducted using an online appstore as a software deployment mechanism, and what battery information was collected. We then describe how people charge their smartphones, the implications on battery life and energy usage, and discuss how to improve users' experience with battery life.

Keywords: Large-scale study, battery life, autonomous logging, smartphones, android.

1 Introduction

Sustainability and energy reduction have emerged as important topics in the social, political and technical agendas in recent decades. The ubiquitous computing research community, with its focus on both design and development of technological systems has had to systematically face a strain between sustainability and usability. On the one hand, users express an interest in adopting more sustainable products and behavior, but on the other hand, they do not wish to do so at the expense of their comfort. Hence it is important that solutions tackling energy reduction take into accounts users' behavior and preferences before making an intervention. One area strongly related to ubiquitous computing research where substantial energy savings can be achieved by introducing more usable systems is smartphones.

Cell phones are increasingly popular and diverse, with worldwide sales approaching 1.6 billion units, just last year [8]. Thanks to the rapid development of wireless technologies, smartphones allow users to be reachable anywhere [3]. As "convergent" devices, smartphones empower users with Internet access, music, audio and video playback and recording, navigation and communication capabilities. However, the growing functionality of smartphones requires more power to support operation throughout the day. Processing power, feature-sets and sensors are bottlenecked by battery life limitations, with the typical battery capacity of smartphones today being barely above 1500 mAh [5]. This is an important limitation because smartphones are increasingly regarded as a gateway to one's daily life,

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providing networking access to email, social networking, and messaging, making the management of battery life an important task.

Despite the important limitations that battery life imposes on users, previous research has shown that existing battery interfaces present limited information, and, as a consequence, users develop inaccurate mental models about how the battery discharges and how the remaining battery percentage shown in the interface correlates to application usage [20]. In addition, users do not completely understand how they should charge their batteries to support their planned use of the phone. As a result, every year $22 million are spent in electric utility costs due to keeping cell phones plugged into outlets for more time than required, to maintain a full charge [8]. On average, cell phone power supplies use 0.2 watts when the charger is left plugged into an electrical socket and the phone is no longer attached, with less sophisticated power supply designs reaching 1 watt [8].

We argue that there exists potential in reducing the energy consumption of smartphones by better understanding users' interactions with smartphones and providing better feedback. While previous studies have focused on the shortcomings of user interfaces in relation to battery life, there is a need to assess the real-world behavior of a large number of users in terms of when, how and how long they charge their batteries. By analyzing users' battery charging behavior, we can assess the extent to which energy is being wasted, explore how often users demonstrate less than optimal charging behavior, how often they interrupt the charging cycle and when this is more likely to happen. We hypothesize that by conducting such a study we can identify design opportunities for reducing energy consumption, increasing battery life, and also predicting when intensive computational operations and long data transfers should be scheduled.

This paper starts by giving an overview of related work and current state of the art on smartphone battery management, followed by a description of how was the study deployed and conducted using the Android Marketplace, and a discussion of implementation concerns. We then present the results and a discussion of users' charging habits, how to tackle the issues of wasted energy and opportunistic processing on smartphones. We conclude with a discussion of how the results can affect the design of a future smartphone for an energy conscious world.

2 Related Work

Most smartphones offer the possibility to add new applications, through distribution channels such as the Google Marketplace for the Android platform or App Store for the iPhone platform. These applications often take advantage of the sensors available, typically GPS and Internet connectivity to develop context-aware applications [10,5], accelerometer for motion tracking [18], Bluetooth for distance measurements from the device [15] and anomaly detection [3,19].

While devices are becoming increasingly mobile, many software developers have limited experience with energy-constrained portable embedded systems such as smartphones, which leads to unnecessarily power-hungry applications that rely on the operating system for power management. In addition, users struggle to determine which applications are energy-efficient, and typically users blame the operating system or hardware platform instead of unfortunate and unintentional software design decisions [21].

