

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/256657412>

Energy Consumption and Efficiency in Mobile Applications: A User Feedback Study

Conference Paper · August 2013

DOI: 10.1109/GreenCom-iThings-CPSCoM.2013.45

CITATIONS

47

READS

610

5 authors, including:



[Claas Wilke](#)

Technische Universität Dresden

52 PUBLICATIONS 436 CITATIONS

SEE PROFILE



[Sebastian Götz](#)

Technische Universität Dresden

93 PUBLICATIONS 747 CITATIONS

SEE PROFILE



[Uwe Assmann](#)

Technische Universität Dresden

228 PUBLICATIONS 1,812 CITATIONS

SEE PROFILE

Some of the authors of this publication are also working on these related projects:



Role-based Software Infrastructures (RoSI) [View project](#)



Cyber-Physical Manufacturing Facility Management (CyPhyMan) [View project](#)

Energy Consumption and Efficiency in Mobile Applications: A User Feedback Study

Claas Wilke, Sebastian Richly, Sebastian Götz, Christian Piechnick, Uwe Aßmann

*Software Technology Group
Technische Universität Dresden
Dresden, Germany*

{claas.wilke, sebastian.richly, christian.piechnick, uwe.assmann}@tu-dresden.de, sebastian.goetz@acm.org

Abstract—The energy efficiency of mobile applications has been a highly tackled research problem within the last years. Many research groups have focused on optimizing the hardware of mobile devices, as well as their middleware and applications, increasing both the devices' uptime and their users' satisfaction. However, only scarce work has analyzed whether users notice and care about energy-efficiency problems in mobile applications. Thus, in this paper, we address these questions by evaluating a large set of user comments extracted from the Google Play market place for Android applications. We analyze more than 9 million user comments and show that more than 18% of all commented applications have comments complaining about energy consumption. Besides, we identify major causes for the inefficiency of many mobile applications.

Keywords—Energy consumption, Mobile devices, Android, User Feedback, User Satisfaction.

I. INTRODUCTION

In the last years, the energy efficiency of mobile applications has been claimed to be of topmost importance and many research groups have focused on energy-optimizing the hardware of mobile devices, as well as their middleware and applications [1]–[3]. Besides increasing device uptimes, one of the major motivations behind all these efforts is to increase the user experience for mobile applications. However, scarce work has focused on the frequency of energy-efficiency issues in mobile applications and their influence on user satisfaction [4], [5].

In this paper, we address this topic by evaluating user feedback extracted from a large market place for mobile applications—namely the Google Play store [6]. We analyze 9 millions user comments on more than 27,000 mobile applications, demonstrating that users of mobile applications are (1) interested in energy-efficient applications and (2) energy-inefficient applications lead to frustrated users, negative feedback and lower application ratings.

The core contributions of this paper are:

- We show that more than 18% of the analyzed applications have user feedback comprising comments on energy-consumption problems.
- We show that energy-efficiency issues negatively influence the grades users give for mobile apps in market places.

- We show that free apps do not have more energy consumption problems than paid apps, rejecting our assumption that more expensive applications are more energy-efficient.
- We identify major causes for energy consumption problems in mobile applications based on their occurrence in user comments and discuss how to address them.

The remainder of this paper is structured as follows: Sect. II presents related work focusing on user satisfaction and feedback w.r.t. the energy efficiency of mobile apps. Following, in Sect. III we describe how we retrieved and edited the data for our analysis. Afterwards, Sect. IV presents investigated research questions, our findings and some ideas about how to avoid identified energy-efficiency problems for future mobile applications. Sect. V discusses threats to validity for our findings and Sect. VI concludes this paper.

II. RELATED WORK

To the best of our knowledge, only scarce work exists that focuses on the frequency of energy-efficiency issues in mobile applications and their influence onto user satisfaction.

For the analysis presented in [4], Pathak et al. crawled several online forums and bug trackers relating to mobile platforms and their applications, searching for energy-efficiency issues. They analyzed posts relating to energy problems and derived a taxonomy for faulty implementations and hardware errors they classified as different types of *energy bugs*. In contrast to our work, Pathak et al. did not analyze the distribution of energy bugs onto individual applications. Neither they analyzed the influence of energy bugs onto user satisfaction and their behavior (e.g., the negative grading of applications due to user dissatisfaction).

Heikkinen et al. [5] conducted two online questionnaires as well as two usage monitoring studies evaluating the influence of usage behavior on energy consumption of mobile applications. Their findings revealed that users are interested in energy consumption statistics of their mobile devices as well as in information on how they could optimize their devices. However, Heikkinen et al. did not evaluate whether or not high energy consumption of a specific application is recognized by users and thus, leads to dissatisfaction.

