Probability of Task Completion and Energy Consumption in Cooperative Pervasive Mobile Computing

Duc V. Le*, Thuong Nguyen†, Hans Scholten*, and Paul J. M. Havinga*
*Department of Computer Science, University of Twente, Enschede, The Netherlands
Email: {v.d.le, hans.scholten, p.j.m.havinga}@utwente.nl
†The Australian e-Health Research Centre, CSIRO, Herston, Queensland, Australia
Email: thuong.nguyen@csiro.au

***Abstract*—It is challenging for multiple smartphones to complete a given task in large-scale pervasive sensing systems cooperatively. Sensing paradigms such as opportunistic sensing, participatory sensing, and hybrid sensing have been used for smartphones to work together seamlessly under different contexts. However, these existing paradigms do not incorporate the energy problem and sharing sensory resources of applications. In this paper, we revisit sensing paradigms regarding the probability of task completion and energy consumption for smartphones to cooperatively complete a sensing task. In addition, we propose a symbiotic sensing paradigm that can significantly save smartphone batteries while maintaining equivalent performance to existing paradigms, provided that the smartphones allow applications to share sensing resources. We also quantitatively evaluate our probabilistic models with a realistic case study. This work is a useful aid to designing and evaluating large-scale smartphone-based sensing systems before deployment, which saves money and effort.**

I. Introduction

The proliferation of smartphones has stimulated researchers in pervasive mobile computing community to develop low-cost, steady, and reliable large-scale sensing systems [1]. One of the main research challenges is how to successfully collaborate smartphones to complete a resource-intensive tasks such as sampling sounds in urban environments. Smartphones are in situ designed for calling, messaging, gaming, etc., but not for crowd sensing. Different smartphones also have different sensing capabilities and contexts. Therefore, the probability of completing a task is difficult to predict in advance, before deploying a sensing application on a large scale.

To this end, some naive sensing strategies have been proposed such as opportunistic sensing [2], participatory sensing [3], [4], and hybrid sensing. Opportunistic sensing executes sensing tasks unobtrusively to the users. Conversely, participatory sensing requests the users to use their smartphones to collect the required data. Hybrid sensing combines both these sensing paradigms. In a nutshell, the principle of these paradigms is that it should sample data if and only if the contexts satisfy the sensing conditions. For example, a smartphone will detect the light intensity with the integrated light sensor if and only if the smartphone is outside of the pocket.

However, with the significant development of smartphone technologies, more sophisticated and power-hungry sensors will be integrated, for instance, dust particle and gas sensors. Consequently, data harvesting through smartphones invokes a variety of challenges to limited resources to overcome. In addition, new updated mobile operating systems also allow more and more applications to share the same resources such as accelerometers, gyroscope, compass, and Global Positioning System (GPS). The surveys from Statista [5], [6] show that the number of applications has increased exponentially, from few thousands in 2008 to more than 3.5 million apps in 2015. Note that the year 2008 is when Lane *et al.* [7] discussed the sensing abstractions and their evaluation models. Moreover, a report from Nielsen.com [8] reveals that the monthly time a person spends on smartphone applications has risen 63% in two years, from 23 hours and two minutes in fourth-quarter 2012 to 37 hours and 28 minutes in fourth-quarter 2014. These phenomena indicate that existing sensing paradigms need to be up-to-date.

In this paper, therefore, we revisit the sensing paradigms regarding the probability of task completion and the power consumption of smartphones, provided that applications can share resources. The probabilities are mathematically modeled and quantitatively evaluated with statistic parameters. The goal of this paper is to provide researchers a tool of aids to estimate the performance of their smartphone-based crowd sensing systems before deployment. The participating smartphones may have different sensing capabilities and operate in dynamic environments and contexts. Nevertheless, our proposed models can be used to estimate roughly the probability of completing resource-intensive tasks as well as the consumed power.

The remainder of this work is organized as follows. Preliminary background is presented in Section II. Section III states the problems and our objectives. Section IV describes a new sensing paradigm as well as the evaluation models. The sensing paradigms are quantitatively evalu-

978-1-5386-3227-7/18/$31.00 ©2018 IEEE

ated in Section V. Finally, we conclude this work with Section VI.

