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CrowdSenSim: a Simulation Platform for Mobile Crowdsensing in Realistic Urban Environments

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***Abstract*—Smart cities take advantage of recent ICT developments to provide added value to existing public services and improve quality of life for the citizens. The Internet of Things (IoT) paradigm makes the Internet more pervasive where objects equipped with computing, storage and sensing capabilities are interconnected with communication technologies. Because of the widespread diffusion of IoT devices, applying the IoT paradigm to smart cities is an excellent solution to build sustainable Information and Communication Technology (ICT) platforms. Having citizens involved in the process through mobile crowdsensing (MCS) techniques augments capabilities of these ICT platforms without additional costs. For proper operation, MCS systems require the contribution from a large number of participants. Simulations are therefore a candidate tool to assess the performance of MCS systems. In this paper, we illustrate the design of CrowdSenSim, a simulator for mobile crowdsensing. CrowdSenSim is designed specifically for realistic urban environments and smart cities services. We demonstrate the effectiveness of CrowdSenSim for the most popular MCS sensing paradigms (participatory and opportunistic) and we present its applicability using a smart public street lighting scenario.**

***Index Terms*—Mobile crowdsensing, simulations, smart cities.**

I. Introduction

WORLD population living in cities has experienced an unprecedented growth over the past century. While only 10% of the population lived in cities during 1900, today this percentage corresponds to 50% and it is projected to further increase beyond such figure [1]. Sustainable development plays therefore a crucial role in city development. While only 2% of the world's surface is occupied by urban environments, cities contribute to 80% of global gas emission, 75% of global energy consumption [2] and 60% of residential water use [1].

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Smart cities rely on Information and Communication Technology (ICT) solutions to improve citizens' quality of life [3], [4]. The application of the Internet of Things (IoT) paradigm to urban scenarios is of special interest to support the smart city vision [4]–[6]. Indeed, IoT is envisioned as a candidate building block to develop sustainable ICT platforms. With IoT, everyday life objects become uniquely identifiable and "smart", i.e., they are equipped with computing, storage and sensing capabilities and can communicate one with each other and with the users to enable pervasive and ubiquitous computing [7]. Including citizens in the loop with crowdsensing approaches augments the capabilities of existing infrastructures without introducing additional costs and has been proved to be a win-win strategy for smart city applications [8]–[10].

Mobile crowdsensing (MCS) has emerged in the recent years, becoming an appealing paradigm for sensing data [11]. In MCS, users contribute data generated from sensors embedded in mobile devices, including smartphones, tablets and IoT devices like wearables. Accelerometer, gyroscope, magnetometer, GPS, microphone and camera are just a representative set of sensors which are nowadays employed to operate a number of applications in many domains, including, among the others, health care, environmental and traffic monitoring and management [12], [13]. To illustrate with a simple example, Google exploits crowd-sourced information about smartphones locations to offer real-time view of congested traffic on roads, or its recently released Science Journal, which permits to collect and visualize data coming from smartphone sensors [14].

The information acquired through MCS platforms is usually aggregated and delivered to a collector typically located in the cloud (see Fig. 1). This enables the so-called Sensing as a Service (S^2aaS) model [5], which makes the collected public data available to developers and end-users. With S^2aaS companies have no longer need to invest and acquire infrastructure to perform a sensing campaign. IoT and MCS are key enablers in the S^2aaS model. Efficiency of S^2aaS models is defined in terms of the revenues obtained from selling data versus the costs of the sensing campaign, which include costs of recruitment and compensation of the participants for their involvement [15]. Also, the users sustain costs while contributing data. These costs correspond to the energy spent from the batteries for sensing and reporting data and, eventually, the data subscription plan if cellular connectivity is used for reporting.

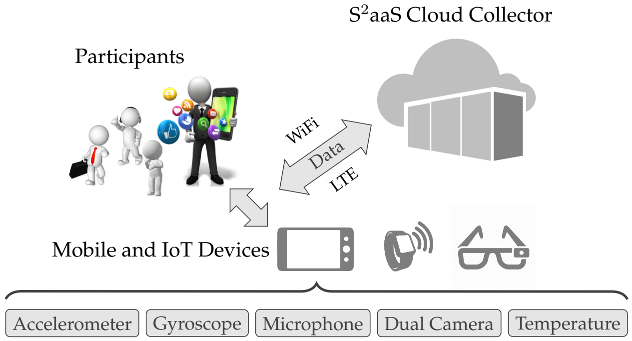


Fig. 1. Cloud-based MCS system

In MCS, data acquisition or collection, can be *participatory* or *opportunistic* [12]. In opportunistic sensing systems, the user involvement is minimal: sensing decisions are application- or device-driven. In participatory sensing systems, users are actively engaged in the sensing process. The users, also called participants in the remainder of the paper, are recruited by a central platform, which dispatches sensing tasks. Users can then decide which request to accept and, after accepting, they have to accomplish specified sensing and data reporting tasks. On one side, opportunistic sensing lowers the burden of user participation as devices or applications are responsible to take sensing decisions. Conversely, participatory sensing systems are tailored to crowdsensing architectures with a “central platform”, which facilitates system control operations like task assignment, user incentives and rewarding to compensate the participants for their contribution.

In this paper we propose CrowdSenSim, a new tool for simulating mobile crowdsensing activities in realistic urban environments. CrowdSenSim is specifically designed to perform analysis in large scale environments and supports both participatory and opportunistic sensing paradigms. CrowdSenSim allows scientists and engineers to investigate performance of the MCS systems, with a focus on data generation and participant recruitment. The simulation platform can visualize the obtained results with unprecedented precision, overlaying them on city maps. In addition to data collection performance, the information about energy spent by participants for both sensing and reporting helps to perform fine-grained system optimization.

The contribution synopsis of this paper is as follows:

- Proposal of CrowdSenSim, a simulation platform for MCS systems deployed in realistic urban environments and presentation of its design features.
- Validation of CrowdSenSim’s performance for opportunistic and participatory sensing systems.
- Application of CrowdSenSim in a public street lighting scenario, an essential service in current and future smart cities.

The paper is organized as follows. Section II illustrates the existing tools for simulation of MCS activities. Section III presents the design criteria of CrowdSenSim, highlighting its objectives and scenarios of applicability. Section IV details CrowdSenSim’s architecture. Section V presents performance evaluation and Section VI illustrates the use of CrowdSenSim for smart lighting. Finally, Section VII concludes the work and outlines directions for future work on the topic.

II. Background on Crowdsensing Simulation Tools

Currently, existing simulation tools for MCS aim either at characterizing and modeling communication aspects or define usage of spatial environment [16]. The following paragraphs overview the main properties of each tool.

