

Programming Ubiquitous Things
2024/25 - Spring 2025 - UiO

Battery Issues

Prof. Paulo Ferreira

paulofe@ifi.uio.no

UiO/IFI/PT

Understanding Application-Battery Interactions on Smartphones: A Large-Scale Empirical Study.
YAO GUO, CHENGKE WANG, and XIANGQUN CHEN.
Key Laboratory of High-Confidence Software Technologies (MOE), School of EECS, Peking University, Beijing 100871, China

© Paulo Ferreira

1



What is this study about ?

- In order to understand how smartphone batteries are consumed, many researchers have performed studies on the interaction of smartphone user behaviour and batteries
- To the best of our knowledge, there have been no existing large-scale user studies on application-battery interactions
- We believe one of the reasons for the lack of this kind of study is that it is difficult to calculate or predict how apps consume energy in the wild
- This study focuses on understanding how different apps consume battery on smartphone devices based on large-scale battery traces
- Large-scale studies are difficult to acquire fine-grained data
- We believe that this is one of the key reasons why earlier large-scale studies have been focused mainly only on user-battery interactions, instead of application-battery interactions

© Paulo Ferreira

2

Goal of this study



- This paper applies an approximate method to calculate app energy consumption rate based on coarse-grained battery traces
- In this calculation method, we rely on the large amount of data available to amortize the errors in each specific trace
- We evaluate this method with measured power numbers using the Monsoon Power Monitor:
  - results show that the difference between the calculated energy consumption rate and the measured power current is less than 10%
  - this shows that the estimation method is pretty accurate with large-scale coarse-grained battery traces
- We have collected app and battery traces on over 120,000 Android smartphones for a four-week period
- After filtering unusable data due to a variety of reasons, we analysed the data on over 80,000 smartphones in this study
- We analyse the types of apps, the battery consumption patterns for different types of apps, and distinctive characteristics for heavy and light users

© Paulo Ferreira

Main findings

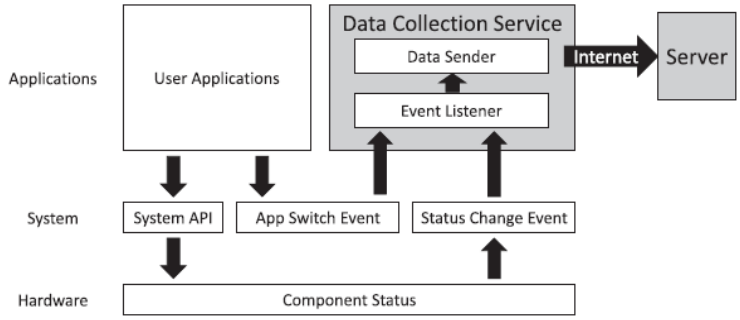


- Only a very small percentage of smartphone time and battery is actually used for the traditional "cellphone" purpose:
  - on average, 5% of battery and 6% of usage time are spent on voice calling
  - this not only confirms our assumption that smartphones are used for a variety of purposes, but also
  - shows that smartphones are not "phones'' anymore (instead should be called a mobile mini-computer with voice calling features)
- Power consumption during standby is actually much higher than expected:
  - results show that the average power consumption during screen-off is 10X higher than the ideal idle state
  - this suggests that there are a lot of things going on in the background that causes standby time of many smartphones being reduced to less than a day
- Despite the widely circulated complaints on the short battery life of many smartphones, we found that most phones could be used for more than one day:
  - considering the fact that many users are willing to (and able to) charge their phones at least once every day, the functionalities of smartphones have weighted more than the shorter battery life

© Paulo Ferreira

Collecting data (1/2)

- Since we collect information in the wild, we should be able to handle all the unusual problems occurring in the data collection process:
  - e.g., user changing batteries or SIM cards, exceptions of data collection service or smartphone devices, irregularities in specific types of devices, etc.