Rahmati *et al.* [16] coined the term *Human-Battery Interaction* (HBI) to describe mobile phone users' interaction with their cell phones to manage the battery available. According to a survey they conducted, 80% of users take measures to increase their battery lifetime, and it can be expected that maximizing battery life will continue to be a key concern for users due to the major usability issues involved in this task. One approach to automatically deal with this issue is to rely on sensor data. For example, recent devices act proactively to reduce their power consumption, either by turning off the screen after a specific amount of time with no new interaction, switching to a lower processing speed (CPU scaling), or disabling wireless interfaces such as Bluetooth and WiFi when battery levels are low. These devices effectively take into account sensed data regarding battery levels, idle time, *etc.*

Oliver *et al.* [7] highlighted the importance of using real user data collected from the world and how it can influence application development, by introducing the Energy Emulation Toolkit (EET) that allows developers to evaluate the energy consumption requirements of their applications against the collected data. As a result, by classifying smartphone users based on their charging characteristics, the energy level can be predicted with 72% accuracy a full day in advance.

A study on the environmental impact of cell phone charging related to national energy consumption and power plant greenhouse gas emissions reveals that the energy consumed by cell phone charging has been reduced by 50% in the past years due to two technology shifts: increased usage of power management and low-power modes of battery chargers; and use of more efficient switch-mode power supplies [8]. Despite these efficiency gains, however, the US could save 300 million kWh in electricity per year, which amounts to $22 million in electric utility costs, or 216.000 tons of CO_2 emissions from power plants.

The study presented here complements Oliver's study on user charging characteristics [7] and Rahmati et *al.*'s [16] study on how users consume battery in their devices. It aims to identify when, how, for how long and how frequently users recharge their devices' batteries, in order to assess the extent to which energy savings can be achieved. At the same time, the collected information can be used to identify design opportunities in order to achieve such energy savings.

3 Study

We conducted a study of battery charging behaviors with 4035 participants over a period of four weeks, during which anonymous battery information was collected from Android devices running Android 1.6 or higher. In total, more than 7 million data points of battery information were collected. The Open Handset Alliance Project "Android" is a complete, free, and open mobile platform, and its API provides open access to the device hardware, abstracted from each device's manufacturer or brand [2, 13], therefore increasing the number of deployable devices. Although the study was conducted solely with Android devices, most of the results should be similar to other smartphone platforms with respect to battery information and user behavior over time [11].

There was no monetary compensation given to the participating users. The developed application, OverCharged, which was developed to help users be more aware of their battery usage, was made available for free on the Google MarketPlace.

The main function of the OverCharged application we developed is to inform participants of their smart phone's current battery level, for how long the phone was running on battery and other miscellaneous information, such as temperature and voltage. As such, the users who downloaded the application and opted in to sharing their data are already concerned with the battery life on their mobile devices. Therefore, they may in fact be atypical users, and our sample may not be representative of what all smartphone owners would do. Nonetheless, our study does serve as the first large collection of battery usage.

During the study, users had the option to opt-in to sharing their battery data anonymously in order to contribute to a better understanding of battery usage patterns.

The application captured *charging activity*, *battery level*, *device type*, *temperature*, *voltage* and *uptime*:

- *Charging activity* captured when the user charged his device, either through USB or an AC outlet.
- *Battery level* reflects the remaining battery and how long it took to discharge or charge.
- *Device type* is the manufacturer, device board, model, Android version and build and the carrier.
- *Temperature* of the battery, both Celsius and Fahrenheit.
- *Voltage* available in millivolts (mV).
- *Uptime* is the amount of time the device was on until being turned off or rebooted.

The combination of *charging activity* and *battery level* allows for the identification of events such as *"unplugged not full", "charged just unplugged"*, "*finished charging"*, "*charging"* and "*running on battery"*, defined as follows:

- *Unplugged not full*: when the user stopped charging, even though the battery was not fully charged.
- *Charged just unplugged*: when the user unplugged the charger and the battery is fully charged.
- *Finished charging*: the moment when the battery is fully charged.
- *Charging*: when the battery starts charging.
- *Running on battery*: when the battery is the only power source.