III. METHODOLOGY

To retrieve a large dataset of representative and up-to-date user feedback, we decided to crawl the Google Play market place [6], since today Android is the most popular and most widely used mobile platform [7]. Furthermore, Android supports a broad range of mobile applications and has a large community of users giving frequent feedback. However, future work should address other mobile app stores to investigate variances in the data throughout different mobile platforms (e.g., by analyzing data from Apple's app store for the iPhone).

The Google Play store lists Android applications, separated into five top-selling categories and further 34 categories, relating apps to individual genres such as *arcade games* or *music & audio* apps. Each category lists up to 40 pages,¹ with 24 apps. For each application, the store provides user comments consisting of a comment and a grade (ranging from 1 (bad) to 5 (perfect) stars), as well as further information as the device of the user, the application version reviewed, and the date of the comment. For each app, the store allows browsing up to 450 pages of user comments, each listing 10 comments, leading to a maximum of 4,500 retrievable comments per app.²

A. Data Retrieval

To retrieve the data for our analysis, we implemented a crawler crawling all categories, applications and user comments listed in Google Play and persisted the crawled data in a relational database. The extracted data also included the applications' price (if not being freely available). For user comments, we also extracted the version being reviewed by the user as well as the grading for the apps (being 1 to 5 stars). We executed the crawler in February 2013, leading to 9.9 million user comments given between May 2009 and February 2013,³ relating to 27,229 apps of which 22,184 had at least one comment.

B. Data Correction

As we retrieved the data from the market place automatically, we had to ensure that the data was extracted without major errors, introducing biases into every analysis based on the extracted data. Thus, we investigated our data set for duplicate entries, which for some reason appeared quite frequently. The reason can be either that the users submitted their reviews multiple times or that our crawler crawled the same reviews multiple times. Besides these comments which obviously happened to exist multiple times accidentally,

¹20 pages listing free and commercial applications respectively.

²However, we were able to crawl up to 9,552 for some apps, as we started the crawling process multiple times within a short time interval, leading to more than 4,500 comments for apps with large user communities giving new feedback during the crawling time.

³However, the reviews do not range over the complete time interval for all apps, as retrieved the 4,500 newest reviews for each app only.

Total number of apps	27,229	100.00%
Apps with comments	22,184	81.47%
Apps without comments	5,045	18.53%
Apps with not-spam comments	22,150	81.35%
Apps with spam comments	11,288	41.46%
Apps with spam comments only	34	0.12%

Table I
NUMBER OF APPS WITH COMMENTS IN THE CORRECTED DATA SET.

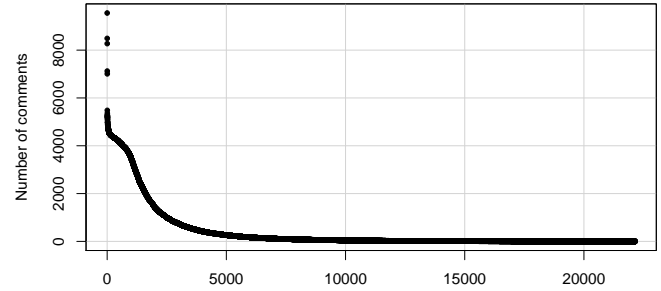


Figure 1. Distribution of comments over apps (apps with at least one comment shown) in the corrected data set.

we found a large number of comments, with default titles and default or empty comments occurring many times for the same or different applications given by anonymous reviewers. We identified these comments as spam comments and excluded them as well as the other found duplicates from our data set to reduce the impact of spam and duplicate comments on our analysis results. All in one we identified a total number of 800,130 duplicate reviews, which we removed from the data set. Table I gives an overview over the number of apps having comments and the number of apps having spam comments. Figure 1 shows the distribution of comments over apps after removing all duplicate and spam comments. In total we gained 22,150 apps with not-spam comments (being 81.35% of all apps within our data set). In the remainder of this paper we will base our analysis on these 22,150 apps only, as we cannot draw any conclusions on apps having no user comments.

C. Data Analysis

After data correction, our data set comprised a total number of 9,114,017 user comments. Analyzing all these comments manually would have led to a large amount of work including the manual processing of many comments not related to any energy-efficiency issues. Thus, we reduced the search space by prefiltering the user comments for energy-related comments automatically.

