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Utility-Based Smartphone Energy Consumption Optimization for Cloud-Based and On-Device Application Uses

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TEMEP Discussion Paper No. 2015:125

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Finally, the current editor of this series would like to thank Prof. Dr. Almas Heshmati for establishing this working paper series in January 2009 and for guiding its development during the course of the first 55 issues. In particular, Prof. Heshmati provided invaluable contributions for setting up the local IT infrastructure, registering the series with RePEc, disseminating the working papers, and setting the quality requirements.

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November 2015

Abstract: As the use of smartphones and its applications continue their rapid growth, prolonging the smartphone battery lifetime has become one of the main concerns for smartphone users if re-charging is not possible. In this paper, we show that, by taking into account the user preferences, the energy consumption of smartphones can be adjusted to maximize the user utility. The user preferences are reflected through the type of application uses, the perceived costs of energy allocation for the different types of applications, and the perceived value of energy remaining in the battery of the smartphone. In particular, we optimize the energy consumption of smartphones through the use of a utility-based energy consumption optimization model, which we developed. We demonstrate the workings of our model by applying it to a simple scenario, in which we vary the perceived value of energy remaining in the smartphone battery and the user's perceived costs for energy consumed by the two types of application uses: cloud-based application uses and on-device application uses. Our results show that, by letting users express their preferences, users can allocate the remaining smartphone energy such that it maximizes their utilities.

Keywords: Smartphones, Apps, Energy Consumption Optimization, Utility Function, Usage Behavior, Cloud Computing, Off-Loading, Application Classification, Energy Allocation.

JEL Classification Numbers: C13, C61, D01, D11, L82, L86, M15.

1. Introduction

The use of smartphones (including PDAs and tablets) together with the applications running on them evolved rapidly [1]. The most popular mobile activities performed with smartphones are web browsing, video watching, gaming, e-mailing, and social networking [2]. Even though battery technology has steadily been improved, it has not been able to match the demand for power for mobile activities. The development of past battery technology could enhance battery capacity by only 5% annually [3]. This limitation of the smartphone batteries results in a limited use of smartphones. Therefore, energy consumption of smartphones has become one of the critical research issues.

Sometimes, users like to get their smartphone battery to last for an entire day [4]. Moreover, it might became important to the user to make the smartphone battery last as long as possible. This, for example, can be achieved by reducing the execution of some applications. Then, the user can execute the most important applications on his smartphone more.

There are many other situations, in which users can make energy preserving decisions. These decisions of a smartphone user can range from choosing which applications to use, how to use an application, to how long the application should be used. For example, it could consider when to make a phone call, what to browse on the Internet, and which video to watch [5]. Consequently, the amount of energy consumed per application is different and the overall energy consumption depends on the user behavior.

Many studies have been conducted on smartphone usage. Some of these studies have investigated how users interact with their phones in the real world [5-12]. Other studies have focused on the charging behavior of users [13-20]. The relationship between the user behavior and the power consumption has also been examined in literature [5-9], [12], [14], [20-21], [31-39]. Their common findings are that all users have a unique usage pattern. Therefore, it is clear that a one-size power management solution cannot fit all and, hence, an appropriate solution must adapt to the behavior of the user [4]. Only then, it is possible to improve the smartphone user experience.

Despite the significant efforts by these studies about human behavior and energy efficiency for mobile devices, they did not consider the user preferences in using the applications. Especially, they did not ask what kind of preference the user has for different types of applications.

The main objective of this work is to understand how the user utility can be maximized, subject to the remaining energy in the battery and the user preferences for different types of applications.

For the purpose of our study, we classify application uses into two categories: on-device application uses, which refer to application uses that do not need Internet connectivity; and cloud-based application uses, which refer to application uses that require Internet connectivity and the cloud.

To address the research objective, we conduct the following steps: First, we propose a utility-based consumption optimization model to describe the user preferences with respect to energy allocation to the two types of smartphone application uses (i.e., on-device application use and cloud-based application use). The shape of the user utility function is defined by the Cobb-Douglas function. Second, considering a scenario that includes on-device and cloud-based application uses, we demonstrate our model and how the optimal energy allocation yields maximum utility subject to the remaining energy and the user preferences for the two types of smartphone application uses.

This work can be used by smartphone users, helping them to get the maximum utility from the remaining energy in their smartphone battery. In detail, we make the following two contributions: (1) a utility-based energy consumption optimization model; (2) the demonstration of the application of the optimization model to two types of application uses (on-device application uses, cloud-based application uses).