3.1 Implementation

Polling a device's state can reduce battery life [10, 12]. The Android API is event-driven, hence gathering the data had a negligible impact on regular battery life. By programming a BroadcastReceiver attached to an Android Service running in the background, whenever the Android OS broadcasts ACTION_BATTERY_ CHANGED, the following battery information was recorded: battery level, battery scale (maximum level value), battery percentage, battery technology (*i.e.* Li-ion), health rating of the battery, whether the phone was plugged to AC/USB, whether the phone is charging, temperature, voltage, uptime and usage uptime, battery status (charging, discharging, full and not charging) and phone events related to battery (fully charged and user just unplugged, charging, finished charging, running on battery, unplugged when not fully charged).

As highlighted by Oliver [10], a large-scale user study distributed across the globe requires the use of UTC timestamps. We captured the UNIX timestamp on the participant's device time zone, which results in consistent times across different time zones (*i.e.*, 8pm is the same for different users at different time zones). These timestamps were used across all data collection and analysis operations.

The application was programmed to start automatically when the device was turned on or rebooted. A small icon in the notification bar at the top of the screen kept users informed that data was being collected and allowed users to view further information [Figure 1].

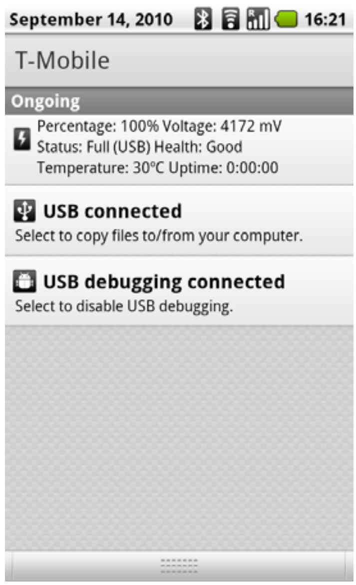

Fig. 1. Notification bar information

3.2 Device Distribution

Of the approximately 17000 people that were using the application at the time the study was conducted, 4035 opted in to participate on our study. After the installation of the application from the MarketPlace, if the user opted in to participate in our study, the application captured device details including device board, service carrier, manufacturer, model, Android version and Android build.

Recent Gartner worldwide mobile device sales reports [7, 19] do not place HTC as the leading sales manufacturer. Originally producing primarily Windows Mobile phones, HTC has changed their focus to Android devices, by manufacturing the Google Nexus One and EVO 4G more recently. Of the phones used by our participants, HTC devices and Sony Ericsson devices were the most popular (44.6% and 29.8% respectively). In third place were Motorola devices with 14.8%, followed by Samsung with 7.5% [Table 1]. Furthermore, Google's statistics claim that Android 2.1 is the most popular version with 41.7%, while in our study we saw that 33% of phones used this version [Table 2]. One surprise in the collected data is that Android 1.6 (Donut) is the leader with 36% of the participating devices using it.

Table 1. Most popular platforms recorded during the study

Platform	Distribution
HTC	44.6%
Sony Ericsson	29.8%
Motorola	14.8%
Samsung	7.5%

Table 2. Google's official Android distribution, as of September 1, 2010 [1]

Platform	API Level	Popularity (Source: Google)	Popularity (Source: Study)
Android 1.5	3	12.0%	-
Android 1.6	4	17.5%	36%
Android 2.1	7	41.7%	33%
Android 2.2	8	28.7%	31%

3.3 How Do Users Manage Battery Life?

Users mostly avoided lower battery levels, with the daily average of the lowest battery percentage values being 30%. This is likely due to the fact that the Android devices' battery icon turns yellow at 30%, and prompts the user with a textual notification to charge the smartphone by the time it reaches 15%.