Therefore we defined a set of keywords expected to lead to a large number of potentially energy-related comments, consisting of keywords like *battery consumption* and *energy drain*. Based on these keywords we formulated a database query to filter potentially relevant comments, which we reviewed and classified manually afterwards. During their

Group 1	Group 2
accu, accum*, batt, battery, bettery, energy, power, juice	affect*, burn*, bleed*, chew*, consum*, decimat*, demolish*, deplet*, devor*, devour*, discharg*, 'doesn't save', drain*, draw*, drie*, dry*, eat*, 'gobble up', gulp*, guzzler, 'heavy on', hog, hungry, kill*, low*, monster, munch*, murder*, nibbl*, rape*, raping, rins*, short*, sipp*, stress*, suck*, thief, thirst*, 'to* much', wast*, uncharg*, usage, 'use up', using, vampire

Table II

KEYWORDS TO EXTRACT POTENTIALLY ENERGY-RELATED COMMENTS.

manual review and classification, we extracted further keywords for our query, leading to further potentially energy-related comments during another iteration of our analysis process. After 3 iterations of filtering and manual analysis, we retrieved a final number of 41,360 comments we analyzed and categorized manually. Table II enlists the final set of all keywords included in our filter query. Stars indicate placeholders leading to groups of keywords (e.g., *affect** includes *affect*, *affects*, and *affecting*). Each entry to be found by our query had to contain at least one of the keywords from *group 1* and one of the keywords from *group 2* leading to many combinations of energy-related noun-verb combinations (e.g., *battery draining*, *dries energy*) or noun-noun combinations (e.g., *battery hog*, *energy vampire*). Of course, the large number of keyword combinations also produced false positives which we had to extract during the manual classification of the retrieved comments. However, the number of false positives was surprisingly low (11.8%).

During the analysis of the filtered comments, we categorized them into eight different categories of comments rating the energy efficiency of apps in a positive or negative manner (cf. Table III). These categories comprise *false positives* (comments not talking on energy-efficiency issues), *energy drain* (comments complaining about apps with bad energy behavior), *energy savers* (comments praising apps for helping to identify energy draining apps or similar tooling), *energy drain after update* of the respective application or *energy fix after update* respectively, *appropriate energy behavior* (comments classifying the energy behavior of apps as appropriate), *intended battery drainers* (apps draining batteries intentionally, e.g., to uncharge them completely before their recharge to increase battery life), and *fake praises* (comments, praising the energy behavior of apps that are obviously fake comments⁴).

Besides the classification of the comments, we also tagged comments that gave identified reasons for the energy problem they were complaining about, whereby each comment could have multiple of these tags. In total, we identified 19 different tags for such identified reasons (cf. Table IV).

⁴For example comments telling fairy-tales about how a specific obvious energy wasting app saved their life by recharging their smart phone.

#	Category	Found Comments
0	False positive	4,884
1	Energy drain	27,744
2	Energy saver	3,191
3	Energy drain after app update	986
4	Energy fix after update	135
5	Appropriate energy behavior	4,340
6	Intended battery drainer	5
7	Fake praise	75
Sum		41,360

Table III

CATEGORIES OF ENERGY-RELATED COMMENTS.

#	Cause	Occurrence
1	Unnecessary background activity	1,739
8	High GPS usage	563
3	High CPU load	493
13	High memory load	429
4	Sync problems	187
16	Advertisement	187
14	Wakelocks	170
5	WiFi traffic	116
2	Locked display or unnecessary display activity	111
6	Mobile network (3G, 4G) traffic	25
17	Auto start / restart in background	23
11	Unnecessary vibration	19
7	Bluetooth traffic	7
9	Use of camera flashlight	7
10	Camera usage	7
15	High GPU load	5
18	High LED activity	5
19	Wrong audio replay	2
12	SD read/write	1

Table IV

CAUSES FOR BAD ENERGY BEHAVIOR OF MOBILE APPLICATIONS.

IV. INVESTIGATED RESEARCH QUESTIONS

In this section, we present the research questions we addressed by this study. For each question we shortly introduce its importance, how we investigated it and present the outcome from our analysis. Finally, we draw conclusions how to avoid and address identified energy consumption problems.

We investigated the following research questions for mobile applications:

- Is energy consumption a significant problem?
- Is energy consumption a problem for all kinds of apps?
- Do energy-efficiency issues affect user ratings?
- Do popular apps have energy-efficiency issues?
- Does their cost influence the energy consumption?
- What are the most frequent causes for energy-efficiency issues?
- Does software evolution and maintenance introduce new energy-efficiency issues?

A. Significance of Energy Issues for Application Users

To check whether or not energy consumption is an important aspect for mobile application users, we evaluated the number of apps having any comments relating to energy-efficiency issues within our data set. As energy-efficiency

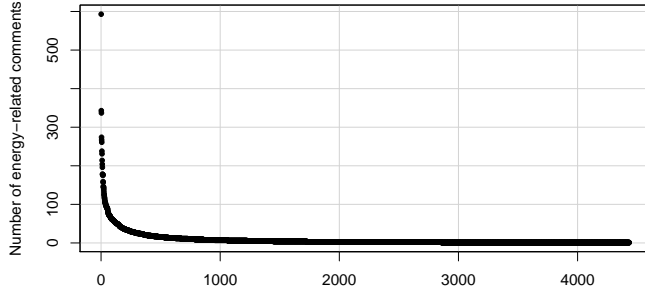


Figure 2. Apps by their number of energy-related comments (only apps with energy-related comments are shown; 20.02% of all apps with not-spam comments).

issues we rated all comments classified as comments of the categories 1 to 6 (cf. Table. III).