© Paulo Ferreira

Collecting data (2/2)

- The collected information includes:
  - Battery level - the battery level is a percentage of the whole battery capacity range from 0% to 100% that denote current remaining power of the smartphone
  - Screen status - screen events have two types: screen on/off event, and brightness level change (denoted by an integer ranging from 0 to 255)
  - Foreground app - this information records the current app in use obtained by recording all app start events and foreground app switch events, such that we are aware which app is in the foreground at each time point
  - Background apps and services - collecting this information can be very large in data size; we record them incrementally meaning that when a smartphone is powered on, we start our data collecting service and record the list of background apps and services; after that, we only record the changes to the list of background apps and service

© Paulo Ferreira

Device information



- We identify smartphones by IMEI (International Mobile Station Equipment Identity) and users by IMSI (International Mobile Subscriber Identity)
- Both IMSIs and IMEIs are anonymized to protect the privacy of the users
- Although most of the IMSIs and IMEIs have a one-to-one correspondence relation, we found that some IMEIs might correspond to several IMSIs:
  - this kind of abnormal data will be filtered before we perform calculations
- We filter out the invalid users using the following steps:
  - unknown phone type
  - unknown or uncertain users
  - minimum data collecting period
  - minimum number of events
  - other abnormal users

  } overall filtering
  - minimum app using time
  - maximum idle time

  } app related filtering

© Paulo Ferreira

Energy calculation (1/2)



- One of the major obstacles is the granularity of the battery traces.
- Because we could only record battery changes at one percentage granularity, many short app traces consumes zero percent battery:
  - in this case, many shorter app traces using less than 1% battery cannot be detected
  - we will show later that we could use a statistical method to calculate a combined average energy consumption rate for all users
- When individual apps are concerned, multiprocessing becomes another major obstacle
- As there are always multiple processes running at the same time, we are unable to distinguish the energy consumed by the foreground and background apps
- As a simple solution, we only consider the foreground app as the current app consuming energy:
  - in this case, because we are able to catch all process switching events, we always know which app is running in the foreground

© Paulo Ferreira

Energy calculation (2/2)



- Apps might be used when the battery is charging
- Thus, we will distinguish between battery charging and discharging, and remove the app events during battery charging while calculating energy consumption rates

- The data collecting service might affect the energy numbers because it also consumes energy
- Because it is very difficult to estimate the energy consumed during data collection, we assume that the data collecting service does not consume any energy
- We did not measure the energy cost of the collecting service because it was integrated into another Android app:
  - however, because we only intercept the system intents that are broadcasted, no extra querying or modifying operations are actually conducted, thus the energy overhead is minimal

© Paulo Ferreira

Calculation method



- In order to calculate energy consumption statistics based on the recorded traces, we need to identify and filter out the events occurred during the charging periods
- Then we can compute average energy consumption rate for each app based on battery trace collected from all user devices
- We can also calculate projected battery life based on the energy consumption pattern of all apps

© Paulo Ferreira

Calculation method-BATTERY LIFE



- We record the history of battery levels for each user with the battery level change events:
  - separate the battery level history into charging regions and discharging regions to analyse charging habits of users and battery life of smartphones
- We consider a charging region as a battery charging event, including charging by A.C. electric sources and USB connections:
  - if a fully-charged smartphone is still connected to an electric source, we will not consider this time period as a charging event
- To analyse user charging behaviour, we record relevant information for each battery charging event:
  - e.g., the time when a charging event starts/ends, the battery level when a charging event starts/ends, etc.

$$AverageDischargeRate = \frac{TotalBatteryDrops}{TotalDischargingTime} \qquad BatteryLife = \frac{100\%}{AverageDischargeRate}$$

Note that we do not consider the battery capacity in this calculation.
The discharge rate here is denoted by the battery percentage level.

© Paulo Ferreira

Calculation method-ENERGY CONSUMPTION RATE FOR APPS (1/2)



- We calculate the power consumption of apps based on statistics with large-scale battery traces
- To reduce the error during calculation:
  - first, we calculate the running time and battery level drops of every battery trace,
  - then simply combine them together to calculate the TotalUsingTime and TotalBatteryLevelDrops
- As defined earlier, an app usage period is the time interval from which the app starts or switched to the foreground, to the app ends or switched to the background (or the smartphone is powered off)

$$AverageDischargeRate = \frac{TotalBatteryDrops}{TotalDischargingTime}$$

© Paulo Ferreira

Calculation method-ENERGY CONSUMPTION RATE FOR APPS (2/2)



- Other challenges:
  - to deal with the charging influence, we detect the charging events using the battery level change events
  - we consider that the mobile device is charging if the battery level goes up
  - when calculating the power consumption, we only consider the running periods without charging
  - to deal with the background battery consumption, we regard all the battery level drops as consumed by the foreground app
  - it is acceptable because foreground apps usually use the CPU, screen and other components
  - much more than the background apps and system services, therefore consuming more energy
  - we consider the background battery consumption as the general running environment of the foreground app in this study
  - because of the timestamp problem, when we calculate the battery level drops, if we use the battery level of the nearest battery level change events to represent the battery level of the app switch event, there may be some errors for each battery trace
  - however, since the battery levels always change by 1%, the error of one battery trace is smaller than 1%
  - we expect that the error could be reduced to a tolerable level by the statistic method with large-scale analysis

