

Diversity in Smartphone Energy Consumption

Earl Oliver
David R. Cheriton School of Computer Science
University of Waterloo
Waterloo, Ontario, Canada
eaoliver@uwaterloo.ca

ABSTRACT

We conduct a large-scale user study to measure the energy consumption characteristics of 17300 BlackBerry smartphone users. Our dataset consists of over 1050 years of cumulative data and is several orders of magnitude larger than any previous work. We identify three distinct user types: opportunistic chargers, light-consumers, and nighttime chargers and report on the energy consumption characteristics of each user type.

Categories and Subject Descriptors

C.4 [Performance of systems]: Measurement techniques

General Terms

Experimentation, human factors

Keywords

Smartphone energy consumption, BlackBerry user study

1. INTRODUCTION

The proliferation of smartphones is driving a near-exponential growth in mobile applications. The design of these applications is governed by several constraints that are unique to mobile computing environments. Of these constraints, energy is the one resource that when depleted will render all of the applications on the mobile device, including emergency and essential applications such as the phone, inoperable. Unfortunately, while global demand and use of mobile applications continue to expand, the energy density of smartphone batteries has grown at a comparably insignificant rate [4]. The energy consumption characteristics of smartphone users should therefore be considered in the considered in the design of mobile applications.

We conduct a large-scale user study that examines the charging characteristics of over 17300 BlackBerry smartphone users. Our dataset contains over 1050 years of cumulative data from users spanning 23 time zones and every

BlackBerry device type released since early 2006. This paper reports on the unique energy characteristics of three distinct BlackBerry user types: opportunistic chargers, light-consumers, and nighttime chargers.

This paper is organized as follows. We begin with a brief overview of our usage study and the dataset that we have built. In Section 3 we provide an overview of our user classification method and describe each user type. We conclude in Section 4.

2. SMARTPHONE USAGE STUDY

We develop two BlackBerry applications to conduct our user study: the Standard Logger and the Background Logger. The Standard Logger is an event-driven BlackBerry application that runs continuously in the background of a device. Upon installation, the logger records the following information:

Charging activity: users' battery charging behaviour can be determined by recording when a device is plugged and unplugged from an external power source such as a USB cable or power adapter.

Battery level: the logger records the battery level every ten minutes to determine how users consume energy throughout the day.

Soft shutdown: the logger records signals that the device is powering on and off to account for inconsistencies in the data. For example, a user may power off a device when the battery is low, plug it in, unplug it at a later time, and power on at a full charge.

Device type: to differentiate BlackBerry devices we record the device type and OS version.

The Standard Logger alone was not capable of achieving our desired scale. We therefore partnered with a major BlackBerry software developer to augment their existing software quality logging tools with a simplified version of the Standard Logger. We refer to this augmentation as the Background Logger. The Background Logger collects the same information as the Standard Logger and uploads the data to the company's servers each week. In the remainder of this paper, we will refer to both loggers generically as the *Logger*. We discuss the technical challenges in building the Loggers in [1].

2.1 Aggregate summary

Over six months of data collection, we constructed a dataset that consists of over 1050 years of cumulative energy consumption traces from a total of 17300 smartphone users. Our participants span 23 time zones and diverse range of de-

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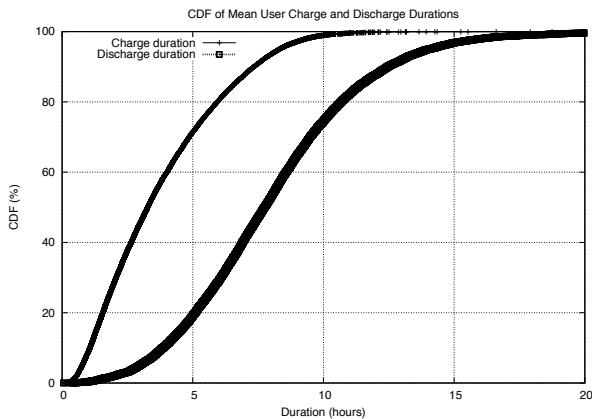


Figure 1: CDF of participants’ mean charge and discharge duration.

vice capabilities: all BlackBerry device types released since early 2006 [3]. These devices cross a wide range of hardware characteristics and similar devices can be found from other manufactures. To the best of our knowledge, our dataset is several orders of magnitude larger than any previous work.