All in one, we categorized 36,139 comments as relating to energy-efficiency issues (either in a positive or a negative manner). These comments belonged to 4,434 applications within our data set, representing 20.02% of all applications having comments within our data set (cf. Fig. 2). If we consider negative comments on energy-efficiency issues only (meaning categories 1 and 3 in Table III), we gain a total number of 28,527 negative comments for 4,118 applications (18,59%).

As these numbers show, for each fifth application within the Google Play market place having any user comments, some of these users complain about problems with energy-efficiency issues. Thus, energy-efficiency issues can be considered as a significant factor for mobile application users and therefore, also for mobile application developers. Hence, application developers should invest some effort into energy quality assurance of their applications (e.g., by applying energy testing as supported by JouleUnit [8]), before deploying them within market place and let their users test the energy efficiency of their applications.

B. Frequency of Energy Issues for Individual Genres

The Google Play market place separates applications into 34 categories, consisting of 8 game and 26 application categories. Thus, we checked, whether energy consumption is relevant for application users using applications from these individual genres. Therefore, we analyzed the number and percentage of applications having comments on energy-efficiency issues for these categories. As can be seen in Table V, the percentage of applications having energy-efficiency issues varies highly for the individual categories. For so-called *app widgets*, 57.27% of all applications with comments have comments on energy consumption. In contrast, only 3.36% of *education* apps have energy-efficiency issues within their comments. Although the percentages of apps having comments varies highly for the individual genres, energy-efficiency issues can be identified for all existing genres. 26.14% of all game apps have energy-

Genre	Comments	Apps	With issues	%
Applications	30,091	16,332	3,037	18.60
App Wallpaper	1,168	432	119	27.55
App Widgets	9,672	915	524	57.27
Books & Reference	125	687	46	6.70
Business	629	489	84	17.18
Comics	42	441	22	4.99
Communication	1,759	811	200	24.66
Education	66	715	24	3.36
Entertainment	479	863	116	13.44
Finance	176	483	54	11.18
Health & Fitness	583	659	90	13.66
Libraries & Demo	71	410	24	5.85
Lifestyle	313	655	70	10.69
Media & Video	385	708	94	13.28
Medical	77	415	16	3.86
Music & Audio	590	835	112	13.41
News & Magazines	974	372	73	19.62
Personalization	3,806	1,147	313	27.29
Photography	314	769	92	11.96
Productivity	3,088	816	221	27.08
Shopping	102	305	26	8.52
Social	1,411	552	157	28.44
Sports	562	529	50	9.45
Tools	2,386	769	266	34.59
Transportation	204	426	55	12.91
Travel & Local	636	642	103	16.04
Weather	473	487	86	17.66
Games	6,039	5,330	1,393	26.14
Arcade	2,431	1,053	464	44.06
Brain	881	937	244	26.04
Cards	446	641	134	20.90
Casual	1,271	945	254	26.88
Game Wallpaper	132	113	22	19.47
Game Widgets	161	364	55	15.11
Racing	328	634	106	16.72
Sports Games	389	643	114	17.73

Table V
ENERGY-RELATED COMMENTS, NUMBER OF APPS, AND NUMBER OF APPS WITH ENERGY-RELATED COMMENTS PER GENRE.

efficiency issues, whereas only 18.60% of the other applications have energy-efficiency issues which also shows that energy consumption is a more frequent problem for mobile gaming apps. One explanation could be their typical higher graphical processing requirements as well as the typical long-time usage of these applications.

C. Energy Bugs Influence User Feedback

Another interesting question is whether or not the application users care about these issues and whether their opinion of the respective applications is affected by the occurrence of energy-efficiency issues. Thus, we analyzed whether energy-efficiency issues affect the grades users give for apps in the market place in a negative manner for negative issues and in a positive manner for positive issues.