© Paulo Ferreira

Calculation method-EVALUATION OF THE ENERGY CALCULATION METHOD (1/4)

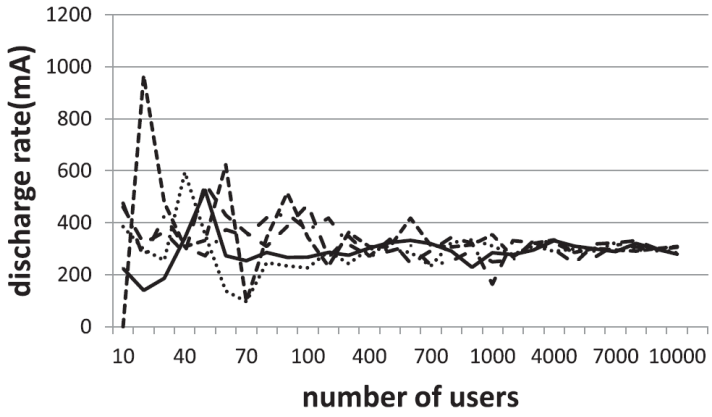


- Although directly using each of the battery traces to calculate the power consumption would be inaccurate, we expect that the large-scale analysis could reduce the error into a tolerable level
- Thus, we perform a series of evaluation of different scale to evaluate our calculation method presented above
- Since the time duration of battery traces vary from several seconds to several hours, it is inappropriate to represent the scale of battery traces by the number of battery traces
- In our evaluation work, we denote the scale of battery traces by the number of users
- In our evaluation, we select several different scales of users to calculate the power consumption, from 10 users to all the 80,000 users
- We randomly select corresponding number of users for 5 times at every scales, from 10 users to about 10,000 users
- Then we calculate the average and standard deviation of the results of each scale

© Paulo Ferreira

Calculation method-EVALUATION OF THE ENERGY CALCULATION METHOD (2/4)

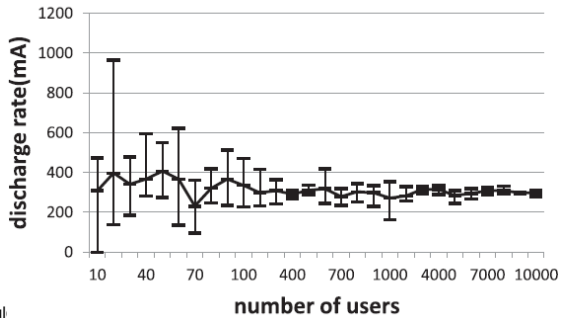
- This Figure shows the results of calculated power consumption of phone call with different scales of battery traces
- It is obvious that the variance becomes smaller when the scale of battery traces increases
- Then we analysed the average, variance and the standard deviation (shown in Figures in the next slide)

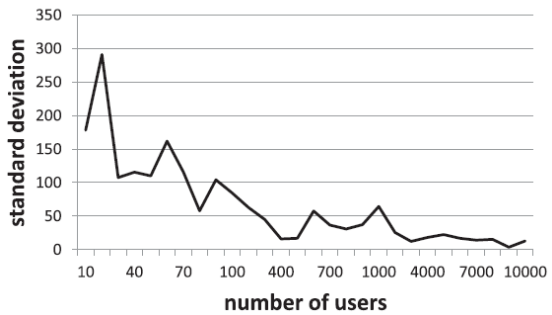


© Paulo Ferreira

Calculation method-EVALUATION OF THE ENERGY CALCULATION METHOD (3/4)

- At the scale of 10 users, the calculated power consumption vary from 0 mA to 474.55 mA, while converge to a variance of 278.89 mA to 309.13 mA at the scale of 10,000 users
- In comparison, we also calculated the power consumption with all the 80,000 users
- The results of all users falls into the range of the variance of the result of 10,000 users