3. ENERGY CHARACTERISTICS

Our analysis of smartphone energy consumption considers the following characteristics:

Charge and discharge durations: The charge and discharge durations are the quantities of time that a device is plugged into or unplugged from an external power source. This property has a direct impact on the device’s battery life. Devices that charge for longer durations could have a higher expected battery level than those that do not. Similarly, devices that discharge for long durations probably have a lower expected battery level.

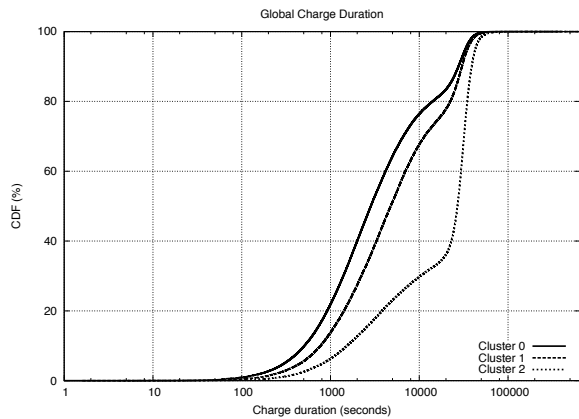
Charge initiation time and level: The charge initiation time is the time of the day when the user begins to charge their device. Regularity in charge initiation time could infer when energy is likely to be replenished. A relationship between charge initiation and battery level could also be used to predict future battery level.

Battery level: Patterns in battery level over the course of a day or week could be an ideal parameter for predicting future battery life.

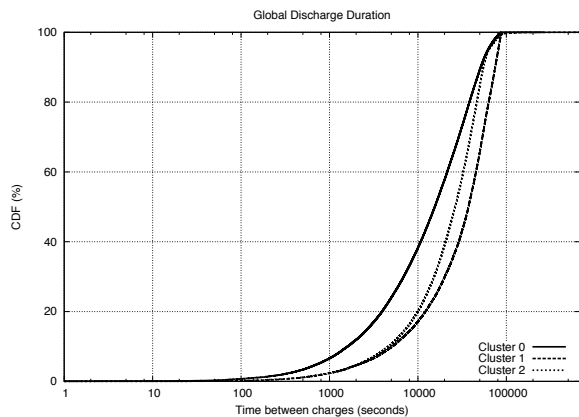
Charge and discharge rates: The charge and discharge rates are the percentage of total battery capacity that is replenished or depleted for every hour that a device is charging or discharging.

3.1 Classification method

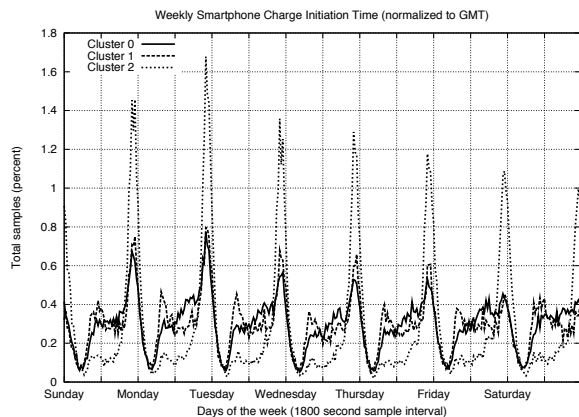
Our user classification method is an iterative process to determine the subset of energy characteristics that *best* differentiate users. Our metric to determine the utility of a characteristic selection is the mean prediction error derived by clustering users on the selected parameters. We found that users are best differentiated by their charge and discharge duration. The CDF for each mean duration is illustrated in Figure 1. For complete details of the user classification process, we encourage the interested reader to review [2].



(a) CDF of charge duration.



(b) CDF of discharge duration.



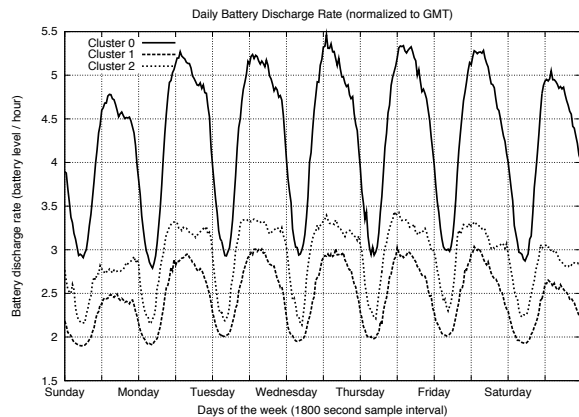
(c) PDF of charge initiation time.