We investigated the number of apps per genre having comments on negative and positive energy-efficiency issues respectively (as negative comments we considered the categories 1 and 3, and as positive comments the categories 2, 4 and 5 as enlisted in Table III) and compared the average grades of these comments to the average grades of all other

Genre	Neg. Comments	Pos. Comments	Neg. Trend	Pos. Trend
Applications	170750	6,924	-1.82	1.90
App Wallpaper	772	286	-1.09	1.18
App Widgets	5,544	2,979	-1.92	2.01
Books & Reference	49	19	-1.05	1.20
Business	416	53	-1.94	2.46
Comics	4	2	0.00	0.00
Communication	1,048	160	-1.41	1.69
Education	33	-	-0.35	-
Entertainment	257	27	-0.78	1.31
Finance	12	3	-0.17	0.87
Health & Fitness	352	90	-1.62	1.74
Libraries & Demo	22	10	-0.88	0.94
Lifestyle	170	36	-1.66	1.99
Media & Video	202	36	-1.08	1.76
Medical	3	1	0.67	-0.67
Music & Audio	342	44	-1.03	1.66
News & Magazines	627	40	-2.41	2.74
Personalization	2,367	1,194	-1.42	1.40
Photography	158	11	-0.76	1.44
Productivity	1,948	803	-2.50	2.59
Shopping	3	1	-4.00	4.00
Social	1,041	73	-1.43	1.70
Sports	344	114	-1.53	1.64
Tools	1,337	815	-1.79	1.90
Transportation	89	13	-1.05	1.16
Travel & Local	331	45	-1.61	1.82
Weather	279	69	-2.05	2.18
Games	3,717	344	0.19	1.28
Arcade	1,818	147	0.32	1.12
Brain	409	48	-0.26	1.23
Cards	195	36	-0.25	1.38
Casual	768	47	0.09	1.18
Game Wallpaper	53	9	0.57	2.36
Game Widgets	88	15	-0.39	1.51
Racing	159	23	-0.32	1.28
Sports Games	227	19	0.18	1.77

Table VI

NUMBER OF NEGATIVE/POSITIVE COMMENTS PER GENRE AND THEIR IMPACT ON GRADES OF THE APPS OF THESE COMMENTS.

comments for the same apps (cf. Table VI).

As can be seen, for all non-game categories, negative energy comments have a negative impact on the grades of these apps and positive comments have a positive impact respectively. The only exceptions are *comics* and *medical* apps, where only scarce positive and negative comments exist. For the category *education* we did not find any app having positive comments. The biggest negative impact can be observed for *shopping* (-4.0 stars), *productivity* (-2.50 stars) and *news & magazines* apps (-2.41 stars). However, the impact for *shopping* apps is based on 3 energy-related comments only and thus, cannot be considered as being representative. Considering positive comments on energy consumption, energy saving features result in better grades for all genres, except for *medical* apps (having a small non-representative set of comments only). The biggest positive impact can be observed for *shopping* (+4.00 stars, but not representative), *news & magazines* (+2.74 stars), and *productivity* apps (+2.59 stars).

In contrast to *application* apps, for *games* no general cor-

Rank	App	Neg. Comments
2	The Economist	323
6	The Weather Channel	178
20	K-9 Mail	100
27	Google+	92
31	Hotmail	90
39	Outlook	70

Table VII

SELECTED APPS FROM ALL APPS RANKED BY THEIR TOTAL NUMBER OF NEGATIVE ENERGY COMMENTS.

Rank	App	Neg. Comments
2	The Economist	13.3%
9	Outlook	6.33%
22	The Weather Channel	3.25%
40	K-9 Mail	2.26%
47	Hotmail	2.08%
49	Google+	2.07%

Table VIII

SELECTED APPLICATIONS FROM ALL APPS RANKED BY THEIR PERCENTAGE OF NEGATIVE ENERGY COMMENTS.

relation between negative energy comments and user ratings can be observed. For all gaming genres their influence on the applications' grades is rather low (between -0.39 stars and +0.57 stars) which can lead to the conclusion that energy consumption is less important for gaming users. However, positive energy-efficiency issues result in better grades for all gaming genres, leading to increases between 1.12 and 2.36 stars.

Summarizing, energy-efficiency issues influence the ratings of users for mobile applications, and therefore, also there popularity, and hence, their sales. This finding further supports our proposal to integrate energy testing into mobile application development processes to avoid (or at least reduce) energy-efficiency issues in mobile applications. However, for gaming apps energy efficiency seems to be less important although energy-efficiency issues appear here more frequently (cf. Sect. IV-B). Most users of mobile games do not mind if they affect their devices' energy consumption in a negative manner as such impact is expected due to additional processing power required for entertaining mobile games.

D. Even Popular Apps can have Energy Issues

Besides, we investigated whether popular applications or apps developed by big software companies are struggling with energy-efficiency issues. Thus, we investigated the apps in our data set ranked by the number of negative energy comments (categories 1 and 3, cf. Table VII) and ranked by the percentage of negative energy comments of all their comments (cf. Table VIII) for apps having at least 50 negative energy comments and searched for popular apps within this ranking.