Tanas et al. propose to exploit Network Simulator 3 (NS-3) for crowdsensing simulations [17]. The objective is to assess performance of a crowdsensing network taking into account the mobility properties of the nodes together with the wireless interface in ad-hoc network mode. Furthermore, the authors present a case study about how participants could report incidents in the public rail transport. NS-3 provides highly accurate estimations of network properties. However, having detailed information on communication properties comes at the expense of scalability. First, it is extremely difficult to perform simulations with a number of users contributing data in the order of tens of thousands. Second, the granularity of the duration of NS-3 simulations is typically in the order of minutes. It reflects the objective to capture insights into the behavior of communication protocols such as TCP, which becomes too detailed as typical duration of a sensing campaign is in the order of hours or days.

In [18], Farkas and Lendák present a simulation environment developed to investigate performance of crowdsensing applications in an urban parking scenario. Although the application domain is only parking-based, the proposed solution can be applied to other crowdsensing scenarios. The simulation scenario considers drivers as type of users that travel from one parking spot to another one. The users are the sensors that trigger parking events.

Mehdi et al. propose CupCarbon [19], which is a discrete-event wireless sensor network (WSN) simulator for IoT and smart cities. One of the major strengths is the possibility to model and simulate WSN on realistic urban environments through OpenStreetMap. To set up the simulation, the researchers are required to individually deploy on the map the various sensors and the nodes such as mobile users, gas and media sensors and base stations. Therefore, the approach is suitable for experiments with scenarios comprising up to hundreds of nodes.

III. CrowdSenSim: Design Principles

This section presents CrowdSenSim in a nutshell, highlighting the principles of the design, its objectives and the scenarios of applicability. Performing simulations in complex environments, such as modern cities, requires the simulation platform to be scalable. In other words, it should not limit the researcher in the choice of key parameters such as the simulation period or the number of users.

Scalability: For proper operation, MCS systems require a large number of contributors. Therefore, CrowdSenSim is designed to take into account participants in the order of tens of thousands that move in a wide realistic urban environment. Each individual can potentially own several mobile and IoT devices. The time dimension is also important. The duration of a sensing campaign can range from hours to days and CrowdSenSim addresses this challenge efficiently. For instance, let us consider 10 000 users producing data with a duration of only 30 minutes per day. Using commonly available sensors on the market like an accelerometer working at 50 Hz frequency 12 bits long samples, the total amount of generated data by each user would be 1.35 GiB. Considering the prolonged duration of the user contribution and additional sensors would considerably augment this figure.

Realistic urban environment: CrowdSenSim relies on realistic urban environments, which makes the simulator flexible and easy to be adopted in any city. Furthermore, it allows to perform analysis that provide meaningful insights to municipalities to understand the feasibility and the potential of public services employing MCS techniques. Simulations over a grid or a square area as abstraction levels lower the complexity, but do not allow taking into account important features such as movements in real streets and physical obstacles such as buildings. CrowdSenSim incorporates this feature allowing users to include the layout of cities as input.

User mobility: Human mobility is defined as sequences of spatiotemporal user movements. Understanding human mobility in an urban environment is crucial to design mobility patterns that meet social behaviors and scale to the requirements of modern smart cities [20]. CrowdSenSim includes a number of human mobility patterns designed for pedestrian mobility in urban environments.

Costs of Sensing: The sensing activity impacts the energy budget of the participants' mobile devices. CrowdSenSim is able to capture the energy directly spent for the sensing tasks as well as the energy spent for communications. IoT and mobile devices are equipped with several communication technologies, including 3G/LTE, WiFi and Bluetooth. Battery usage of the mobile devices differs with respect to the communication technology, and can have associated costs (e.g., users have a limited monthly plan) [21].

IV. The CrowdSenSim Architecture

The architecture of CrowdSenSim follows the design specifications illustrated in Section III, implementing independent modules to characterize the urban environment, the user mobility, the communication and the crowdsensing inputs, which depend on the application and specific sensing paradigm utilized. Fig. 2 shows graphically the relations between the modules, and Table I lists description of symbols that are explained in detail hereafter.

TABLE I
SYMBOLS LIST AND DESCRIPTION

Symbol	Description
C	Set of coordinates defining the city layout
T_{move}	Amount of time each user moves in the city
S_{move}	Velocity of user movement
c_a	Coordinate where a user starts moving
t_a	Time when a user starts moving from c_a
c_{next}	Next coordinate of user movement
t_{next}	Time of arrival in the next coordinate c_{next}
t_{travel}	Time necessary to move between two coordinates
E	Energy spent for communication purposes
P_{tx}	Power consumed for transmission over WiFi link

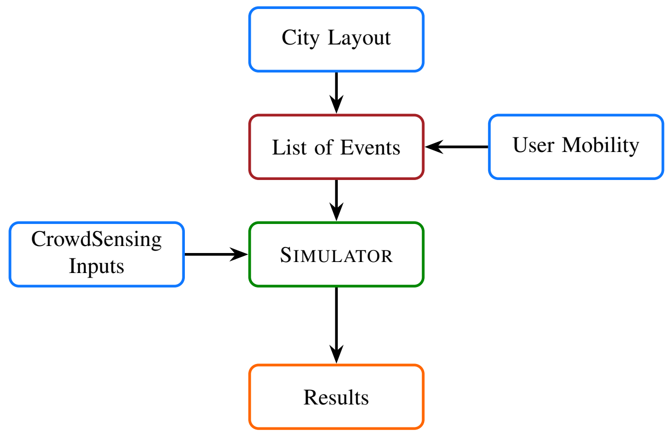
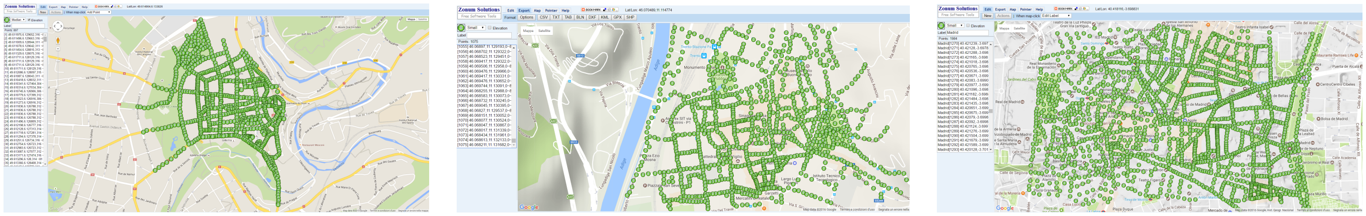