The visualization in Figure 2 shows the average battery available at different hours of the day, across all the users, and how frequently the percentage was observed, when the battery was not being charged. Each bubble represents a different day of the study, for a given hour (with a bubble created only when there were at least 1000 datapoints for the selected day-hour combination). Hence, the visualization contains three dimensions (Percentage, Time and Frequency), with frequency (low to high) highlighted both by size (small to big) and color (light yellow to dark red). The most frequent battery averages are above the 30% battery level.

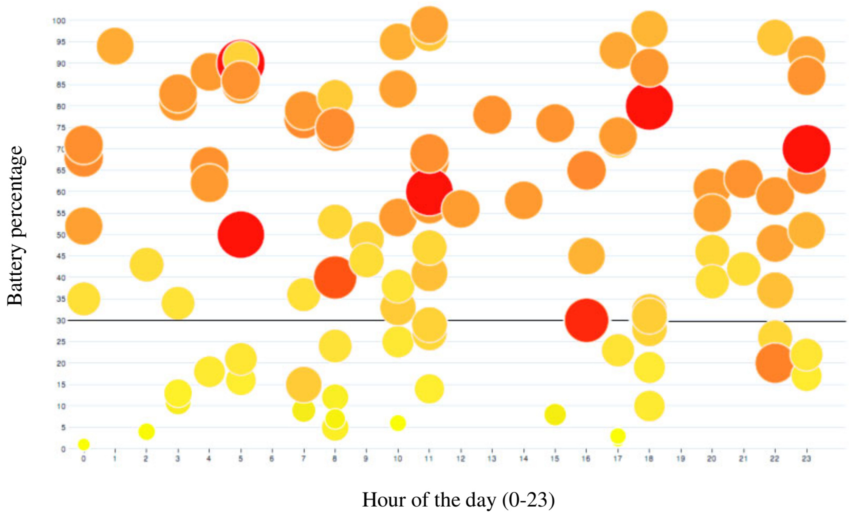

Fig. 2. Average battery levels during the day (when not charging)

On average the lowest average battery level was 65% at midnight, while the highest was 74% at 5AM. We expected that battery levels would be lowest at the end of the day, and the results confirmed it. The average battery percentage is 67% across all users throughout the day [Figure 3].

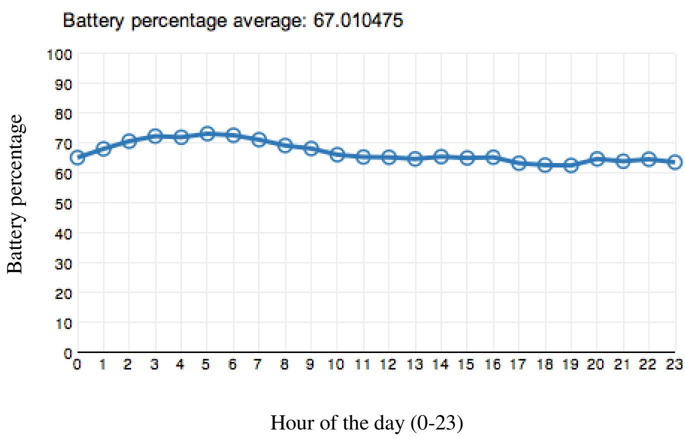

Fig. 3. Average battery levels throughout the day for the whole population

Despite the small variation of hourly battery levels across the whole population, individual users exhibited varying charging patterns. Some prefer to charge for short amounts of time throughout the day, while others allow the battery to discharge and charge it for longer periods of time until full [Figure 4].