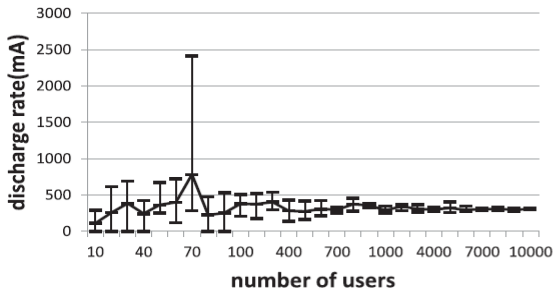


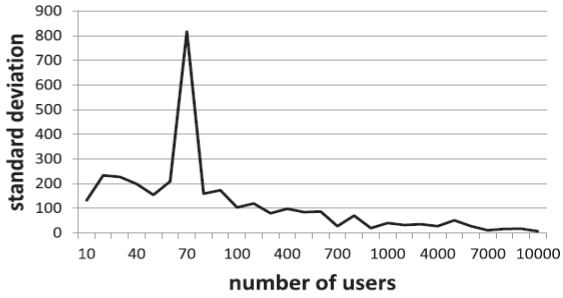


© Paul

Calculation method-EVALUATION OF THE ENERGY CALCULATION METHOD (4/4)

- We also conduct similar experiments for two other applications
- The Figures in this slide and in the next show the results of Angry Birds and Sina Weibo
- We can also see that the energy consumption rate of each app converges to a fixed number when the number of users becomes larger and larger





© Paulo Ferreira

Results

- Overall, the results show that:
  - the power consumption rate of each app converges after the number of users reaches 10000,
  - thus, we are able to achieve an accurate estimation with the combined average in our experiments
  - it indicates that a relative high number (up to 10000) of users is needed in order to provide accurate power estimation in this kind of study

© Paulo Ferreira

Accuracy of the method (1/2)

- To further confirm the accuracy of the calculation method, an experiment environment using the Monsoon Power Monitor was devised
- Measurements on a set of representative benchmarks from different categories using the power monitor
- The measured data is compared to the calculated power numbers to check their accuracy
- Smartphone used:
  - Tianyu W806 device with dual-core Nvidia Tegra2 processor at 1GHz and 4.3 inch screen
  - this model is representative of the mainstream smartphones in the market during the data collection period
- The Table in this slide shows:
  - the comparison between average measured power current and average energy consumption rate calculated in the study
  - the difference between the measured data and the calculated power numbers are very small, with all differences less than 10%

App	Measured current (mA)	Calculated energy consum. rate (mA)	Diff.
phonecall	276.83	295.96	6.91%
fruitninja	291.49	278.38	-4.50%
qiyi video	272.08	246.45	9.42%
estrongs	196.89	202.74	-2.88%
tencent WBlog	195.96	191.30	2.43%

© Paulo Ferreira

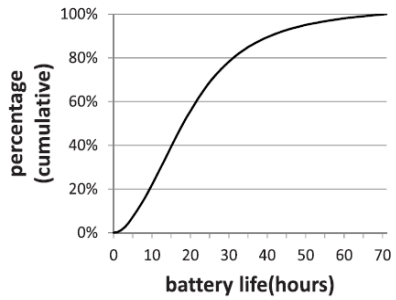
Accuracy of the method (2/2)

- Although this is only done for a particular device, it shows that:
  - although data collection and energy calculation method might not be accurate enough to calculate energy numbers for individual users with limited data,
  - it is good enough to estimate the energy consumption rate of different apps over a large-scale data

© Paulo Ferreira

Overall Results and Analysis (1/9)

- We first present the battery statistics based on the data collected on 80000 valid users

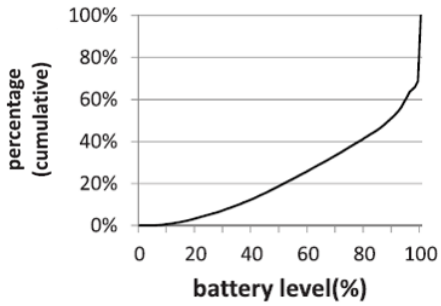


- Battery life:
  - see figure in this slide with distribution of battery life of all users
  - we notice that the battery life of about 75% smartphones can last more than 12 hours, with an average battery life of about 22.6 hours
  - it suggests that most smartphone users could keep their battery alive if they can charge once or twice every day
- How many times do batteries die?
  - we attempt to identify a battery dead event if a low level of battery (less than 5% in this study) appears before a relatively long period of time (more than 1 hour in this study) in which the phone is not used
- On average, batteries died roughly once in a month per user
- It shows that although batteries lasting less than a whole day for many users, they are able to charge the battery in time such that phone availability is rarely affected due to battery
- We only consider the long period of power-off events after a low battery level, which we think more likely to be battery died events

© Paulo Ferreira

Overall Results and Analysis (2/9)