The rankings comprise the following applications:

- *The Economist* is the app of a British weekly newspaper, downloaded 1 to 5 million times via Google Play.

Price [€]	Apps	Com.	Issues	Issues / C. [%]	Issues per app
free	13,706	5,804,899	23,174	0.40	1.69
charged	8,444	857,273	5,353	0.62	0.63
00.01–09.99	8,249	821,832	4,987	0.61	0.60
10.00–19.99	113	32,820	314	0.96	2.78
20.00–29.99	39	1,255	18	1.43	0.46
30.00–39.99	15	484	6	1.24	0.40
40.00–49.99	15	364	19	5.22	1.27
50.00–59.99	5	518	9	1.74	1.80

Table IX

NUMBER OF APPS WITH COMMENTS, COMMENTS, NEGATIVE ENERGY COMMENTS, PERCENTAGE OF NEGATIVE COMMENTS, AND AVERAGE NEGATIVE COMMENTS PER APP GROUPED BY THEIR PRICE.

It appeared on the second rank in both rankings, having 323 negative comments, 13.3% of all its comments.

- *The Weather Channel*, a popular weather forecast app (10 to 50 million downloads) was the app with the 6th most negative comments (178) and had the 22nd rank in the percentage ranking (3.25%).
- *K-9 Mail*, one of the most famous mailing apps for Android (1 to 5 million downloads) was on rank 20 in the number of comments (100) and on the 40th rank in the percentage ranking (2.26%).
- Microsoft's email clients *Hotmail* and *Outlook* (10 to 50/1 to 5 million downloads) were ranked 31st and 39th in number of comments (90/70) and 47th and 9th in the percentage ranking (2.08%/6.33%).
- *Google+*, the client for Google's social network (100 to 500 million downloads), appeared to be 27th in the number of negative comments (92) and 49th in the percentage ranking (2.07%).

These numbers show that even large software companies such as Microsoft and Google have problems with energy-efficiency issues in their mobile apps. This may lead to the conclusion that quality assurance w.r.t. energy consumption is yet to be developed and improved; which would allow the systematic test of energy consumption before apps are released. This could avoid such negative feedback and negative impact onto app ratings as identified in Sect IV-C.

E. The Price of Apps does not Affect their Energy Efficiency

Another research question related to the previous one is the question whether or not free apps contain more energy-efficiency issues than apps that cost money. Thus, we analyzed the negative energy comments for free apps, non-free apps and non-free apps categorized by their price in the Google Play market place (cf. Table IX).

Surprisingly, free apps do not have more negative energy-related comments than apps that cost money. Although the total number of negative comments is higher, the percentage of all comments remains almost the same. In total, 0.40% of all comments of free apps complain about energy consumption, and 0.62% of all apps that cost money. Thus,

the assumption that commercial apps are more energy-efficient than free apps can be considered disproved. Which is surprising as freely available applications are likely to contain advertisement which is known to be a major driver for energy-efficiency issues in mobile apps.

F. Major Causes for Energy-Efficiency Issues

After showing the significance of energy-efficiency issues for mobile applications, we also analyzed the major reasons and causes for energy-efficiency issues. Thus, we analyzed the number of comments tagged with causes for their energy-efficiency issues as discussed in Sect. III-C and enlisted in Table IV).

As can be seen, the most users complain about unnecessary background activities (1,739 comments). These issues could be avoided if application developers would check their apps for such background activities before they release them. For example a small set of energy tests, profiling an app's energy consumption while installed on a mobile device and running in background (e.g., with enabled and disabled display) could help to identify background activity issues before releasing apps in the market place.

Following, faulty GPS behavior (563 comments), unnecessary CPU activities (493 comments), and high RAM utilization (493 comments) are further complaints. Such problems could be avoided by using computing resources more carefully. Especially for sensors such as the GPS module, which are known for their high impact on energy consumption [2], developers should optimize their applications w.r.t. less frequent utilization these modules.

Synchronization problems (187 comments), advertisement (187 comments), and wakelocks (170 comments) are also problems identified by many users. This matches with observations from related work [4], [9]. Synchronization problems could be decreased by testing applications' synchronization mechanisms. How do apps behave if synchronization is not possible (e.g., WiFi or 3G disabled)? Do they try to synchronize until aborted or killed by the user? If so, such behavior should be improved to avoid unnecessary energy consumption. Furthermore, developers should consider to decrease the overall data being synchronized. Could the necessary traffic for synchronization be reduced? If application developers intent to integrate advertisement into their applications, they should at least test the impact of advertisement onto the apps' energy consumption. Advertisement can increase applications' energy consumption by up to 75% [9]. Thus, developers should profile the energy consumption with and without advertisement and decide where, when and how frequent advertisement banners should be included in their apps, finding an optimal tradeoff between profit and decreased user satisfaction due to increased energy consumption. To identify wakelocks, developers could apply static analysis technology, analyzing the control flow of