The remainder of this paper is structured as follows. In the next section, we present a literature overview about smartphone user behavior and energy consumption of smartphones. Section3 introduces our utility-based energy consumption optimization model. Section4 presents the scenario and the workings of our model. Section5 concludes the paper with a brief overview, the research limitations, and our future work.

2. Background

2.1. Smartphone Usage

Smartphones are used to perform many jobs such as phone calling, Internet browsing, watching videos, downloading files, and sending emails. User behavior has a significant effect on the energy consumption. Many studies on smartphone usage have been conducted to understand how users interact with their phones in the real world [5-12]. A typical methodology that has been used is to install a logger application on smartphone of the users and collect actual usage data. Their common findings are that all users have a unique device usage pattern. For example, Kang et al. [9], who analyze high-level smartphone usage patterns, developed a battery logger for thee Android mobile platform and collected usage log data from 20 smartphone users over a two-months period. Their results showed that all 20 users have their own usage pattern. They also presented a case study, in order to show how to apply usage pattern information to smartphone power management. Another example is the work of Froehlich et al. [11], who developed MyExperience for gathering traces from user's smartphones and for analyzing the smartphone usage differences in user activities.

Many user studies have also focused on the relationship between the user behavior and the energy consumption of devices [5], [7], [12], [14], [20-21], [31-39]. For example, Kang et al. [8] proposed a method of predicting the battery lifetime of mobile devices based on usage patterns. Using detailed traces from 255 users, Falaki et al. [5] have conducted a comprehensive study of smartphone use. They measured the energy consumption and application usage behavior of 33 Android and 222 Windows Mobile devices. They also found immense diversity among users' behaviors. They make important observations that are relevant to our work. That is, they found that users do not use a large number of different applications (much less than the number of installed applications) but give a large portion of their attention to a small subset of the applications installed. With a large-scale smartphone user study, Oliver [12] examines how users interact and how users consume energy on their personal mobile devices. Shye et al. [7] presented a comprehensive analysis of high-level characteristics of smartphone power consumption. They developed a logger application for Android G1 mobile phones and used it to collect smartphone usage data over a 6-months period from 20 users. Using this data, they applied a linear regression method to build a power model describing the relationship between the power consumption and the user activities. With this model, they also explored optimization potentials.

2.2. Human-Battery Interactions

Many studies have been devoted to the human-battery interaction [13-20]. The term human-battery interaction (HBI) was first coined by Rahmati et al. [13], to describe mobile phone users' interactions with their cell phones and to manage the battery energy available. In their user studies on HBI [14, 15], Rahmati et al. investigated users' attitudes and perceptions of mobile battery life. In particular, they evaluated various aspects of human-battery interactions, including charging behavior, battery indicators, user interfaces for power saving settings, user knowledge, and user reaction. In their experiments, users had to use unfamiliar devices for a period of a month. According to their results, most mobile users had no knowledge of the power characteristics of their devices and applications. Moreover, most mobile users underused the power saving settings of their devices. Although the studies of Rahmati et al. were the first to qualitatively and quantitatively assess how users consumed energy [14, 15], their studies were conducted in 2006-2007, still before the market launch of the iPhone. Due to the rapid growth of smartphones and their applications, the user behavior (e.g., multimedia playing, gaming) has significantly changed.

In addition to enhancing the energy efficiency by taking into account the user behavior, is also believed that tools for predicting battery life by considering the relationship between power consumption and user activities can help users to extend their mobile battery life [4]. Athukorala et al. [22] conducted a study with 1140 users on how the mobile battery-awareness application changes user behavior. The Carat application provides a user with information on the energy consumption of applications. In their study, they classified users into two groups. Users, who had used Carat for more than three months, were considered Advanced Users. Users, who had used it for a shorter time period, were classified as Beginners. Their result showed that advanced users stop using applications that were identified by Carat as highly energy-consuming applications more often than beginners. All users learned to better manage their battery over time.

3. Utility-Based Energy Consumption Optimization Model

3.1. Classification of Application Uses on Smartphones

Given that smartphones are rich in the number of applications installed, some applications (e.g., video streaming and gaming [24]) are very much resource intensive in terms of processing power and data transfer [23]. They are highly energy-consuming applications and, consequently, drain smartphone batteries very quickly.