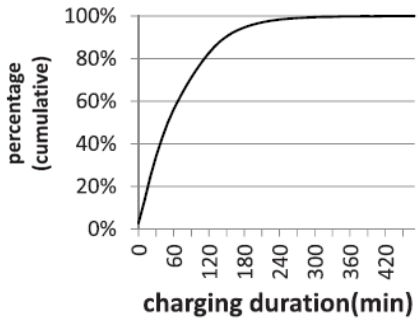
- Battery charging habits:
  - the Figure in this slide shows the distribution of battery levels at the end of each charging period
  - half of the battery levels of smartphones are more than 90% when charging ends
  - the result indicates that users consider little about their battery level when they decide to charge
  - and rarely stop charging before their batteries are fully charged to gain a longer battery life



© Paulo Ferreira

Overall Results and Analysis (3/9)

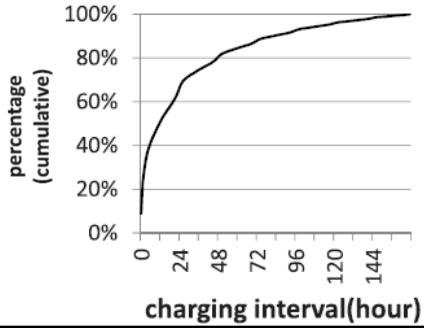
- Battery charging habits:
  - the Figure in this slide presents the distribution of the charging periods
  - it shows that more than 80% of all charging events last for less than two hours
  - the results suggests that smartphone users tend to charge their batteries more frequently by a relatively short time period



© Paulo Ferreira

Overall Results and Analysis (4/9)

- Battery charging habits:
  - the Figure in this slide presents the average charging frequencies for all users
  - it shows that 70% of the users are able to charge once or more per day on average
  - about half of the users charge their batteries more than twice per day on average
  - considering this together with the battery life data earlier, we could conclude that most of the smartphone users can always get their batteries charged in time
  - although smartphone batteries last less than a day, most users are able to charge their phones in time



© Paulo Ferreira

Overall Results and Analysis (5/9)

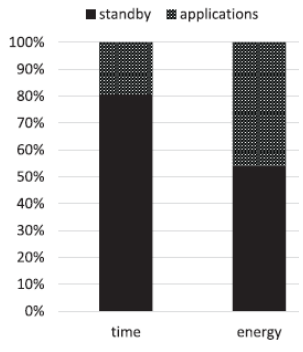
- Diversity in apps:
  - collected information on more than 23000 different Android apps
  - to understand the behaviour of these apps better, we classify the top 200 apps based on total usage time into 7 categories (shown in the Table in this slide)
  - each category represents a set of apps performing similar functions or using similar components of the smartphone, such that we expect them to behave similarly regarding user activity and energy dissipation
  - although these 200 apps only account for less than 1% of all the apps, the running time of these apps accounts for 82% of all the running time
  - thus, these 200 apps can be considered as a good representative
  - standby can be considered as a special "app'' category, which represents the time period when users do not use their smartphones explicitly
  - these time periods are identified with the screen off status
  - however, standby in a smartphone is not the same as idle as when a smartphone is in standby mode, there might exist some apps and services or some network data transfer activity running (background)
  - standby states behave differently in energy dissipation compared to real idle states

Category	Description	Examples
phone	voice phone calls	phonecall
game	smartphone games	angrybirds
internet	web app, navigation	ucbrower
chat/SMS	chat tools, SMS	minifetion
video/camera	video player, camera	kasend_video
others	others	estrongs
standby	idle, background	standby

© Paulo Ferreira

Overall Results and Analysis (6/9)

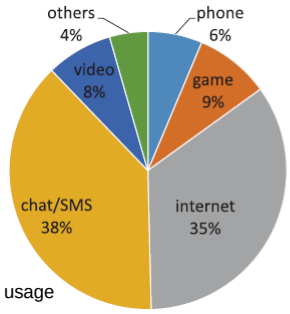
- App distribution:
  - we show the time and energy of a smartphone in use compared to when it is in standby in the Figure in this slide
  - it shows that users use their phones for about 20% of the total time (around 4.8 hours each day), while consuming 45% of the total energy
  - more than half of the energy are consumed during standby while users are not explicitly operating on the phones
  - it indicates that even when the phone is in standby mode, there are still many activities going, such that about half of the battery are consumed during standby