II. Preliminary Background

A. Sensing Paradigms

Most current sensing systems are developed based on either participatory sensing [4], opportunistic sensing [2], or hybrid sensing [9]. Participatory sensing requires users to participate in sampling data actively. Meanwhile, opportunistic sensing systems can run unobtrusively, and the users may not be aware of that the sensing applications are performing sensing tasks on their smartphones. In other words, the burden of sensing places on either users or smartphones. These extreme sensing paradigms technically restrain researchers from utilizing sensing opportunities provided by users and smartphones. To this end, a new trend of developing applications based on a hybrid paradigm is proposed. For example, Bubble-Sensing [9], a hybrid paradigm, binds a sensing task to the physical world using smartphones. Bubble-Sensing considers the places of interests as the sensing condition. Once a smartphone is present in the places of interests, corresponding sensing tasks will be submitted to the smartphone.

B. Probability of Task Completion

When designing an urban sensing system, its performance on a large scale is usually hard to conjecture since it depends on multiple uncertain parameters (e.g., the number of smartphones, the number of applications, the probability of having a specific type of sensors). To deal with such daunting challenge, Lane *et al.* [7] propose evaluation models.

Assume that the sensing system requests N smartphones installed the sensing application to collect data in a region of interest, then to send the data to a central server. Examples include collecting environmental noise, temperature, dust particles, and carbon dioxide. The smartphones can only perform collecting data provided that the sensing conditions are satisfied (e.g., location, time, available sensor type, orientation, societal altruism). Let P_p (*Probability of Permission*) be the probability that a user agrees to take part in collecting data when there is a request. Let P_u (*Probability of User*) be the probability that a user participates in collecting data. For example, the probability of that a user pulls their smartphone out of the pocket just to measure the street noise when they are on the street. Let P_c (*Probability of Context*) be the probability that a smartphone has its context matched with the sensing requirements. For example, when a smartphone is outside of the pocket for some other purposes but also can thus be used to record environmental noise. Let P_s (*Probability of Sensor*) be the probability that a smartphone is integrated with the sensor type that is required by the sensing task.

The probability of task completion using the opportunistic sensing is given by

$$P_{opportunistic} = 1 - (1 - P_s P_c)^N. \tag{1}$$

The term $(1 - P_s P_c)$ indicates that the smartphone cannot perform the task since it does not possess the required sensor and/or the appropriate context.

With the participatory sensing, the probability of task completion is given by

$$P_{participatory} = 1 - (1 - P_p P_s (P_c + \bar{P}_c P_u))^N, \tag{2}$$

where $\bar{P} = 1 - P$.

The term $P_p P_s (P_c + \bar{P}_c P_u)$ indicates that either the smartphone has the appropriate conditions to collect data or that the user is willing to make the sensing conditions happened.

III. Problem Statements

The recent development and proliferation of smartphones have raised new challenges for cooperative sensing with smartphones. The challenges include power consumption, non-deterministic platforms, and exclusive resources. The existing sensing paradigms and evaluation models need to be improved to incorporate such challenges.

A. Power consumption

More and more sophisticated and power-hungry sensors have been integrated, for instance, dust particle sensors and gas sensors. Also more applications are installed and used daily [5], [6]. Users also spend more time on smartphones [8]. Although the new MEMS sensors and battery technologies have improved the battery issue, the power consumption is still one of the most concerns from users, which may deter them from installing the sensing applications.

In this paper, we propose new evaluation models to compute the probability of energy consumption to complete a sensing task. We consider various parameters including energy consumption of sensors, localization systems, and communication.

B. Non-deterministic platform

Unlike dedicated sensing devices in traditional sensing systems, smartphones are non-deterministic since they are in situ designed not for sensing [10]. Smartphones also have more diverse brands, models, operating versions. In addition, smartphones frequently function in multiple roles. These factors indeed influence the reliability.

In this paper, we propose that each sensing task has to be performed by at least M smartphones to enhance the reliability. For example, sampling the sounds at a location needs to be done by at least some smartphones. With the advantage of the crowd, the quality of information would be improved. We also propose evaluation models with regards to this reliability enhancement.

C. Exclusive Resources

Since smartphones are an attractive platform for pervasive mobile computing, smartphone-based sensing applications have become popular. However, exclusive resources such as cameras and microphones cannot be shared among the applications in mobile operating systems such as current Android. In other words, it is not possible for more than one application to use an exclusive sensor at the same time.