Fig. 2. Main modules of CrowdSenSim

A. City Layout Module

The module in charge of defining the city layout allows the researcher to input into the simulator the city where simulations will be performed. Specifically, the layout of the city is defined in terms of a set of coordinates C containing information on *<latitude, longitude, altitude>*. The set of coordinates compose the streets of the city where the users will move during simulation runtime and can be obtained with online tools like OpenStreetMaps or DigiPoint. In this version of the simulator, we rely on Digipoint, which is a crowdsourced application providing free access to street-level maps [22]. Fig. 3 shows the urban environments currently available for simulations, namely the city center of Luxembourg (see Fig. 3(a)), Trento (see Fig. 3(b)) and Madrid (see Fig. 3(c)). The center of Luxembourg city covers an area of 1.11 km^2 with a population of 110 499 inhabitants as of the end of 2015 and is the home of many national and international institutional buildings. The city center of Trento occupies an area of 1.18 km^2 and has a population of 117 317 inhabitants as of the beginning of 2016 and is the capital of the homonym Province. The city center of Madrid covers approximately an area of 5.23 km^2 with a resident population of 149 718 residing inhabitants.

The city layout module allows the researcher to define the size of the city and the level of detail of the urban environment. High resolution of the city layout, which corresponds to choose a higher number of coordinates, increases the precision of user movements at the cost of longer and more computationally expensive simulations. Viceversa, a coarse resolution of the city layout makes the simulations to run faster, but lowers the accuracy of users movements and precision of the urban environment. The latter component is important: having a high resolution of the urban environment permits to characterize places, e.g., to identify among the others bars, restaurants,



(a) Luxembourg (b) Trento (c) Madrid

Fig. 3. Maps of cities obtained from DigiPoint

schools or hospitals.

B. User Mobility Module

The user mobility module defines the spatiotemporal properties of user movements in the urban environment, which compose the so-called *list of events* (see Fig. 2). We define an *event* as "the arrival of an user in a given coordinate at a given instant of time."

The module defines the following steps to determine the spatiotemporal list of events:

- *Initialization*: it characterizes the *location* and *time* of user arrival.
- *Mobility*: it characterizes the user movements after arrival.

1) Initialization: This initial step is in charge of determining where and when each user starts moving in the city. Each user arrival is therefore characterized by a coordinate c_a and time t_a. In the current version of the simulator, the location is randomly determined among the set of coordinates C of the map. The design choice builds on the assumption that each of the coordinates has the same relevance, i.e., it does not exist a difference between popularity of places. Future implementations will allow the researchers to choose between random and popularity-driven assignment of user location. The time of user arrival can be either randomized or based on real-world traces, which are the results of a study on pedestrian mobility and are public available on Crawdad (ostermalm_dense_run2) [23]. Fig. 4 shows the probability density function of the user arrival resulting from the study of the traces. In practice, to obtain the results presented later in Section V-A2, the density computed in Fig. 4 was adapted to an arrival time period between 8:00 AM - 1:40 PM instead of 720 s and for 20 000 users. The probability density function of user arrival is indeed determined by two global simulation inputs: the total number of users in the system and the simulation period. In random user arrival modes, the default probability density function is uniform, i.e., during the simulation period each minute has the same probability to be chosen as arrival time for each user. The researcher can easily modify the user arrival time by changing the probability density function. In the case study presented in Section VI, we will present a modification of the probability density function of user arrival suitable for the application of public street lighting.

2) Mobility: In the default setting, each user moves over the set of coordinates C for a predefined amount of time T_{move} which is uniformly distributed between $[10, 20]$ minutes

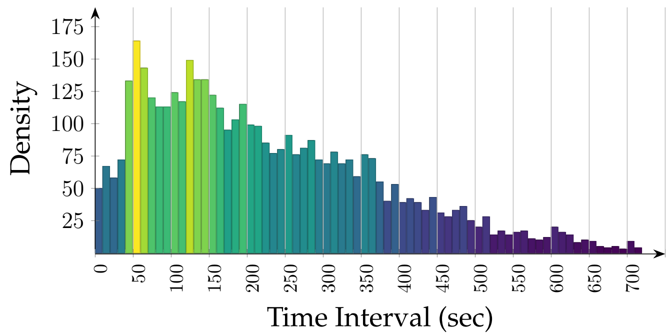


Fig. 4. User distribution of mobility trace "kth/walkers"

with an average speed S_{move} uniformly distributed between $[1, 1.5]$ m/s. The default setting can be easily modified. After the arrival in c_a at time t_a, the next move makes the user to *jump* in c_{next} at time t_{next}. The simulator chooses c_{next} to be physically in proximity of c_a, i.e., CrowdSenSim chooses a coordinate among C which is on the same street or square with distance below a maximum radius. No obstacles are considered between the move from one coordinate to another one. Once c_{next} has been determined, the simulator computes t_{next} on the basis of the physical distance between c_a and c_{next} and the speed of the user. The distance is computed by using the Haversine formula [27] and, along with the speed of the movements, permits to determine the amount of time it takes between the two points t_{travel}. Then, t_{next} is determined as follows:

$$t_{\text{next}} = t_a + t_{\text{travel}}, \tag{1}$$

and the total amount of time the user is allowed to travel T_{move} is updated as follows:

$$T_{\text{move}} = T_{\text{move}} - t_{\text{travel}}. \tag{2}$$

The user stops moving when $T_{\text{move}} \leq 0$. It is worth to highlight that during each movement the speed of the movement S_{move} changes. The new value is generated again uniformly distributed between $[1, 1.5]$ m/s to mimic the change of velocity during walking.

In the current version, users move only once during the simulation period, and it is not possible yet to define a direction of movement for each user. We plan to extend the simulator to take into account this possibility in the future extension of this study.

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TABLE II
SENSOR AND COMMUNICATION EQUIPMENT PARAMETERS USED FOR PERFORMANCE EVALUATION

SENSOR	PARAMETER	VALUE	UNIT
Accelerometer	Sample rate	50	Hz
	Sample size	12	Bits
	Current	35	μA
Temperature	Sample rate	182	Hz
	Sample size	16	Bits
	Current	182	μA
Pressure	Sample rate	157	Hz
	Sample size	16	Bits
	Current	423.9	μA

(a) Sensor Equipment [24], [25]

SYMBOL	VALUE	UNIT	DESCRIPTION
ρ_{id}	3.68	W	Power in idle mode
ρ_{tx}	0.37	W	Transmission power
ρ_{rx}	0.31	W	Reception power
λ_g	1000	fps	Rate of generation of packets
γ_{xg}	$0.11 \cdot 10^{-3}$	J	Energy cost to elaborate a generated packet

(b) Communication Equipment [26]

C. Crowdsensing Inputs Module

This module defines the inputs specific to crowdsensing analysis. CrowdSenSim relies on two types of inputs. The first set does not depend on the sensing paradigm employed and comprises all the parameters related to sensing and communication operations. The second set includes parameters that are specific to the participatory sensing paradigm. Unlike the opportunistic sensing paradigm which does not have particular input parameters, in participatory systems it is necessary to define the concept of task and how to assign tasks to users.