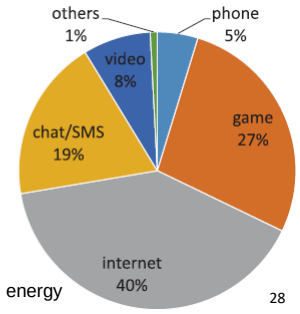


© Paulo Ferreira

Overall Results and Analysis (7/9)

- App distribution:
  - we consider the different categories of apps used (see Figures in this slide) presenting the distribution of each app category based on their total use of time and energy consumption
  - the most used apps are chat tools and Internet apps, which occupy more than 70% in total usage time
  - internet apps and games are more energy-hungry apps that consume 67% of the total energy consumption
  - phone calls only record 6% of total usage time and 5% of total energy consumption, which shows that voice calling is far from the mostly used feature on a smartphone
  - a majority of people tend to use their smartphones as a “minicomputer'' to access the Internet, play games and read e-books, instead of as a traditional feature mobile phone simply making phone calls





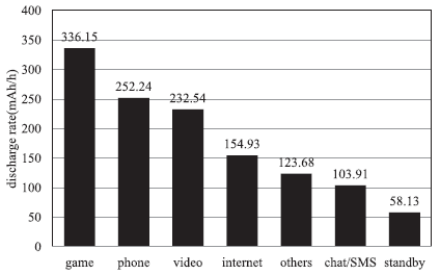
© Paulo Ferreira

28

28

Overall Results and Analysis (8/9)

- Energy consumption rate of apps:
  - to analyse the energy consumption patterns of different apps, we calculate an average energy consumption rate for each app category
  - the Figure in this slide shows the energy consumption rate for each app category (including video, calling, SMS, standby, etc.)
  - the numbers here are adjusted to the default battery capacity for each phone model, thus all numbers are absolute consumption rate, instead of percentages obtained in the Android system
  - apps related to gaming is the most power consuming apps, with a 336.15 mA energy consumption rate
  - regarding voice calling and video apps, whose energy consumption rates are about 252.24 mA and 232.54 mA, respectively
  - chat tools and text messaging consume the least energy, the energy consumption rate is 103.91 mA
  - there is a 3-4x difference in energy consumption rate among these app categories



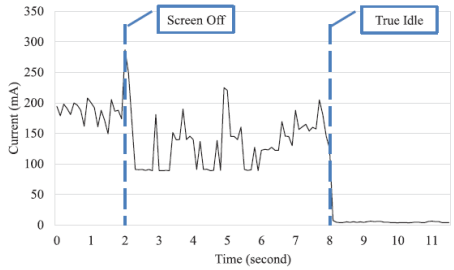
29

© Paulo Ferreira

29

Overall Results and Analysis (9/9)

- Standby energy:
  - one result is the power consumption rate for standby, which is more than 58mA on average
  - based on the measurements, an ideal idle state with no activities normally consumes only around 5mA, which shows a 10X difference between an ideal idle state and the actual standby mode
  - to understand the battery dissipation pattern during standby, we performed an experiment with the Power Monitor to record the power current data, which is shown (Figure in this slide) while
  - not running any apps on the phone
  - the screen is turned off at the 2nd second
  - after the screen is turned off, the power did not go down immediately.



  - it took about 6 seconds before the phone is actually “idle'' and the current is low stabilized
  - after screen off, other activities could still happen during standby, such as background services and apps, network data transportation, reading or writing the SD cards, etc.
  - this suggests that the standby mode could still consume significant energy in smartphones, which could explain why the standby time of smartphones are much shorter compared to that of traditional feature phones

© Paulo Ferreira

Diversity of Mobile Users (1/6)

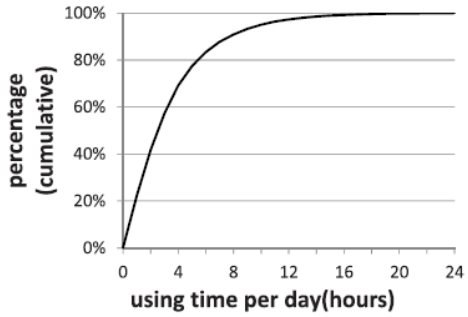
- We have shown that mobile users use smartphones to perform a wide variety of tasks compared to traditional feature phones
- In order to understand the behaviour of different mobile users, we perform a diversity study to compare different users based on their usage time distribution