In this paper, we propose a new sensing paradigm that addresses the resource-sharing and cooperative-computing ability. The new paradigm, called symbiotic sensing, enables the sensing applications to be able to deploy on a large scale with numerous smartphones. Sensing tasks are carried out cooperatively to reduce the resource consumption.

IV. New Evaluation Models

In this section, we derive the quantitative models to evaluate the sensing paradigms, which are commonly used as strategies for sensing applications. We address the evaluation models with regards to the new challenges that are discussed in Section III: power consumption, non-deterministic platform, and exclusive resources. Specifically, we propose the evaluation models regarding the probability of success and expectation of energy consumption, when completing a sensing task.

Without loss of generality, we formulate the evaluation models for the data collection task. A mobile application has to be installed on a minimum number of smartphones, denoted by N, to perform the data collection. Whenever a smartphone satisfies the predefined sensing conditions, such as its location, time, physical position, and orientation, the application automatically executes the task or requests the smartphone's user to collect data. The collected data then will be sent to a central server. Each kind of data needs to be collected by at least M smartphones, $M \leqslant N$, to obtain the reliability.

A. Probability of Success

Given the probability that the sensing application can perform a sensing task by a single smartphone is p, the probability that the sensing task can be performed by at least M smartphones among N smartphones is given by:

$$P = 1 - \sum_{k=0}^{M-1} C_N^k p^k (1-p)^{N-k}, \tag{3}$$

where $C_N^k = \frac{N!}{(k!(N-k)!)}$ is the number of k-combinations of N elements.

Note that the probabilities of success defined in (1) and (2) are under the assumption of that the required sensors are always ready to sample data as long as the smartphone owns them. However, it is likely that the sensor on a smartphone might not be always available as if it is exclusive and being used by another application. For example, microphones and cameras cannot be accessed by multiple applications on the current Android operating systems. Hence, we propose a complementary sensing paradigm to reflect this problem, namely *symbiotic sensing.*

Symbiotic sensing is a sensing paradigm that allows sensing applications to share either resources or sensing results with each other to avoid acquiring or processing the same sensory data multiple times. Applications designed with symbiotic sensing do not detriment each other, but they benefit from the association by gaining the shared resources and results

Let P_o (Probability of Occupation) be the probability that the required sensors are being occupied by another application given the matched context, for example, the percentage of time the user using their smartphone to take a picture. Equation (3) for symbiotic sensing can be expressed in detail as follows.

In symbiotic sensing, a smartphone completes a sensing task only if it have the required sensor, it is in relevant context, and there is another application using the required sensor. In other words, the probability that the smartphone completes the sensing task is a joint probability $p = P_s P_c P_o$. Therefore, the *probability of success with symbiotic sensing* is given by

$$P_{symbiotic} = 1 - \sum_{k=0}^{M-1} C_N^k \left(P_s P_c P_o\right)^k \left(1 - P_s P_c P_o\right)^{N-k}. \tag{4}$$

On the other hand, in opportunistic sensing, a smartphone completes a sensing task only if the required sensor is not being used by any other application. Thus, the probability that the smartphone can complete the sensing task is $p = P_s P_c \bar{P}_o$. The *probability of success with opportunistic sensing* is given by

$$P_{opportunistic} = 1 - \sum_{k=0}^{M-1} C_N^k \left(P_s P_c \bar{P}_o\right)^k \times \left(1 - P_s P_c \bar{P}_o\right)^{N-k}. \tag{5}$$

In participatory sensing, there are two scenarios that a sensing task is completed. When the sensing context is matched, the smartphone may execute the sensing task without the help from the user with probability $P_p P_s P_c \bar{P}_o$. Otherwise, if the sensing context is not matched, the application will request the user to help. However, the user might be reluctant to do so with a probability of P_u. Therefore, we have the *probability of success with participatory sensing* is given by

$$P_{participatory} = 1 - \sum_{k=0}^{M-1} C_N^k \left[P_p P_s \left(P_c \bar{P}_o + \bar{P}_c P_u\right)\right]^k \times \left[1 - P_p P_s \left(P_c \bar{P}_o + \bar{P}_c P_u\right)\right]^{N-k}. \tag{6}$$