Figure 2: Statistics by user type.

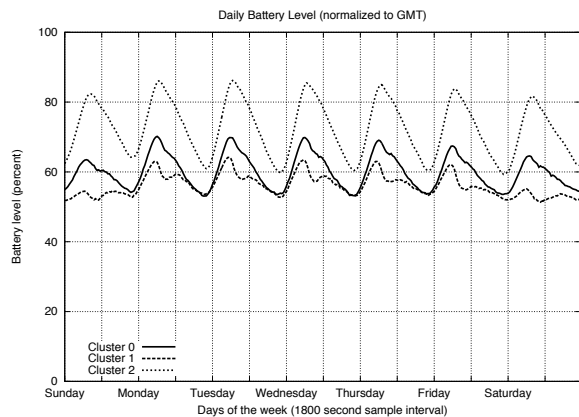
3.2 User types

Our classification scheme identified the following distinct BlackBerry user types:

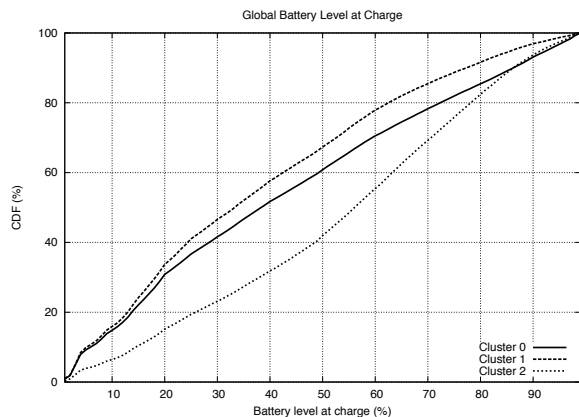
Opportunistic chargers: Opportunistic chargers are the most common type of smartphone user and represent approximately 63% of the population. These users are primarily characterized by frequent, short charge durations during the hours of 8am to 5pm. The CDF of charge duration for opportunistic chargers, identified as ‘Cluster 0’, is illustrated



(a) Discharge rate over the week.



(b) Mean battery level over the week.



(c) CDF of battery level when initiating a charge.

Figure 3: Statistics by user type.

in Figure 2(a). Of the three user types, these users are the most aggressive energy consumers, consuming nearly 4.8% of their device’s energy per hour. The discharge rates for each user type throughout the week are illustrated in Figure 3(a).

Light-consumers: Light-consumers have the lowest energy discharge rate among all three user types. These users represent approximately 20% of the population and are identified as ‘Cluster 1’ in each figure. These users charge for

longer durations than opportunistic chargers, but discharge their devices over a longer duration. The CDF of discharge duration is illustrated in Figure 2(b). Despite having the lowest discharge rate, light-consumers surprisingly maintain the lowest mean battery level of 56.0% as illustrated in Figure 3(b). These users also allow their battery to drop to its lowest level before initiating a charge. On average, a light-consumer initiates a charge when their battery level has dropped to 34%. The CDF of battery level when a charge is initiated is illustrated in Figure 3(c).

Nighttime chargers: Our final class of users is the nighttime chargers. These users represent 17% of the population and are identified as ‘Cluster 2’ in each figure. The charging behaviour of the user is best illustrated in Figure 2(c) as the PDF of the time that users initiate a charge. The daily spike between the hours of 10pm to 11pm illustrate that these users initiate a charge (probably) before going to bed. Given that these users charge predominantly during the night, their mean charge duration is significantly higher than the other two groups, as illustrated in Figure 2(a). Although nighttime chargers consume only 0.5% more of their battery per hour than light-consumers, their long charging durations serve to maintain an mean battery level of 72.5%. Similarly, nighttime chargers initiate a charge at an average battery level of 56%.

4. CONCLUSION

We present the results of a large-scale smartphone user study that examines how users consume energy on their personal mobile devices. Our dataset contains over 1050 years of cumulative data for 17300 users from around the globe. We identify three distinct user types: opportunistic chargers, light-consumers, and nighttime chargers and report on the energy consumption characteristics of each user type. This work also serves as the basis for subsequent work in smartphone energy-level prediction [2]. Although our work focuses exclusively on energy consumption, we believe that it contains a wealth of knowledge outside this context; spanning areas such as interaction design, battery provisioning, and non-technical domains such as addictology, polysomnography, and psychology.

5. REFERENCES

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