Many of the popular activities (e.g., messaging, multimedia streaming, gaming, and e-mailing) on smartphones can be performed either local or through cloud-based services. For example, if a smartphone user wants to answer an email, the user can perform the activity online or the user can perform it off-line and send the email later. Another example is that a user wants to modify her time scheduler, where the user has the choice of synchronizing the scheduler with the cloud-based scheduler immediately or later. Therefore, we classify these smartphone application uses into two categories: on-device application uses, referring to applications that can be executed on the smartphone locally; and cloud-based application uses, referring to applications, which require data transfer and processing power on the cloud. We consider these two application use categories to differ in their utility to the user, depending on the energy stored in the battery.

3.2. Utility Function

In spite of the large number of applications installed on smartphones, users do not use them equally. In fact, as users have different preferences for their application uses, their valuation of the amount of energy consumed per type of application use is different. Some users may value playing online games very highly, while others are content playing local games. Within this paper, we consider the preferences for two types of application uses (section 3.1), namely on-device application use and cloud-based application use.

For smartphone users, the trade-off between using an application on-device or cloud-based is significant. That is, both alternatives can be thought of as representing a bundle of different characteristics: execution time, energy consumption, and monetary cost. For example, considering the battery constraint of the smartphone, the user might wish to maximize her utility from the amount of energy remaining on her smartphone, as an opportunity for charging the smartphone does not exist in the near future. To express the user preference for each type of application use, it is necessary to apply the theory of consumer behavior [29] and define the user's utility function.

With respect to the utility function, the Cobb-Douglas is useful, as it is well-behaved (i.e., more of a good is preferred to less of a good [29]). Furthermore, Cobb-Douglas functions are widely used in economics to represent the preferences between goods and the utility that can be obtained by those goods [25-26]. Hasan et al. [27] used a Cobb-Douglas stochastic frontier model to measure the domestic bank efficiency in Malaysia. Hayes [28] applies the Cobb-Douglas model to the association of research libraries.

The Cobb-Douglas indifference curves show combinations of on-device application use and cloud-based application use, which result in the same utility for the user. Therefore, our user utility function is represented by the following Cobb-Douglas function:

$$U(E_{local}, E_{cloud}) = (E_{local})^{\alpha} (E_{cloud})^{\beta} \quad (1)$$

where E_{local} is the energy planned to be consumed through on-device application use, E_{cloud} is the energy planned to be consumed through cloud-based application use. The unit of E_{local} and E_{cloud} is [Wmin].

The exponents, α and β, of the Cobb-Douglas utility function should be defined, such that they express the long-term preferences of the user for the two types of energy use. For our model, we consider the past consumption of energy for on-device application use E^{H}_{local} and the past consumption of energy for cloud-based application use E^{H}_{cloud}. The past consumption of energy can be obtained through monitoring applications, running on the smartphone of the user. The relative ratio of E^{H}_{local} and E^{H}_{cloud} is used to set α and β as shown in the following two equations:

$$\alpha = \frac{E^{H}_{local}}{E^{H}_{local}+E^{H}_{cloud}} \quad (2)$$

$$\beta = \frac{E^{H}_{cloud}}{E^{H}_{local}+E^{H}_{cloud}} \quad (3)$$

According to the definition of Eq 2 and Eq 3, the factors α and β are positive and fulfil α+β=1.

To calculate the optimal allocation of energy E^{*}_{local} and E^{*}_{cloud} to the two types of application use, we also need to consider the budget constraint, which is expressed with the following equation:

$$E_{local} * P^{E}_{local} + E_{cloud} * P^{E}_{cloud} = m \quad (4)$$

To be able to use Eq 4, a user is asked to express her perception of the budget *m* (i.e., express her valuation of the amount of energy that is left in the battery) and her preferences for consuming energy for on-device application uses and for cloud-based application uses.

The user's preference for using an application type can be expressed by stating the perceived cost (P^{E}_{local} and P^{E}_{cloud} [$/Wmin]) for the energy for both types of application uses. In this regard, we would like to note that user's perceived cost refers to the user's valuation for energy planned to be consumed by on-device applications or cloud-based applications but not to the real prices of energy. Different users may have different perceived costs.

With respect to the user's perception of the budget, the budget *m* can be interpreted as the user's monetary valuation of the available energy in the battery. This way, the budget can be used to capture the time before it is possible to recharge the battery again. As only the user knows how long it will take before the battery can be recharged, the user needs to express this information. For example, the longer it takes before the battery can be recharged, the lower the budget is. If the battery can be recharged immediately, the budget is 100 $. For our model, we assume to have values of *m* between 0 $ and 100 $.