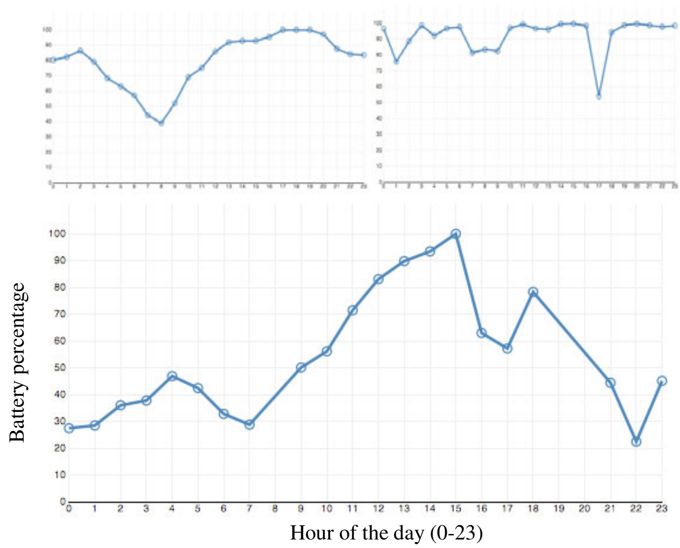

Fig. 4. Battery level during a single day for three different users

The data reveals two major charging schedules: one between 6PM and 8PM, with the majority of users initiating charging when the battery levels are at 40%, and another charging schedule between 1AM and 2AM, with a majority initiating charging when battery is at 30%. Another frequent charging event happens at 8AM, with battery levels at 80% on average [Figure 5].

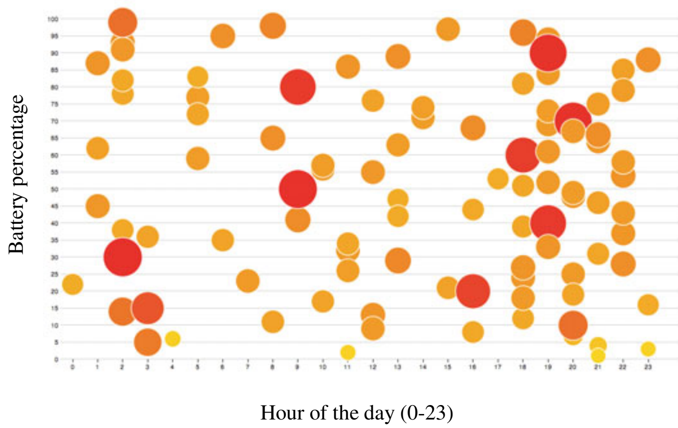

Fig. 5. Average battery levels during the day at the moment when charging begins

The majority of the charging instances occur for a very small period of time (up to thirty minutes) or between one to two hours, which is the average required time to recharge completely a battery (left side of the graph). [Figure 6].

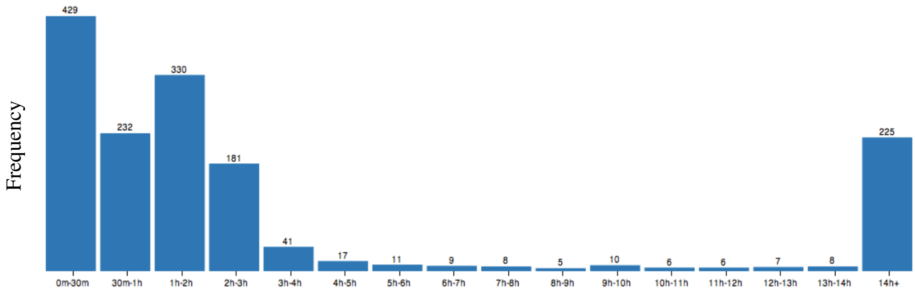

Fig. 6. Charging duration (amount of time the phone remains plugged in)

As expected, a lot of charging instances happen overnight, for 14 hours or more (right side of Figure 6). The average charging time across the whole population is approximately 3 hours and 54 minutes, but there is certainly a bimodal distribution, with the majority of charging instances lasting less than 3 hours. By charging time, we mean the time since the user plugged his device to charge until unplugged from the outlet.