- User-related filtering:
  - before conducting user diversity analysis, we need to identify user characteristics
  - in order to classify users based on their usage time, each user should have a relative long “power on” time
  - although we collect the traces from the previously evaluated 80,000 valid users during a four-week period, some of the users have a very power-on time that is not meaningful to perform further study
  - thus, we perform some filtering work to remove these users
  - specifically, we removed the users whose total power-on time are less than 5 days
  - the final number of remaining users in this diversity study is about 50000

© Paulo Ferreira

Diversity of Mobile Users (2/6)

- User classification:
  - to classify users based on their using frequencies, we calculate average using time per day for each user
  - this using time considers the total time of user apps such as video, games and phone call, etc.
  - the Figure in this slide shows the distribution of average using time per day of the 50000 users
  - the variation of using time per day is from about 5 minutes for the least frequent users to about 20 hours for the most frequent users



© Paulo Ferreira

Diversity of Mobile Users (3/6)

- User classification:
  - this result shows that the using time vary widely among different users
  - based on this data, we classify the top 20% of the users as heavy users, while the bottom 20% of users are regarded as light users
  - accordingly, the rest 60% of the users are classified as normal users
  - as a result, the heavy users use their smartphones more than 6 hours per day, while the light users use their smartphones less than 1 hour per day
  - on average, the using time of heavy users is 8.6 hours per day, while the using time of light users is about 0.9 hours
  - this gap in using time demonstrates the diversity of smartphone users

© Paulo Ferreira

Diversity of Mobile Users (4/6)

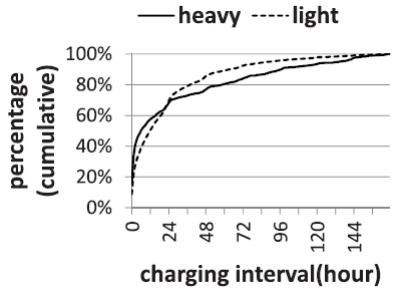
- User diversity in apps used:
  - we compare the distribution of using time and battery consumption among different app categories for three groups of users, respectively (Table in this slide)
  - for heavy users, the category “phonecall'' ranks the last among the 5 app categories if we do not account for “standby'' and “others”
  - however, “phonecall'' ranks in the third place for light users
  - this shows that heavy users are more intended to user their smartphones for various purposes other than voice calling
  - another interesting result is that while heavy users spent about 40% of their batteries on standby mode, light users spent almost 80% of their batteries on standby
  - this is because light users only use their phones for less than one hour on average, thus most of the battery is consumed during standby as expected, the using time and energy of normal users generally falls between the heavy and light users

category	using time			energy		
	heavy	normal	light	heavy	normal	light
phonecall	1.67%	0.75%	0.82%	1.66%	1.93%	2.66%
game	2.03%	1.81%	0.66%	15.11%	13.39%	5.79%
internet	9.18%	7.29%	2.34%	24.34%	20.01%	7.38%
chat/SMS	10.91%	7.73%	2.46%	11.96%	9.45%	2.99%
video	2.69%	1.41%	0.45%	4.79%	3.76%	1.49%
other	1.91%	6.35%	0.18%	0.56%	2.54%	0.21%
standby	71.6%	74.7%	93.1%	41.8%	48.9%	79.5%

© Paulo Ferreira

Diversity of Mobile Users (5/6)

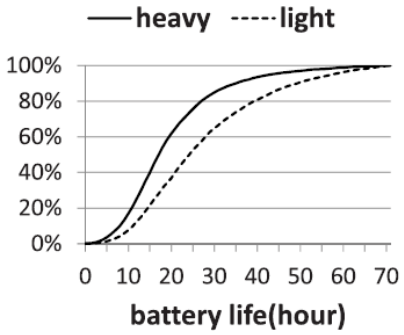
- User diversity in charging habits and battery life:
  - because of the difference of app usage between heavy and light users, we want to check whether it will cause some differences in their charging habits and battery life
  - the Figure in this slide presents the distribution of charging frequencies of heavy users and light users
  - on average, heavy users charge their batteries every 23 hours, while light users charge their phones every 29 hours
  - these results suggest that heavy users tend to charge more frequently
  - however, the results also shows that most users still need to charge their smartphones at least once every day, even when they only use their phones for less than an hour every day



© Paulo Ferreira

Diversity of Mobile Users (6/6)