As the budget is an abstract construct, it is also sufficient to state the rate of substitution RS for the cost of the two types of application uses. Therefore, a user must only state how much of the energy for one type of application use she is willing to substitute for consuming one more unit [Wmin] for the other type of application use:

$$RS = \frac{P^{E}_{local}}{P^{E}_{cloud}} \quad (5)$$

For example, if the perceived cost of energy consumption by on-device application uses is 2$/Wmin and the perceived cost of energy consumption by cloud-based application uses is 1$/Wmin, then the rate of substitution for this user is 2. That means, the user is willing to give up 1 unit [Wmin] of energy for cloud-based application uses only if the user obtains 2 units [Wmin] of energy for on-device application use.

With input values for E^{H}_{local}, E^{H}_{cloud}, P^{E}_{local}, P^{E}_{cloud}, and m, the utility-maximizing allocation to on-device application uses E^{*}_{local} and cloud-based application uses E^{*}_{cloud} can be calculated by using the Lagrange multipliers theorem [30]. The results provide the optimal amounts of energy that should be consumed through on-device application uses and through cloud-based application uses. They also provide the level at which the energy should be consumed at most (i.e., the amount of units [Wmin]). In detail, the results are as follows:

$$E^{*}_{local} = \frac{\alpha}{\alpha+\beta}\frac{m}{P^{E}_{local}} \tag{6}$$

$$E^{*}_{cloud} = \frac{\beta}{\alpha+\beta}\frac{m}{P^{E}_{cloud}} \tag{7}$$

4. Application Example of the Optimization Model

4.1. Parameter Settings

To demonstrate the workings of our utility-based energy consumption optimization model, we assume a simple scenario with 5 users:

Each user is assumed to have an average amount of battery energy consumed through on-device application uses E^{H}_{local} and cloud-based application uses E^{H}_{cloud} during the past month. The values have been obtained by monitoring the users' application uses.

Based on these data of past behaviors, we can model the long-term preferences for each user using the utility function (Eq 1) with α (Eq 2) and β (Eq 3) based on the two types of application uses for each user. Columns 2 and 3 of Table 1 show the preferences for the on-device application uses and cloud-based application uses for the five users according to their average energy consumption through the two types of applications uses during the past month.

Table 1. The long-term preferences based on the past energy consumption through on-device application uses and cloud-based application uses for five users are shown.

User	E^{H}_{local} [Wmin]	E^{H}_{Cloud} [Wmin]	α	β
1	40	60	0.40	0.60
2	66.7	33.3	0.67	0.33
3	50	50	0.50	0.50
4	33.3	66.7	0.33	0.67
5	70	30	0.70	0.30

Table 1 shows that users' past consumptions for the two types of applications uses set the two exponents of the utility function, α and β, in the same ratio. For example, for User 2, the ratio of the past energy consumption for on-device application uses and cloud-based application uses has been 2:1. In the same ratio, the exponents α and β are set. That means that User 2's preference for on-device application uses is twice as high as User 2's preference for cloud-based application uses. In case of User 3, the ratio of the past energy consumption through the two types of application uses is 1:1. As the ratio of the exponents α and β is also 1:1, User 3 is modeled to be indifferent to the two types of application uses.

4.2. Modeling Results

Assuming that User 4 wants to maximize the utility from the energy remaining in the smartphone battery, the smartphone user needs to express the perceived energy budget m in [$]. In our scenario, User 4 states that the remaining energy in her smartphone is worth m=60 $.

The perceived costs for allocating energy to on-device application uses and to cloud-based application uses (P^E_{local} and P^E_{cloud} [$/Wmin]) also needs to be set by User 4. To see the effect of setting those two values, six different pairs of values are analyzed in Table 2. All of these pairs of values have the same rate of substitution (Eq 5), namely RS=1/2. That means that User 4 would be willing to sacrifice two units of energy of on-device application uses to consume one more unit of energy for cloud-based application uses.

Based on these values, the utility-maximizing combination of on-device application uses E^*_{local} and cloud-based application uses E^*_{cloud} can be calculated using Eq 6 and Eq 7. The results are also shown in Table 2.