Sensing and Communication Parameters: In CrowdSenSim, data generation takes into account sensors commonly available in current IoT and mobile devices. Table II presents the detailed information on sensors and communication parameters. Specifically, CrowdSenSim generates sensing readings from the FXOS8700CQ 3axis linear accelerometer from Freescale Semiconductor [24] and the BMP280 from Bosch [25], which is a digital pressure and temperature sensor. For a worst scenario analysis, in the default settings the sensors keep generating data according to their sampling frequency for the entire period of users movements.

For communication purposes, the current version of the simulator employs only WiFi technology. Based on the sample resolution of the sensors, data is first organized in packets of 1 500 Bytes and delivered to the collector continuously during users movements. Each user transmits data to the closes WiFi Access Point (AP). The APs are characterized by <*latitude, longitude*>, not necessarily from the set C. For the city of Luxembourg, the precise location of WiFi APs was obtained from an online tool[1].

Parameters for Participatory Sensing Paradigm: CrowdSenSim defines the following properties for tasks: location, time of deployment, duration and coverage. With the default settings, all the parameters are randomly selected from the set of coordinates C, uniformly distributed within the simulation period and as fraction of the simulation period for location, time of deployment and duration respectively. The task coverage defines the maximum radius where users can actively contribute to the task and is fixed for all the tasks. The researcher can also provide a file in input to the simulator describing the aforementioned properties.

[1]Online: https://www.hotcity.lu/en/laptop/www/About/Wi-Fi-coverage

D. Simulator and Results

During simulation CrowdSenSim computes runtime a number of statistics, including energy consumption and amount of data generated and provides the researcher to a visualization tool to display the results. For example, with the help of Google Heatmap tool[2], CrowdSenSim draws on the real maps the most populated tasks or most utilized WiFi APs. To illustrate considering the former case as an example, CrowdSenSim collects statistics about the number of users recruited for each task. At the end of the simulation period, it outputs these statistics along with the location of each task in terms of latitude and longitude. The result obtained is then employed as input of the Google Heatmap tool (see Fig. 5).

The energy E spent for communication purposes is computed as follows. E is consumed during a transmission time τ_{tx} and is defined as:

$$E = \int_0^{\tau_{tx}} P_{tx}\,\mathrm{d}t, \tag{3}$$

where P_{tx} is the power consumed for transmissions of WiFi packets generated at rate λ_g [26]:

$$P_{tx} = \rho_{id} + \rho_{tx} \cdot \tau_{tx} + \gamma_{xg} \cdot \lambda_g. \tag{4}$$

V. PERFORMANCE EVALUATION

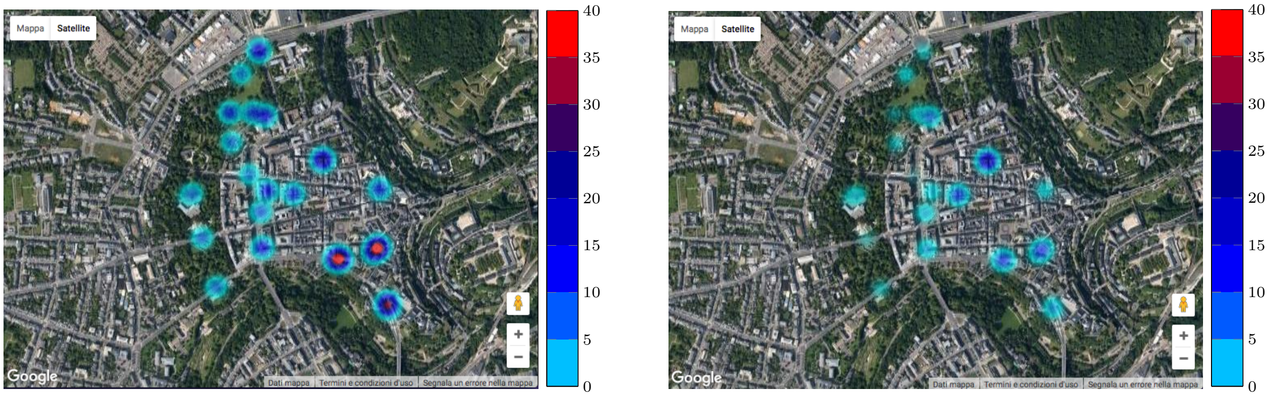
This section provides performance analysis of CrowdSenSim. First, the results obtained for participatory and opportunistic sensing systems are illustrated, with a focus on participant recruitment for the former sensing paradigm and energy consumption and amount of data collected for the latter sensing paradigm. Second, technical evaluation of the simulator is shown, with a focus on CPU, processing time and memory utilization.

For performance evaluation, the simulations are carried out using a Linux workstation equipped with Ubuntu 14.10. Furthermore, the machine supports an Intel ®Core ™ i3 2.27 GHz CPU and a system memory of 1916 MiB.

A. Analysis of Participatory and Opportunistic Crowdsensing Scenarios

1) Participatory Sensing Scenario: In the participatory sensing scenario, we employ CrowdSenSim in the context of

[2]Online: https://developers.google.com/maps/documentation/javascript/examples/layer-heatmap



(a) SDRP Policy

(b) DBRP Policy

Fig. 5. User recruitment for sensing tasks deployed in the city of Luxembourg

TABLE III
SIMULATION SETTINGS FOR ANALYSIS OF PARTICIPANT RECRUITMENT POLICY

PARAMETER	VALUE
Number of users	[10 000]
Overall evaluation period	8:00 AM - 2:00 PM
Time of travel per user	Uniformly distributed in [10, 20] min
Average user velocity	Uniformly distributed in [1, 1.5] m/s
Timeslot duration	1 minute
Task duration	30 timeslots
Number of tasks	25
$D_{\max}$	30 m