- User diversity in charging habits and battery life:
  - the Figure in this slide shows the battery life distribution of heavy users and light users
  - the difference of battery life between heavy users and light users is also obvious
  - the heavy users have a relatively higher discharging rate but a shorter battery life
  - on average, the battery life of heavy users is 21.2 hours, while the battery life of light users is 28.8 hours
  - although the difference in battery life is not so big compared to the average using time per day, it still shows a more than 30% difference
  - the explanation here is that most smartphones are running various background services, such that standby power is much larger compared to traditional feature phones, as shown in earlier results



© Paulo Ferreira

Limitations

- There exist some limitations in this study:
  - some of them are inherent to this type of study, some are our choices in order to simplify the study
  - for simplicity, we choose to attribute all energy consumed during a specific period to the foreground apps
  - although we are able to retrieve the list of background processes and services, it is very difficult to distribute battery consumption to each of them
  - neither did we consider the energy consumed by the operating system, because it is difficult to perform a more fine-grained analysis
  - nonetheless, the energy consumption by background services and OS itself is very important and should be studied with further techniques
  - for a large-scale study, we focus on app categories and how they consume battery power
  - we have taken into consideration some device information such as phone type and battery capacity
  - however, there are much more device features that could affect the battery consumption, such as screen sizes, standard CPU frequency, network access traffic etc.
  - we believe more detailed study on these factors could reveal many important results

© Paulo Ferreira

Doze in Android (1/2)

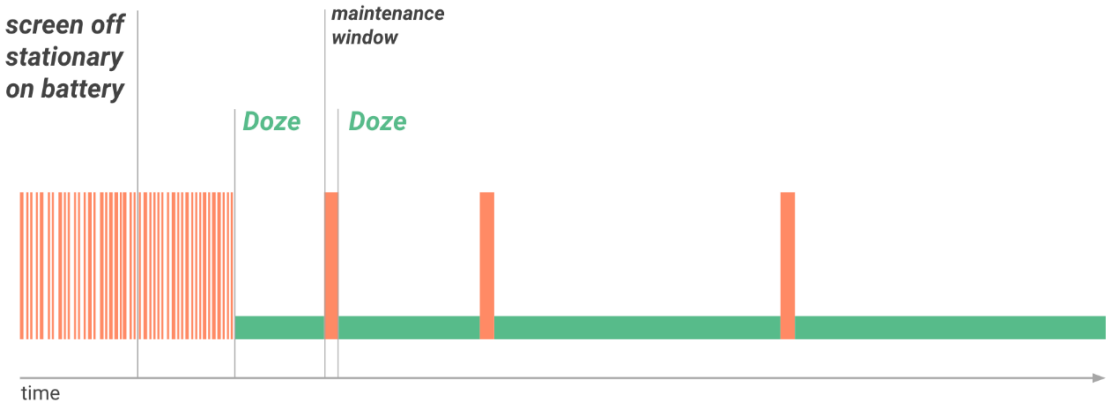


- If a user leaves a device unplugged and stationary for a period of time, with the screen off, the device enters Doze mode
- In Doze mode, the system attempts to conserve battery by restricting apps' access to network and CPU-intensive services
- It also prevents apps from accessing the network and defers their jobs, syncs, and standard alarms
- Periodically, the system exits Doze for a brief time to let apps complete their deferred activities
- During this *maintenance window*, the system runs all pending syncs, jobs, and alarms, and lets apps access the network

© Paulo Ferreira

Doze in Android (2/2)





© Paulo Ferreira

Doze Restrictions



- Network access is suspended
- The system ignores wake locks
- Standard AlarmManager alarms (including setExact() and setWindow()) are deferred to the next maintenance window
- If you need to set alarms that fire while in Doze, use setAndAllowWhileIdle() or setExactAndAllowWhileIdle()
- Alarms set with setAlarmClock() continue to fire normally — the system exits Doze shortly before those alarms fire
- The system does not perform Wi-Fi scans
- The system does not allow sync adapters to run
- The system does not allow JobScheduler to run
- Doze is particularly likely to affect activities that AlarmManager alarms and timers manage (alarms in Android 5.1-API level 22 or lower do not fire when the system is in Doze)

© Paulo Ferreira

Conclusion



- Performed a large-scale battery study on over 80000 smartphones and presented several sets of results related to apps and batteries based on the collected data
- Applied a method to calculate energy consumption rate of each app based on large-scale coarse-grained battery traces
- Found many interesting statistics and facts on app usage patterns, app energy consumption rate and mobile user diversity
- This type of study is able to reveal more information that could not be otherwise discovered in a small-scale lab study on limited number of devices
- Future work includes performing further data analysis and exploring possible optimizations based on these findings

© Paulo Ferreira