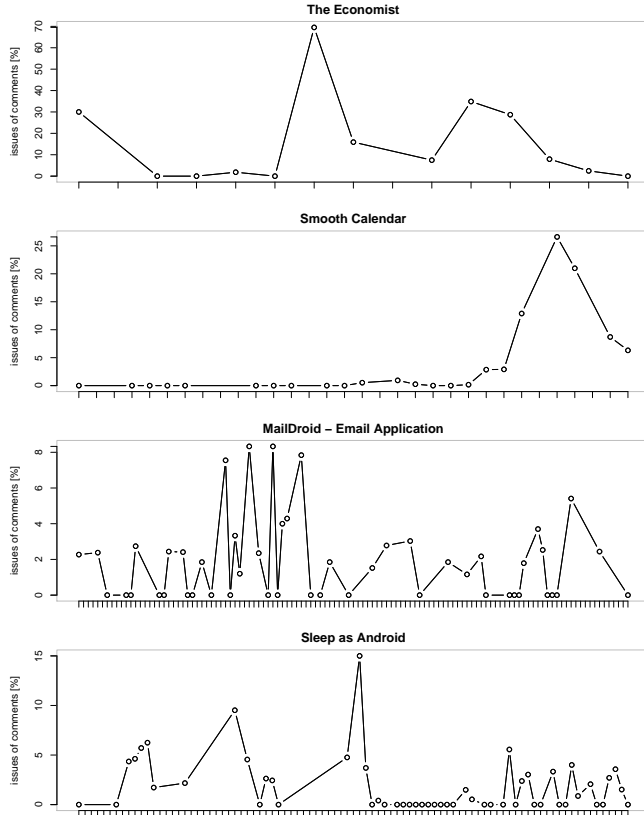


Figure 3. Amount of negative energy comments for selected apps per app version (versions with less than 20 comments are excluded).

their applications and identifying typical wakelocks, as e.g. proposed by Pathak et al. [10].

G. Energy-Efficiency Issues and Software Evolution

Besides general issues causing energy consumption problems, we also investigated whether energy-efficiency issues are likely to be introduced by software maintenance and evolution, and thus, whether newly released versions of applications are likely to introduce new energy bugs. 986 of all categorized comments within our data set reported such energy-efficiency issues introduced by app updates, which is a first indicator that such update-related energy-efficiency issues are likely to happen.

To further investigate the impact of software evolution onto energy consumption, we investigated the number of negative energy comments over all versions of selected apps from our data set. The general assumption was that we should find both, applications that have energy problems during their whole life cycle and applications, where new energy problems are introduced by specific and removed in subsequent releases. Fig. 3 shows the percentage of negative energy comments of all comments for all versions of four selected apps. For application versions having less than 20 comments we excluded the data, to avoid biases and

outliers due to versions with only scarce comments. As can be seen, we found examples for both kinds of applications: the apps *The Economist* (the newspaper application discussed above) and the *Smooth Calendar* (a calendar widget) suffer from energy-efficiency issues introduced in specific versions. In both applications the developers seem to have addressed these issues successfully as the complaints on energy-efficiency issues decrease for the following versions. In contrast, the applications *Mail Droid* (an email client) and *Sleep as Android* (an alarm clock and sleep tracking app) suffer from energy-efficiency issues in almost all releases.

Thus, energy-efficiency issues can be separated into issues introduced by software evolution and issues existing over longer time periods and several releases. It can be assumed, that some of the issues introduced by software evolution could be avoided, if mobile applications would be tested w.r.t. energy efficiency during their development (e.g., by applying techniques such as regression testing and continuous integration for the assurance of energy efficiency).

V. THREATS TO VALIDITY

In this section, we discuss some threats to validity that should be considered in the context of our analysis results.

First, we only extracted English comments from Google Play. As Android is a world-wide spread mobile platform, many comments formulated in other languages exist. Although it is possible that comments in other languages rate energy-efficiency issues differently, we do not expect major influences on our results by considering English comments only.

Second, we extracted a limited amount of data from Google Play, as we were not able to crawl all apps not listed within the 480 most popular apps of one of the categories (cf. Sect. III-A). However, as we extracted more than 27,000 apps with more than 9.1 million comments, we do not think that our results would significantly differ for a larger data set comprising more apps and comments.

Third, we prefiltered the extracted comments automatically to avoid the manual review and categorization of all 9,1 million comments and reviewed only 41,000 comments manually. It is likely that we have overseen some comments not filtered by our automated keyword search. Besides, as we used a set of manually-defined keywords to extract the reviewed comments, it is likely that we may have overseen comments containing spelling mistakes (apart from mistakes likely to occur and thus, being contained in our keyword set such as 'bettery'). Although, these overseen comments, would have increased the percentage of energy-related comments, their exclusion does not influence the conclusions drawn from our findings.