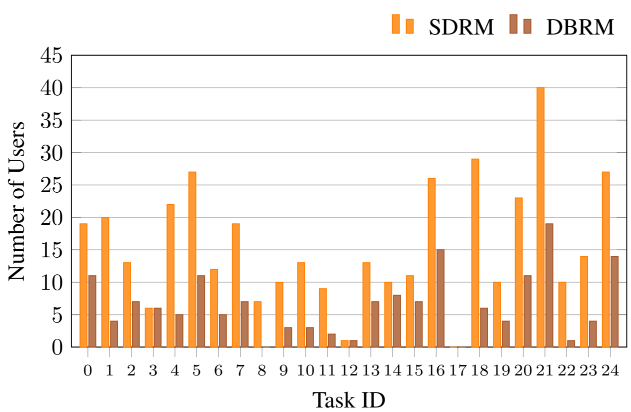


Fig. 6. Number of recruited users using SDRM and DBRM

participant recruitment and to implement a policy defining user recruitment and task assignment [15]. Devising proper recruitment policy is important: on one hand, it allows the organizer to minimize the expenditure, while on the other hand, it helps to choose the users that will successfully carry out the sensing task. For example, in the public safety context, it is essential to select users to maximize the trustworthiness of collected data [28]–[30]. Such policy can be employed using *distance-based recruitment mode* (DBRM) or *sociability-driven recruitment mode* (SDRM). In DBRM, the spatial distance between the users and the sensing task is the discriminant factor defining user eligibility. Users far from the sensing task i more than $D_{\max}$ are never considered as potential contributors in that task. In SDRM, the user sociability, defined as amount of data users consume or the time they spend using mobile social network applications [31], is the discriminant factor for the recruitment.

Table III lists the details of the simulation set-up. We employ CrowdSenSim for demonstration purposes to visualize the distribution of user recruitment and refer the reader for further details on the results to [15]. Fig. 5 compares the number of users recruited in SDRM and DBRM for all the deployed 25 tasks in Luxembourg city center using the Google Heatmaps tool. Tasks with higher number of users recruited are marked with a bigger radius and with brighter and more intense colors. Fig. 6 shows that SDRM outperforms DBRM as the number of recruited users is higher for all the deployed tasks. Moreover, for task with ID equal to 8, the SDRM is able to recruit users where the DBRM fails.

2) Opportunistic Sensing Scenario: In the opportunistic sensing scenario, users contribute continuously data even if they do not receive a specific task. In this context, CrowdSenSim is employed for evaluation of data generation with a fixed the number of participants set to 20 000. The objective of the experiment is to assess during the simulation period from 8:00 AM to 2:00 PM the energy consumption attributed to sensing and reporting operations and the amount of generated data. The analysis is carried under the two different user arrival patterns. Users move according to the predefined settings illustrated in Section IV-B. In the first user arrival pattern, the starting time of the walk is uniformly distributed between 8:00 AM and 1:40 PM to allow users starting moving towards the end of the period to correctly end their journey at 2:00 PM. The second arrival pattern is based on the data set with traces of pedestrian mobility (ostermalm_dense_run2) [23].

Energy Cost for Sensing and Reporting: Fig. 7 presents the distribution of users and their energy spent for sensing with the uniform and traces-based user arrival patterns. For demonstration purposes, we show the results obtained for the sole city of Luxembourg. As expected, the user arrival pattern does not influence the energy consumption, which only depends on the amount of time the users generate data. As the users contribute data for time periods as low as 10 minutes up

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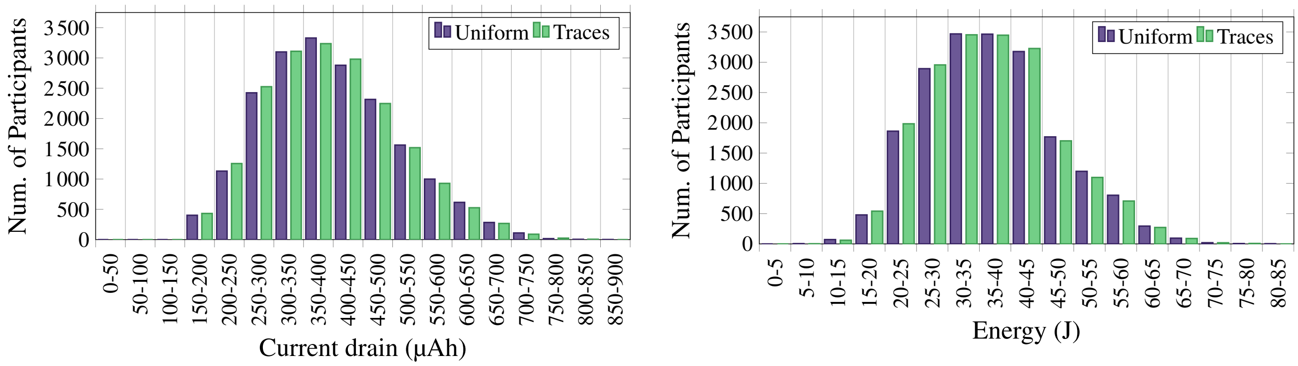

(a) Sensing Cost

(b) Communication Cost

Fig. 7. Energy spent for sensing and communication

to time periods of a maximum of 20 minutes, the profiles of Fig. 7(b) and Fig. 7(a) follow a normal distribution. Current drain of sensing operations is on average 373.41 µAh and 368.80 µAh for uniform and traces-based arrival patterns. In the worst case, few users experience a cost that is nearly more than double with respect to the average. Comparing to the battery capacity available in modern smartphones, which is in the order of 2 000 mAh, it is possible to conclude that the energy cost for sensing is negligible with respect to the energy spent for communications (see Fig. 7(b)).

Amount of Data Collected: The amount of information reported by users devices is unveiled in the following experiments, which evaluate the amount of data generated per single sensor for the two different user arrival patterns and the distribution of the data collected.

Fig. 8 shows the total amount of data collected along with the simulation period for the two user arrival patterns. As expected, the amount of data is proportional to the sampling frequencies of the three considered sensors. Recalling that each user contributes only during a short period of time (from 10 to 20 minutes), the amount of collected information is considerable. For example, 20 000 users arriving according to the uniform arrival pattern would generate 2.62 GiB, 12.71 GiB and 10.96 GiB for the accelerometer, temperature and pressure sensors respectively. Fig. 8(a) shows the results for the uniformly distributed arrival pattern. As expected, the amount of contribution remains constant after the initial set up as the number of users arriving in a given time window is constant along the simulation period. Fig. 8(b) illustrates the results for the user arrival pattern based on the data set. Unlike the previous case, the shape of the curve follows the probability density function of the traces as in Fig. 4.