The hybrid sensing paradigm is slightly different to participatory sensing. When the sensing context is matched, the smartphone will sample data regardless of the availability of the required sensor with the support of a resource sharing application service. Additionally, a hybrid sensing application does not request the user to support in collecting data if sensing context is matched. If the sensing context is unmatched, the application will request the user to assist in sampling data. Thus we can define the *probability of success with hybrid sensing* as

$$P_{hybrid} = 1 - \sum_{k=0}^{M-1} C_N^k \left[P_s\left(P_c + \bar{P}_c P_p P_u\right)\right]^k \times \left[1 - P_s\left(P_c + \bar{P}_c P_p P_u\right)\right]^{N-k}. \quad (7)$$

B. Estimated energy consumption

The application needs to be installed on N smartphones so that a sensing task can be accomplished by at least M smartphones. As the task execution is probabilistic, we need to estimate the total energy consumption of the application on such N devices.

Estimated Energy Consumption of a sensing paradigm is the estimated quantity of energy consumed by the application installed on N devices of the system during a unit of time, such that a sensing task is performed by at least M smartphones to obtain a certain level of accuracy, $M \leqslant N$. Energy consumption of a sensing system consists of multiple aspects, e.g., the energy to run the phone and sensors in idle mode, the power to run the sensors for data collection, data transmission energy. Therefore, we denote the main components of energy consumption as follows.

Let e_i (Idle Energy Consumption) be the energy that the application consumes during a unit of time when it is idle, without capturing any data from sensors or doing localization. Let e_s (Sensor Energy Consumption) be the extra energy that the requested sensor consumes while performing the sensing task during a unit of time. Let e_l (Localization Energy Consumption) be the extra energy that a localization system consumes to update the location information of sampled data during a unit of time. Let e_c (Communication Energy Consumption) be the extra energy that a device consumes to transmit sampled data to another device or a server during a unit of time; Given the above definitions of energy consumption, the expectation of total energy E consumed by the system is given by

$$\bar{E} = \frac{N+M}{2} p\left(e_s + e_l + e_c\right) + Ne_i \quad (8)$$

where M is the required minimum number of smartphones that perform the sensing task and N is the number of smartphones installed the sensing application.

For *symbiotic sensing*, as shown in Eq. (4), the probability that the sensing application performs the task is $p = P_s P_c P_o$. We can replace this probability p in Eq. (8). However, unlike other sensing paradigms, a symbiotic sensing application does not consume extra energy to activate the sensor as it reuses the data sampled by another host application. It can also retrieve the location information which recently retrieved by another application, such as Google maps or Facebook. Furthermore, it is possible to piggyback on another application to transmit sampled data without consuming extra power by increasing bandwidth or data rate as being studied in [11]. Therefore, e_s, e_l and e_c in (8) can be omitted for symbiotic sensing in most cases. In other words, we have the expected energy consumption of symbiotic sensing given by

$$\bar{E}_{symbiotic} = Ne_i. \quad (9)$$

The expectation of energy consumption with *opportunistic sensing* is give by

$$\bar{E}_{opportunistic} = \frac{N+M}{2} P_s P_c \bar{P}_o\left(e_s + e_l + e_c\right) + Ne_i. \quad (10)$$

The expectation of energy consumption with *participatory sensing* is given by

$$\bar{E}_{participatory} = \frac{N+M}{2} P_p P_s\left(P_c \bar{P}_o + \bar{P}_c P_u\right) \times \left(e_s + e_l + e_c\right) + Ne_i. \quad (11)$$

For *hybrid sensing* as shown in Eq. (7), the probability that the sensing application performs the sensing task is $p = P_s\left(P_c + \bar{P}_c P_p P_u\right)$. However, the probability that the application executes the sampling task by acquiring sensors is only $P_s\left[P_c\left(1 - P_o\right) + \bar{P}_c P_p P_u\right]$. For the rest of the probability, $P_s P_c P_o$, the application piggybacks on other applications to gain the power consumption benefit. Therefore, the expected energy consumption of hybrid sensing is given by

$$\bar{E}_{hybrid} = \frac{N+M}{2} P_s\left[P_c\left(1 - P_o\right) + \bar{P}_c P_p P_u\right] \times \left(e_s + e_l + e_c\right) + Ne_i. \quad (12)$$

V. Quantitative Evaluation

In this section, we evaluate the symbiotic, opportunistic, participatory and hybrid sensing paradigms regarding the models given in Section IV. We address a noise map app using onboard microphones of smartphones carried by citizens since it is an attractive topic [12]–[14]. The application addresses helping citizens understand the noise pollution of their city by measuring and mapping noise data with their smartphones.