Fourth, we analyzed comments for Android applications only and thus, the results may not be representative for other mobile platforms as, for example, iOS. Thus, although similar problems may be identified for mobile apps of

other platforms (as their general development processes are quite similar), future work should address the distribution of energy-efficiency issues for other mobile platforms.

Finally, we identified a large number of spam comments (cf. Sect. III-B). As we extracted spam comments from our data set in a semi-automated matter (by marking duplicate comments or excluding comments occurring multiple times for the same app) it is likely that we have overseen further spam comments still belonging to our data set and thus, influencing our analysis results. However, as the extracted spam comments rated applications in an overall generous way (the average grade of all spam comments was 4.67 stars, variance 0.56 stars, median 5 stars), we do not expect major influence of these spam comments onto our findings.

VI. CONCLUSION

In this paper, we analyzed a large data set of apps and user comments extracted from the Google Play market place to evaluate the significance of energy-efficiency issues for mobile apps. We showed that over 18% of all Android apps having any user comments comprise comments complaining about energy efficiency. Besides, we showed that commercial apps do not have less problems with energy consumption than freely-available applications. We categorized user comments talking on energy-efficiency issues w.r.t. the causes for their energy problems and showed that background activity, GPS usage and CPU usage are the causes named most frequently for unnecessary energy consumption. Thus, we outlined some ideas to tackle such problems for future development of mobile apps. We showed that energy-efficiency issues influence the user ratings for mobile apps. However, for gaming apps this influence was much smaller than for other kinds of applications. We identified energy-efficiency issues introduced into mobile apps during software evolution and maintenance and showed that—in general—apps that cost money do not contain less energy-efficiency issues than freely available applications. To the best of our knowledge, this work is the first analysis of the impact of energy-efficiency issues onto user feedback for Android applications.

To allow other research groups the reproduction of our analyses as well as further analysis on the crawled data, we made the relational data of this study publicly available [11].

ACKNOWLEDGMENT

This research has been funded by the European Social Fund (ESF) and Federal State of Saxony within the ZESSY project #080951806, and within the Collaborative Research Center 912 (HAEC), funded by the DFG. Besides, we like to thank the encouraging and constructive feedback of our reviewers that helped to improve the content of this paper.

REFERENCES

- [1] K. Naik, “A Survey of Software Based Energy Saving Methodologies for Handheld Wireless Communication Devices,” University of Waterloo, ON, CA, Technical Report 2010-1, 2010.
- [2] Z. Zhuang, K. Kim, and J. Singh, “Improving energy efficiency of location sensing on smartphones,” in *MobiSys '10*. ACM, 2010, pp. 315–330.
- [3] A. Pathak, Y. C. Hu, and M. Zhang, “Where is the energy spent inside my app?: fine grained energy accounting on smartphones with Eprof,” in *EuroSys '12*. ACM, 2012, pp. 29–42.
- [4] A. Pathak, Y. Hu, and M. Zhang, “Bootstrapping energy debugging on smartphones: a first look at energy bugs in mobile devices,” in *HotNets-X*. ACM, 2011, Article No. 5.
- [5] M. V. Heikkinen, J. K. Nurminen, T. Smura, and H. Hämmäinen, “Energy efficiency of mobile handsets: Measuring user attitudes and behavior,” *Telematics and Informatics*, vol. 29, no. 4, pp. 387–399, 2012.
- [6] Google, “Google Play,” Website, May 2013, <http://play.google.com/>.
- [7] N. Mawston, “Global Smartphone OS Market Share by Region: Q4 2012,” Strategy Analytics, Newton, MA, Tech. Rep., Feb. 2013.
- [8] C. Wilke, S. Götz, and S. Richly, “JouleUnit - A Generic Framework for Software Energy Profiling and Testing,” in *GIBSE '13*. ACM, 2013, pp. 9–14.
- [9] C. Wilke, S. Richly, S. Götz, C. Piechnick, G. Püschel, and U. Aßmann, “Comparing Mobile Applications’ Energy Consumption,” in *SAC 2013*. ACM, 2013, pp. 1177–1179.
- [10] A. Pathak, A. Jindal, Y. C. Hu, and S. P. Midkiff, “What is keeping my phone awake?: characterizing and detecting no-sleep energy bugs in smartphone apps,” in *MobiSys '12*. ACM, 2012, pp. 267–280.
- [11] Google, “User Comments crawled from Google Play,” RAR Archive, May 2013, <http://is.gd/ecomment>.