Having the knowledge on the amount of data the users can contribute is important, but for more precise evaluation it is also fundamental to determine where and when these samples are generated. CrowdSenSim provides the researchers the capability to graphically visualize the data generation process. With a number of users set to 20 000, Fig. 9 shows the geographical distribution of the amount of collected data at the end of the simulation period for Luxembourg, Trento and Madrid. To better analyze the data generation process, we define a new performance metric, called Sample Distribution Coefficient (SDC), which measures the amount of generated samples per meter and is defined as follows:

$$\mathrm{SDC} = \frac{N_t}{\overline{\Delta}}, \tag{5}$$

where $\overline{\Delta}$ is the average distance between samples and N_t is the number of samples generated during the time period t. The parameter $\overline{\Delta}$ is defined as follows:

$$\overline{\Delta} = \frac{\sum_{\substack{i,j \\ i \geq j}}^{n} d(i,j)}{\frac{n(n-1)}{2}}. \tag{6}$$

The term $d(i, j)$ is the distance (in meters) between the location where the samples i and j were generated and the denominator accounts for the number of pairs of samples. SDC can be computed at any temporal and spatial resolution. The time granularity can be fine or coarse, e.g., minute, hour or day whereas the spatial granularity can be at block-, district- or even city-level. For example, SCD can be employed to analyze the per-hour data generation process in a downtown district vs suburban district.

Fig. 10 shows the distribution of SDC for Luxembourg, Trento and Madrid for the entire simulation period. In this experiment, the users are located with the uniform arrival pattern. It is interesting to notice that the lowest values of SDC occur for the initial and final time intervals (8:00 AM - 9:00 AM and 1:00 PM - 2:00 PM). During the initial and final time intervals the number of participants is lower than in the other intervals as the simulator locates the users with a uniform distribution between 8:00 AM and 1:40 PM and they move for at maximum 20 minutes. Having set the same number of users for the experiment, the relation between the SDC coefficient and the size of the area considered is inversely proportional. The city center of Luxembourg is smaller than Trento and Madrid. As a result, the obtained SDC value for Luxembourg is higher.

B. Performance of the Simulator

This section provides a technical evaluation of the simulator performance. The metrics evaluated concern processing time, CPU and memory utilization.

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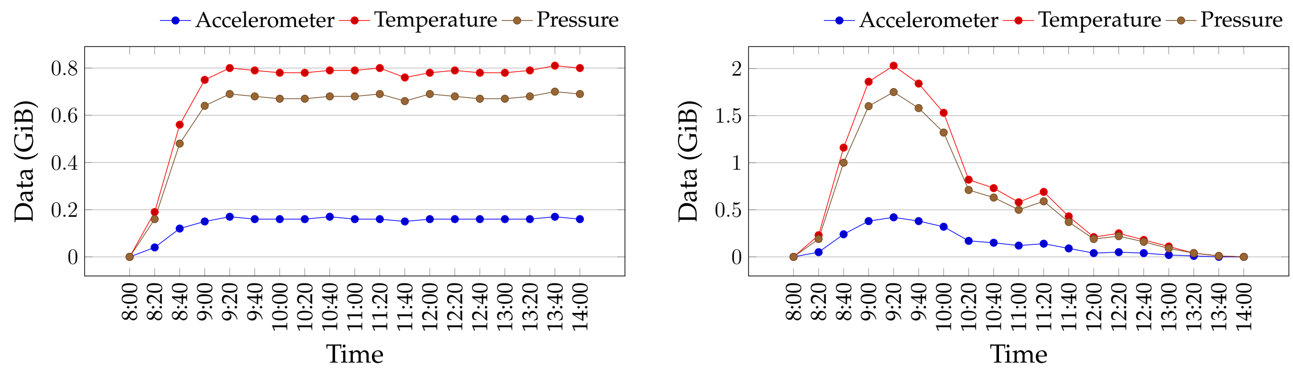
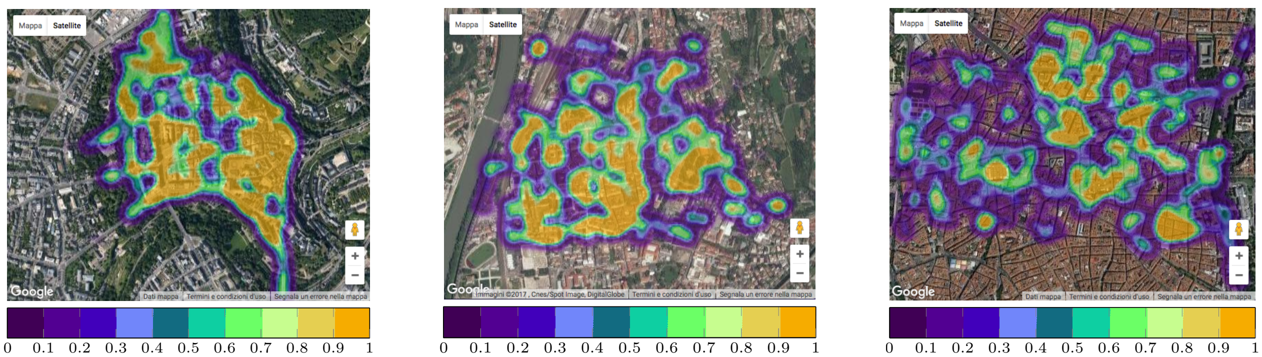


(a) Arrival pattern with uniform distribution

(b) Arrival pattern based on traces

Fig. 8. Amount of data generated

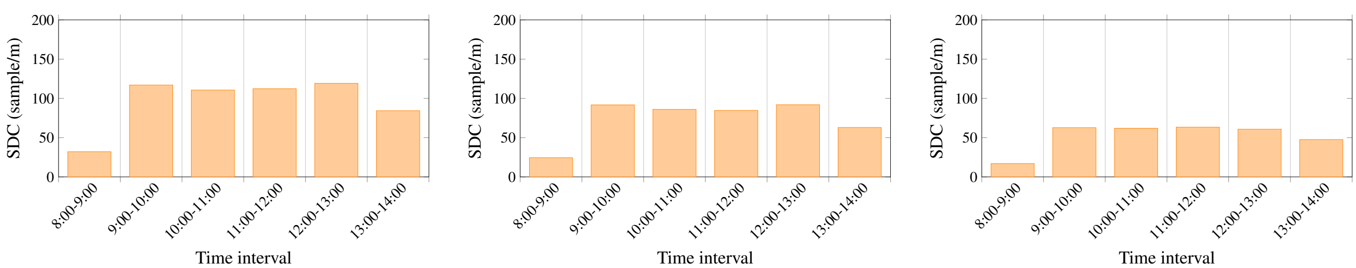


(a) Luxembourg

(b) Trento

(c) Madrid

Fig. 9. Normalized distribution of amount of collected data for the different cities over the time period 8:00 AM - 2:00 PM



(a) Luxembourg

(b) Trento

(c) Madrid

Fig. 10. Sample Distribution Coefficient for the different cities over the time period 8:00 AM - 2:00 PM

Fig. 12 shows the profile of the CPU utilization expressed in percentage obtained with the `dstat` tool[3]. The experiment analyzes the performance in a scenario with a huge number of users, 100 000, in the city of Luxembourg. The statistics obtained have been filtered to spot the profile of the process running the simulation. The resulting graph shows that the CPU utilization can occupy as much as 25% of the available resources and this happens at the beginning where most of the computation occurs to process the events.