A. Evaluation of Probability of Success

It is likely that every single smartphone has at least one microphone; therefore, we set $P_s = 1$ for the microphone sensor type. Since recording sound when the smartphone is in a pocket has dramatically low quality, we define when the smartphone is out of pocket as the context matching. In 2012, Britons spent average 90 minutes per day on their smartphones [15]. This number can be used as an approximate probability of the context matching. Thus we set $P_c = 90/(24 \times 60) = 0.0625$. The survey [15] also shows that Britons used their mobile phone 17% of such usage time for the making phone calls. Because the microphone is an exclusive sensor that typically cannot be accessed by multiple applications at the same time except building some middleware platform for cross-sensor applications, we conservatively set $P_o = 0.17$.

To derive P_p and P_u, we map conceptually it to the probability of the first contact rates surveyed in a report on the feasibility of cell phone surveys [16]. In particular, the civilians were first called through their cell phones if they are willing to participate in a survey, in which they are supposed to answer a list of interview questions. The study results show that 1561 over 4448 agreed to participate in the interview. Therefore, we set $P_p = 0.3$. The results also show that only 318 participant completed all the questions. That completion indeed requires some modification of planned behaviors conceptually relates to the probability of that a user participates in sampling data. Hence, we set $P_u = 0.2$.

Given these probability values, the relationship between the derived values of success probabilities versus the number of smartphones for symbiotic, opportunistic, participatory, and hybrid sensing paradigms are plotted in Fig. 1. In particular, Fig. 1(a), (b), and (c) show the graphs of the success probabilities when the sensing application requires at least 1, 5, and 10 smartphones to sense the same event simultaneously, respectively. Apparently, the hybrid sensing paradigm always has the highest probability of success regardless the values of the parameters. In this scenario, the opportunistic and participatory sensing paradigms have the similar probability of success when varying number of smartphones. The symbiotic sensing paradigm has the lowest probability of success as it only utilizes sensors occupied by other applications to save energy consumption, which is 0.17. Nevertheless, when increasing the number of smartphones, the success probability values of the symbiotic paradigm also increase. This phenomenon confirms the hypothesis; the symbiotic sensing paradigm can perform as well as other sensing paradigms without consuming many extra resources if more smartphones can collaborate.

B. Evaluation of Energy Consumption

The power consumption of sensors and wireless interfaces on smartphones have been analyzed in some works [17]–[20]. Among those works, the Monsoon Power Monitor [20] gives the possibility to analyze data quite accurately since it measures the energy consumption of each component by directly accessing to the battery of the smartphone by a hardware device, which comes with a software tool. [21] uses the Monsoon Power Monitor tool to measure the power consumption of microphones and GPS in a Samsung Galaxy i9250. From their measured data, we find that the extra energy consumed when activating microphones (recording) 0.4154 mAh, and that of GPS is 1.5959 mAh. Therefore, we set $e_s = 0.4154$ mAh and $e_l = 1.5959$ mAh. We also find the application itself consumes 1.6582 mAh when it does not perform any sensing tasks. Hence, we set $e_i = 1.6582$ mAh.

For the power consumption to transmit sensory data to a base station, WiFi is the most sustainable interface to transfer audio data from smartphones to a server. Compared to other wireless interfaces that are available on most smartphones, such as Global System for Mobile Communications (GSM) 3G, and Long-Term Evolution (LTE), WiFi consumes at least five times lesser power consumption [22]. Bluetooth also has low power consumption, but its coverage is limited, shorter than 10 meters. As measured by [22], the extra power consumption of WiFi when actively transferring data is 650 mAh. Thus, we set $e_c = 650$ mAh.

Dividing the total expected energy consumption values by the corresponding smartphone quantities, symbiotic sensing consumes much less energy consumption per device as plotted in Fig. 2(b), which is about 2.5 mAh. Moreover, data are collected from many more smartphones with symbiotic sensing. Fig. 2(a) compares the expected smartphones that sample and send data back to the server, which provides more reliability and accuracy.