Most charging instances start between 5PM and 9PM, while the least popular time to *begin charging* is from 3AM to 8AM [Figure 7], although the data in Figure 6 shows that it is likely that phones are being charged during this time.

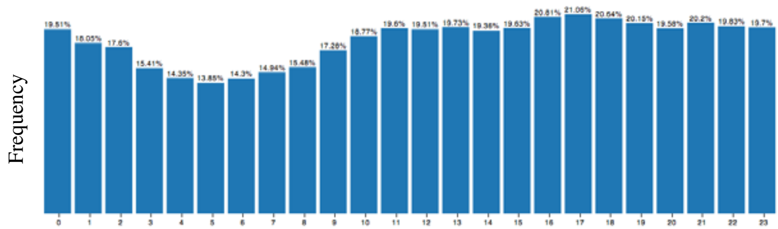

Fig. 7. Charging schedule (times when users have their phones plugged in)

3.4 How Much Energy Do Users Waste?

Overall, in 23% of the charging instances, the phone is unplugged from the charger (USB and AC) within the first 30 minutes after the battery is fully charged, while in the remaining 77%, the phone is plugged in for longer periods thus leading to energy waste. On average, users keep the phones plugged for 4 hours and 39 minutes after charging has been completed [Figure 8].

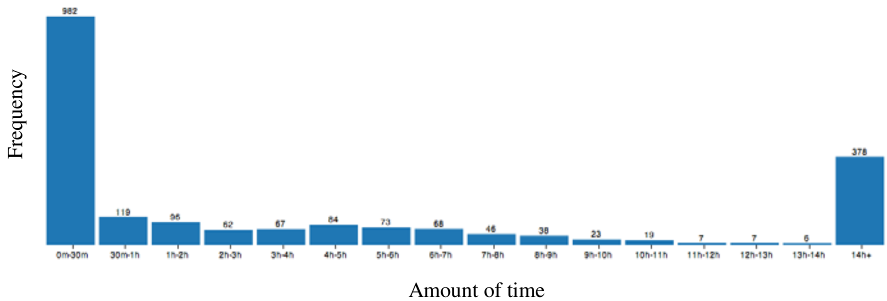

Fig. 8. Time until unplugged after the battery is full

Monitoring when the device has finished charging, we calculated how long the user took to unplug the device from the charger (USB and AC). The amount of time is greater as expected during the night, starting most often at 11PM and lasting until 8AM [Figure 9].

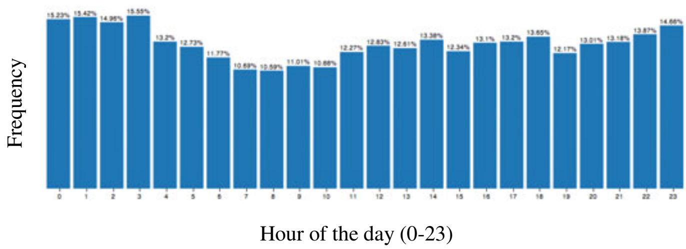

Fig. 9. Overcharging schedule

3.5 How Does Charging Happen?

As predicted, for longer charging periods AC is the preferred choice for phone charging. For short charges (30 minutes or less), USB charging is much more frequent. On average, users charge their phones 39% of the time using USB, and 61% of the time using AC [Figure 10].

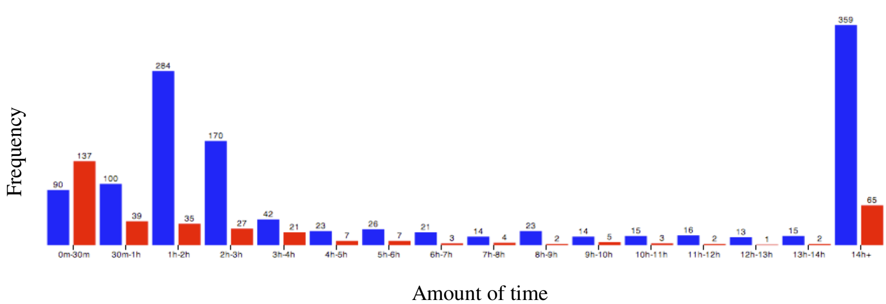

Fig. 10. Amount of time charging with USB (red) vs. AC (blue)