The next set of experiments aims at assessing the performance of processing time and memory occupancy. Unlike the previous result, these experiments are carried out deploying CrowdSenSim in a Virtual Machine (VM) running Ubuntu 14.10 with two different profile settings, namely 1024 MiB and 2048 MiB of memory. The setting allows us to profile the performance of the simulator perceived by the end users. The VM is equipped with GNOME System Monitor which permits to verify the system performance. Fig. 11 shows an example for a simulation with 20 000 participants in opportunistic sensing scenario. Fig. 13 shows the results obtained. Both experiments were performed for the city of Luxembourg, with both VMs configurations and with an increasing number of participants from the set $\{1\,000, 5\,000, 10\,000, 20\,000, 50\,000, 70\,000, 100\,000\}$. The maximum number of users was selected consistently with the population of the city. Fig. 13(a) analyzes the processing time, which remains almost constant for a number of participants lower than 10 000 and then it increases exponentially for both the configuration settings. Fig. 13(b) analyzes the memory

[3]Available on: http://dag.wiee.rs/home-made/dstat/

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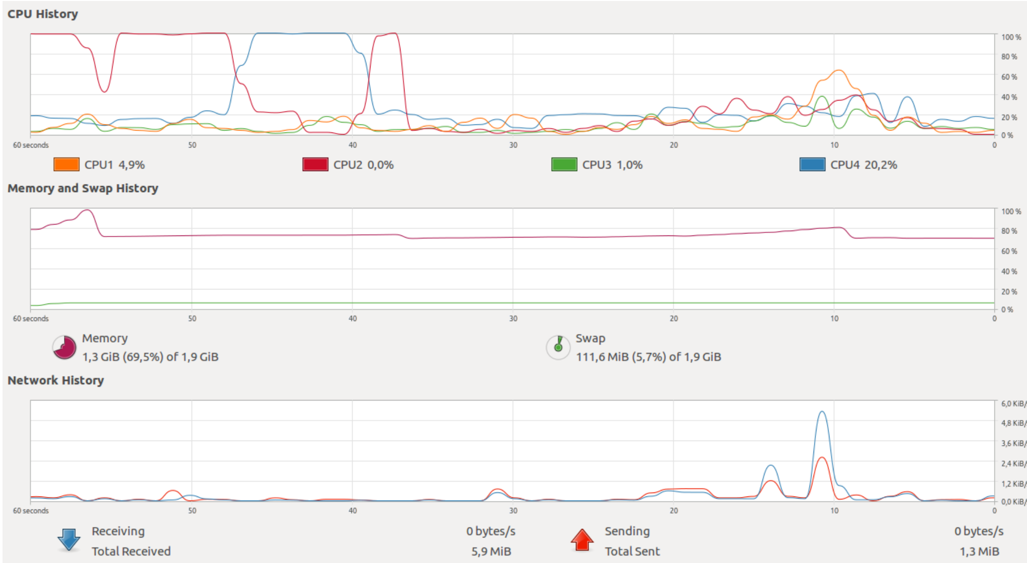

Fig. 11. GNOME System Monitor

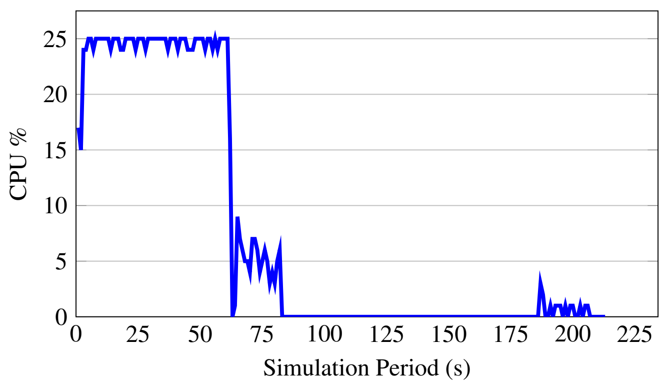

Fig. 12. CPU utilization for a simulation run with 100 000 users

consumption with a focus on the Resident Set Size (RSS), which defines the amount of memory the process occupies in the RAM. For both configurations of the VM, the RSS remains almost identical for a number of participants lower than 20 000, then the process tends to occupy as much as possible all the available resources.

VI. Case study: Smart Lighting

CrowdSenSim is a candidate tool for analysis of smart city services. This section presents a case study where the simulator is employed to assess the performance of public street lighting. However, the capabilities of the simulator are not restrained to this particular application scenario. We are currently working to extend the simulator capabilities to include vehicles as contributors to the data collection process and to analyze other important and challenging issues of modern cities, e.g., waste management. Waste management involves the whole process of monitoring waste locations, truck routes, collection phases and waste disposal.

A. The problem of Smart Lighting in Modern Smart Cities

Public lighting is a traditional city service provided by lampposts widely distributed in streets and roads. Lighting causes nearly 19% of worldwide use of electrical energy and entails a 6% of global emissions of greenhouse gases. A decrease of 40% of energy spent for lighting purposes is equivalent to eliminate half of the emissions from the production of electricity and heat generation of the US [32]. Specifically, public street lightning, which is an essential community service, impacts for around 40% on the cities' energy budget. Consequently, in preparation of the EU commitments, optimizing the lighting service is a primary objective for the municipalities [33].

The street lighting solutions currently implemented in cities are not energy efficient. Typically, every lamp operates at full intensity 12 hours a day on average: 8 hours during summer and 14 hours during winter period [33]. As a result, the costs the municipalities sustain are high [32]. A number of different types of lamps are applicable for public street lighting, including High Pressure Sodium (HPS), Metal-halide (MH) lamps, Compact Fluorescent lamps (CFL) and Light-emitting diode (LED). LEDs have an average lifetime 4 times longer than HPS lamps and 10 times longer if compared to MH lamps. Installing LEDs is effective to reduce hardware, installation and maintenance costs. Low wattage provides significant energy savings and allows increasing the lamp efficiency [34], [35]. The HPS lamps do not support dimming and only LEDs can be employed to perform dimming properly. The use of LEDs is gradually gaining popularity due to its photo metric characteristics, such as low weighted energy consumption (kW/1000hrs), high luminous efficacy (lm / W), high mechanical strength, long lifespan and reduction of light pollution. LED lamps can dim the light intensity by more than 50% modifying therefore the output level of light according to the circumstances. For example, when traffic is low or in rarely visited areas of the city, like the parks at night. The