VI. Conclusion

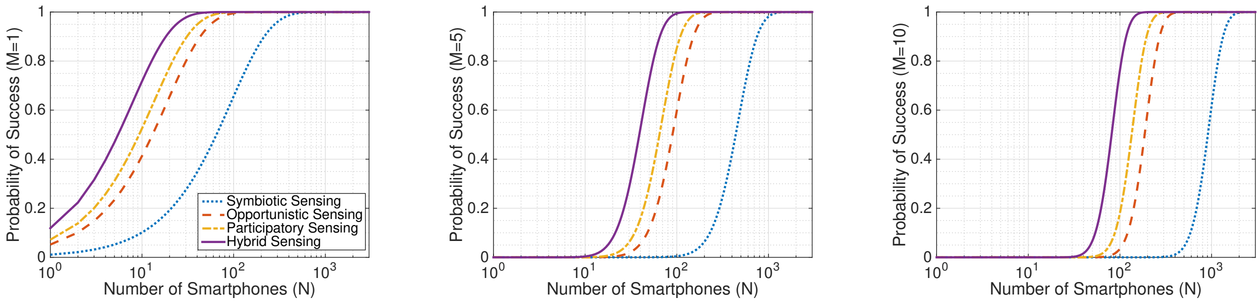
We revisited sensing paradigms for energy-saving sensing systems based on smartphone platforms. Since the number of smartphone applications has increased significantly while the sensing resources on smartphones are limited, we proposed the symbiotic sensing approach that addresses sharing the resources as well as outcomes among the applications. We also proposed new evaluation models for the new and the existing sensing paradigms. Through quantitative evaluation of the models given surveyed data from the real world, we showed that symbiotic sensing is complementary to existing the sensing approaches. Though the application diversity should be considered, the symbiotic sensing paradigm has a potential to be a better choice than opportunistic sensing large scale, where there are enormous numbers smartphones and applications. Although the comparison results from quantitative evaluation show the probabilities of success when using different approaches, building out these sensing techniques will provide more conclusive evidence into which one is the best choice for a large-scale sensing system.

Acknowledgment

This research is partly supported by the COPAS project (Grant No. 629.002.203) in the NWO Indo Dutch Joint Programme for ICT.

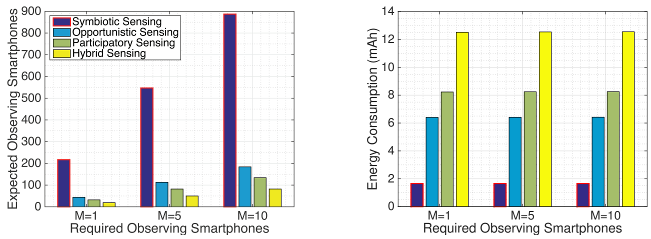
References

[1] N. D. Lane, P. Georgiev, and L. Qendro, "DeepEar: robust smartphone audio sensing in unconstrained acoustic environments using deep learning," in *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 2015, pp. 283–294.



(a) (b) (c)

Fig. 1. The success probability of executing a noise measurement with citizen's smartphones for a city-sound-map application with different sensing strategies.



(a) (b)

Fig. 2. The energy consumption of executing a noise measurement with citizen's smartphones for a city-sound-map application with different sensing strategies.

[2] A. T. Campbell, S. B. Eisenman, N. D. Lane, E. Miluzzo, and R. A. Peterson, "People-centric urban sensing," in *Proceedings of the 2nd annual international workshop on Wireless internet*. ACM, 2006, p. 18.

[3] M. B. Srivastava, J. A. Burke, M. Hansen, A. Parker, S. Reddy, T. Schmid, K. Chang, S. Ganeriwal, M. Allman, V. Paxson *et al.*, "Network system challenges in selective sharing and verification for personal, social, and urban-scale sensing applications," *Center for Embedded Network Sensing*, 2006.

[4] J. A. Burke, D. Estrin, M. Hansen, A. Parker, N. Ramanathan, S. Reddy, and M. B. Srivastava, "Participatory sensing," *Center for Embedded Network Sensing*, 2006.