In Figure 10, blue represents AC, and red is USB charging. The initial pair on the left represents charging between 0-30 minutes, in which charging is mostly USB for this specific period of time. AC charging has two peaks, one between 1-3h of charging time and 14 hours or more for overnight charging.

3.6 How Often Is the Phone Rebooted/Turned Off?

Uptime is the time elapsed before the phone is rebooted or turned off. In our study, all participants' devices are on for at least up to a full day [Figure 11]. The results show that the likelihood of having a device on for up to two days is 33%, 18% for up to three and 11% for up to four days.

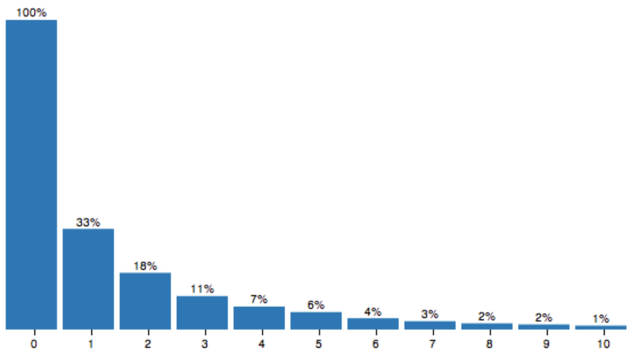

Fig. 11. Uptime in days

4 Discussion

The large-scale study described here was conducted in order to assess the extent to which energy is being wasted, explore how often users demonstrate less than optimal charging behavior, how often they interrupt the charging cycle and when this is more likely to happen. We hypothesized that by conducting such a study we could identify design opportunities for reducing energy consumption, increasing battery life, and also predicting when intensive computational operations and long data transfers should be scheduled.

Previous studies have shown that users have inadequate knowledge of smartphone power characteristics and are often unaware of power-saving settings on smartphones [16]. Users should be provided with options on how to better manage the remaining battery, and, to some extent, automated power features can also help them use the device as intended [12, 20]. Most smartphones alert the user that they need to be charged when the battery reaches critical levels [16,17], but do not notify the user when it has finished charging. For instance, explicitly notifying the user that the device is running low on battery is something Android does when the battery is at 15%.

Battery management requires user intervention in two respects: to keep track of the battery available so that users can decide how to prioritize amongst the tasks the device can perform; and to physically plug the device to the charger and surrender its mobility [17]. There is an opportunity to optimize which functionality should remain active based on the user's lifestyle and battery charging habits, improving the human-battery interface (HBI) with the user. Each user is unique and as such, the optimization system must learn and adapt to the user. The results show important differences between users' behavior and preferences, but also highlight common patterns that can be useful in understanding aggregate behavior and developing software that taps into those behaviors.

The findings of this study show that users

- demonstrate systematic but at times erratic charging behavior (mostly due to the fact that charging takes place when the phones are connected to a PC);
- mostly choose to interrupt their phones' charging cycle thus reducing battery life.
- aim to keep their battery levels above 30% due to an automatic ambient notification; and
- consistently overcharge their phones (especially during the night);

4.1 Users' Charging Habits

The study shows that users charged throughout the day resulting in erratic charging patterns and disrupted charging cycles that can reduce the lifetime of the battery [Figure 4]. A potential design opportunity exists here, whereby erratic charging behavior can be avoided by implementing a timer threshold that will prevent batteries from charging for short periods of times, *e.g.*, for less than 5 minutes. The results [Figure 10] demonstrate that charging using USB could be triggered by command from the user (a feature already seen with some HTC Sense® devices) or if the battery percentage available is below 30%.