Table 2. Utility-maximizing combination of energy allocation to on-device application uses E^*_{local} and to cloud-based application uses E^*_{cloud} for User 4 (α=0.33 and β=0.67). While the budget has been fixed (m=60 $), different values for P^E_{local} and P^E_{cloud} have been used.

m [$]	P^E_{local} [$/Wmin]	P^E_{cloud} [$/Wmin]	RS	E^*_{local} [Wmin]	E^*_{cloud} [Wmin]
60	0.5	1	0.5	39.60	40.20
60	1	2	0.5	19.80	20.10
60	2	4	0.5	9.90	10.05
60	3	6	0.5	6.60	6.70
60	4	8	0.5	4.95	5.03
60	5	10	0.5	3.96	4.02

The results of Table 2 show that, if User 4's perceived value for the energy allocation to on-device application uses is 0.5 $/Wmin and for the energy allocation to cloud-based application uses is 1 $/Wmin, then the energy allocation ratio for cloud-based application uses is 1.015 of the on-device application uses. This combination of the energy allocation to the two types of application uses maximizes the utility of User 4. Table 2 also shows that the energy allocation ratio for the other pairs of values of P^{E}_{local} and P^{E}_{cloud} is also 1.015. The knowledge, which can be gained about User 4 preferences, is that the battery energy can be consumed much faster for the values 0.5 $/Wmin and 1 $/Wmin than for the other pairs of values. If the pair of values is 5 $/Wmin and 10 $/Wmin, then the battery energy should be consumed very slowly.

Table 3. Utility-maximizing combination of energy allocation to on-device application uses and cloud-based application uses for User 4 (with α=0.33 and β=0.67). While the energy budget m is varied, the values of P^{E}_{local} and P^{E}_{cloud} are set to 1 $/Wmin and 2 $/Wmin, respectively.

m [$]	P^{E}_{local} [$/Wmin]	P^{E}_{cloud} [$/Wmin]	E^{*}_{local} [Wmin]	E^{*}_{cloud} [Wmin]
100	1	2	33	33.5
90	1	2	29.7	30.15
80	1	2	26.4	26.8
70	1	2	23.1	23.45
60	1	2	19.8	20.1
50	1	2	16.5	16.75
40	1	2	13.2	13.4
30	1	2	9.9	10.05
20	1	2	6.6	6.7
10	1	2	3.3	3.35

Table 3 shows that, if the perceived budget of the remaining energy in the battery is high, the utility-maximizing energy allocations to on-device application uses E^{*}_{local} and cloud-based application uses E^{*}_{cloud} are high. For instance, for the battery energy budget m=90 $, the energy allocation to on-device application uses is 33 Wmin. The values of the energy allocation decrease, as the perceived budget of the remaining energy in the battery gets low. For instance, if m=10 $, the energy allocation to on-device application uses is 3.3 Wmin only. This difference of the energy allocation shows the User 4 preferences for the battery energy consumption. User 4 states with a perceived low energy budget that the energy consumption should be much slower than for a perceived high energy budget. The energy of the battery should last for very long.

Since our study focuses on applying the consumer behavior theory in studying the energy consumption, all results presented in Table 1, Table 2, and Table 3 show the workings of our proposed model. That is, a smartphone user with a Cobb-Douglas utility function can maximize her utility by allocating a fraction of her remaining energy to each type of application uses. The size of the fraction is determined by the user's preference for both types of application uses, the perceived cost of energy for both types, and the perceived value of the energy remaining in the smartphone battery.

5. Conclusion

In this paper, we propose a utility-based energy consumption optimization model, which considers the user's preferences with respect to energy consumption aspects when using smartphone applications. Compared to other studies about smartphone usage and energy consumption, our study represents a novel approach to allocate energy to applications. It considers two types of application uses: on-device application uses and cloud-based application uses. These two types of application uses are the goods considered in the user's utility function, which is based on a Cobb-Douglas function. The users' preferences are described through past patterns of energy consumption, the perceived value of energy remaining in the smartphone battery, and the perceived costs for allocating energy to each type of application uses.

To demonstrate the working of our approach, we apply our approach to a simple scenario. The results based on the scenario show that an optimal (i.e., utility maximizing) allocation of energy to different types of application uses is possible for a user. The allocation by the user determines not only the ratio between the two types of application uses but also the quantity with which the energy in the battery should be consumed. The user only needs to specify the perceived cost of energy for each type of application and the perceived value of energy remaining in the smartphone battery.

We argue that this work will contribute to the line of studies assessing the effect of usage behavior on energy consumption optimization of smartphones. It can be used by smartphone users to obtain the maximum utility from the remaining energy in their smartphones battery.

In the future, we plan to conduct studies with real smartphone users and to analyze their value setting for perceived costs and perceived energy budget.

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