[5] "Number of available applications in the Google play store from December 2009 to November 2015," http://www.statista.com/statistics/266210/number-of-available-applications-in-the-google-play-store/, 2015.

[6] "Number of available apps in the Apple app store from July 2008 to June 2015," http://www.statista.com/statistics/263795/number-of-available-apps-in-the-apple-app-store/, 2015.

[7] N. D. Lane, S. B. Eisenman, M. Musolesi, E. Miluzzo, and A. T. Campbell, "Urban sensing systems: opportunistic or participatory?" in *Proceedings of the 9th workshop on Mobile computing systems and applications*. ACM, 2008, pp. 11–16.

[8] "So many apps, so much more time for entertainment," http://www.nielsen.com/us/en/insights/news/2015/so-many-apps-so-much-more-time-for-entertainment.html, 2015.

[9] H. Lu, N. D. Lane, S. B. Eisenman, and A. T. Campbell, "Bubble-sensing: Binding sensing tasks to the physical world," *Pervasive and Mobile Computing*, vol. 6, no. 1, pp. 58–71, 2010.

[10] D. V. Le, J. W. Kamminga, H. Scholten, and P. J. Havinga, "Nondeterministic sound source localization with smartphones in crowdsensing," in *Pervasive Computing and Communication Workshops (PerCom Workshops), 2016 IEEE International Conference on.* IEEE, 2016, pp. 1–7.

[11] D. Halperin, B. Greenstein, A. Sheth, and D. Wetherall, "Demystifying 802.11 n power consumption," in *Proceedings of the 2010 international conference on Power aware computing and systems.* USENIX Association, 2010, p. 1.

[12] N. Maisonneuve, M. Stevens, and B. Ochab, "Participatory noise pollution monitoring using mobile phones," *Information Polity*, vol. 15, no. 1, 2, pp. 51–71, 2010.

[13] S. Leao, K.-L. Ong, and A. Krezel, "2loud?: Community mapping of exposure to traffic noise with mobile phones," *Environmental monitoring and assessment*, vol. 186, no. 10, pp. 6193–6206, 2014.

[14] S. Hachem, V. Mallet, R. Ventura, A. Pathak, V. Issarny, P.-G. Raverdy, and R. Bhatia, "Monitoring noise pollution using the urban civics middleware," in *Big Data Computing Service and Applications (BigDataService), 2015 IEEE First International Conference on.* IEEE, 2015, pp. 52–61.

[15] "Average Britons spends almost 34 entire days on mobile phone per year," http://www.mobileinsurance.co.uk/blog/average-britons-spends-almost-34-entire-days-on-mobile-phone-per-year/, March 2013.

[16] J. M. Brick, P. D. Brick, S. Dipko, S. Presser, C. Tucker, and Y. Yuan, "Cell phone survey feasibility in the us: Sampling and calling cell numbers versus landline numbers," *Public Opinion Quarterly*, vol. 71, no. 1, pp. 23–39, 2007.

[17] N. Balasubramanian, A. Balasubramanian, and A. Venkataramani, "Energy consumption in mobile phones: a measurement study and implications for network applications," in *Proceedings of the 9th ACM SIGCOMM conference on Internet measurement conference.* ACM, 2009, pp. 280–293.

[18] C. Thompson, D. Schmidt, H. Turner, and J. White, *Advances and Applications in Model-Driven Engineering*, 2011, ch. Analyzing mobile application software power consumption via model-driven engineering, pp. 342–367.

[19] R. Mittal, A. Kansal, and R. Chandra, "Empowering developers to estimate app energy consumption," in *Proceedings of the 18th annual international conference on Mobile computing and networking.* ACM, 2012, pp. 317–328.

[20] "Monsoon power monitor tool," https://www.msoon.com/LabEquipment/PowerMonitor/, 2016.

[21] M. Ciman and O. Gaggi, "Evaluating impact of cross-platform frameworks in energy consumption of mobile applications." in *WEBIST (1)*, 2014, pp. 423–431.

[22] A. Nika, Y. Zhu, N. Ding, A. Jindal, Y. C. Hu, X. Zhou, B. Y. Zhao, and H. Zheng, "Energy and performance of smartphone radio bundling in outdoor environments," in *Proceedings of the 24th International Conference on World Wide Web.* International World Wide Web Conferences Steering Committee, 2015, pp. 809–819.