Interrupted charging cycles [Figure 11] leads to the necessity of battery calibration (drain the battery until depletion and fully charging it). The "memory effect", is a term loosely applied to a variety of battery ills [9]. From Corey's research [5], overcharging, over discharge, excessive charge/discharge rates and extreme temperatures of operation will cause the batteries to die prematurely. Users in this study consistently kept the battery from reaching lower levels, with an average lower percentage of 30% of battery power by charging throughout the day (*e.g.*, plugging their devices to the car dock for navigation at 8AM [Figure 5] or charging while transferring files). Software updates and backup routines could take these moments to run power intensive operations only if the user has his phone plugged in for more than 30 minutes, since according to the results, there is a very high probability the user will charge for at least 1-2 hours.

4.2 Avoiding Energy Waste

Another problem that our study highlights in relation to charging duration is the amount of time the users keep their phones connected unnecessarily. In the past, charging a battery for a long period of time would damage the battery from overheating and overvoltage [4, 5, 21]. Modern Li-ion and Li-poly batteries come from the manufacturer prepared to interrupt charging as soon as they are fully charged

[14], but this still results in unnecessary power consumption. This study shows that this happens frequently, which suggests that manufacturers should make an effort to improve their chargers to cutoff the charging as soon as the battery is full or after some time in cases where the phone is being powered directly from the charger.

In addition, there is a design opportunity to give feedback to users the moment they plug in their phone – they usually look for confirmation that the phone is charging. At that moment feedback could be provided to change users' behavior. For example, we can predict when a "plugged in" event is likely to result in a long power consumption session, specially if it happens around 11PM. At that moment a message could inform the user that "your phone will be fully charged in X minutes", prompting them to remember to unplug it, to minimize the time when the phone is plugged in when it is already fully charged.

The combination of erratic charging and unnecessary charging observed in this study shows that users appear to have two types of charging needs: short bursts of charging to get through the day, and long charging periods during the night. One mechanism to reconcile these two distinct requirements is to allow for batteries to have a "slow-charge" mode, whereby they do not charge as fast as possible, but charge at a rate that will reduce the amount of unnecessary charging. A rule of thumb can be derived from [Figure 6], which suggests that an effective rate for "slow-charge" rate could kick-in after 30 minutes and aim for a full charge in 4 hours (the average overcharging length). A more sophisticated approach could incorporate a learning algorithm on the smartphone or even the battery itself.

4.3 Opportunistic Processing on Smartphones

In terms of identifying opportunities for intensive operations on the smartphone, the results suggest that there exists an important 30-minute threshold once charging begins. If a charging session lasts more than 30 minutes, it is very likely that it will last for a substantially longer period. Charging that uses AC is also an indicator that the user will be likely to charge for a longer period of time. Combined, the 30-minute threshold and AC power source provide a good indication as to when applications should perform power intensive operations on smartphones: large data transfers, computationally intensive activities, *etc*.

5 Conclusion

More than ever, industry and academic research have an opportunity to resolve numerous issues and conduct studies using published applications to support users' needs. Marketing and mobile phone manufacturers study a variety of user needs, focusing on the design of new handsets and/or new services [15]. Using automatic logging, in which software automatically captures user's actions for later analysis provides researchers with the opportunity to gather data continuously, regardless of location or activity the user might be performing, without being intrusive.

Asking users to anonymously collect battery information using a Google Marketplace application was a success: at the time of writing, 7 million battery information points and 4000 participating devices from all over the world were loaded into our database from which the battery charging patterns were explored.

The results provide application developers and manufacturers with information about how the batteries are being charged by a large population. The design considerations highlight how can we improve users' experience with their battery life and educate them about the limited power their devices have.

We look forward to seeing the next generation of smartphones, that learn from the user's charging routines and changes their operation and charging behavior accordingly.

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