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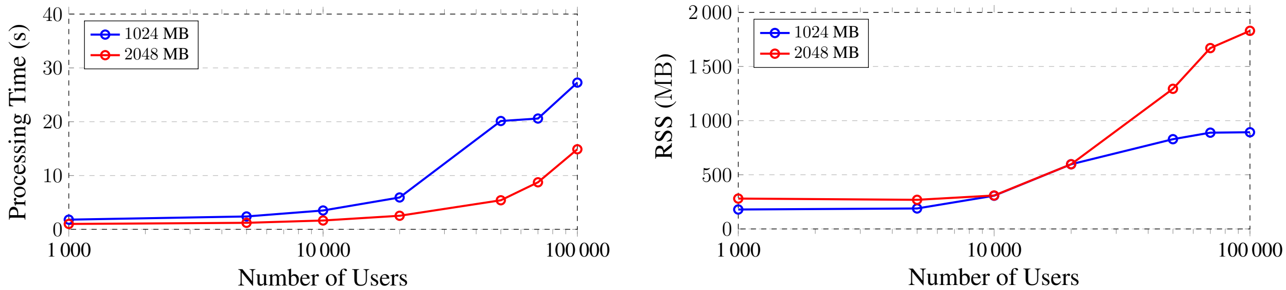

(a) (b)

Fig. 13. Analysis of a) processing time and b) memory with increasing number of users

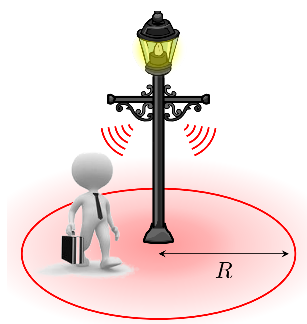

Fig. 14. Coverage radius R. The presence of sensors at the lampposts enables recognition of citizens within a radius of R.

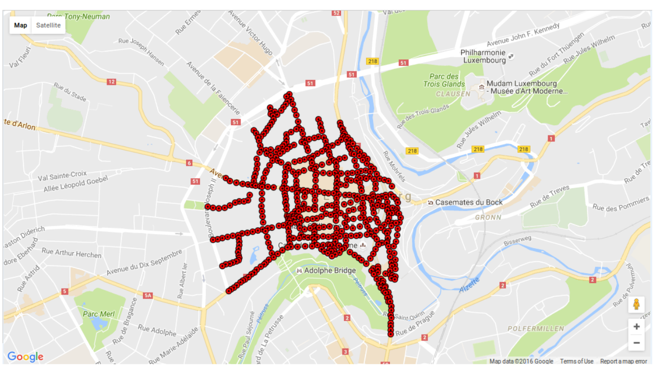

Fig. 15. Position of lampposts in Luxembourg city center

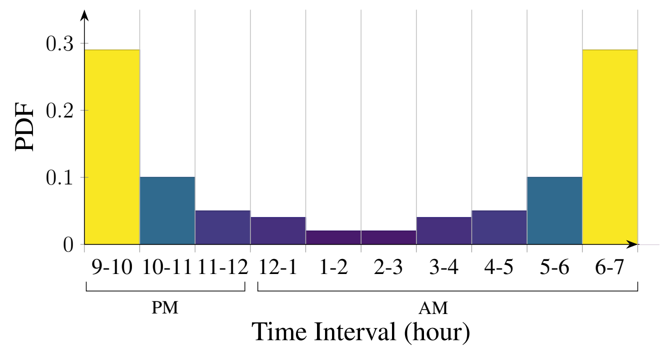

Fig. 16. Probability density function of user mobility during the evaluation period. Probability of a user to change their location is higher in early morning or late evening hours.

city of Brittany in France, dims street lights by 60% between 11:00 PM and 5:00 AM to decrease waste energy [33].

We devise a smart lighting method for smart cities which dims the light of lampposts in proportion to the number of users in the vicinity. To detect the presence of users nearby the lampposts a presence sensor like the SE-10 PIR motion sensor is assumed to be installed on site [36]. With presence sensors, every lamppost is able to recognize the presence of citizens within a certain radius R like illustrated in Fig. 14. Similarly to the solution adopted in Brittany, i.e., the minimum light intensity level is 60% if no users are within the coverage radius R and increases or decreases proportionally on the basis of the passage of the users. In more details, if the number of users is increasing, then the light intensity increases or remains at 100%, while if the number of users reduces from previous status, then the light intensity diminishes until it reaches the minimum level.

B. Evaluating Smart Lighting Solutions with CrowdSenSim

To evaluate the proposed smart lighting solution with CrowdSenSim, a set of 537 lampposts has been deployed according to their physical location in the streets and squares of Luxembourg City. Fig. 15 details the position of each lamppost given in terms of coordinates *<latitude, longitude, altitude>*. We compare two cases. In the proposed smart lighting solution each lamp is equipped with LED technology and at full light intensity consumes 82.7 kW/1000hrs. In current implementation, each lamp is equipped with HPS technology consuming 172.7 kW/1000hrs at full light intensity.

The number of users moving in the city is set to 5 000. Each of them walks for a period of time that is uniformly distributed in $[10, 20]$ minutes with an average speed uniformly distributed between $[1, 1.5]$ m/s. The users begin walking according to a specific arrival pattern. During the evaluation period, set between 9:00 PM and 7:00 AM, each user has a probability to start traveling that is defined by the probability density function (PDF) illustrated in Fig. 16. In more details, during 9:00 PM and 10:00 PM nearly one third of the total number of users starts walking and at 7:00 AM all 5 000 users end traveling.

Fig. 17 shows the results of the lamppost activity obtained through CrowdSenSim. On average, the smart lighting solution with LED technology and light dimming saves nearly 68% of energy consumption with respect to the current adopted

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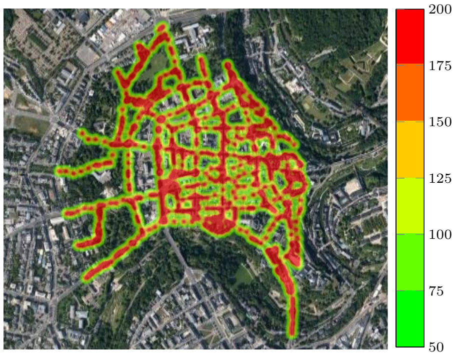
(a) Lampposts activity with LEDs



(b) Lampposts activity with current technology method

Fig. 17. Heatmap of lampposts activity (values in kWh)

solution. Indeed, the set of lampposts consumes on average 298.5 kWh per day with dimming and a fix amount of energy of 927.4 kWh per day with current implementation.

VII. Conclusion

In this paper we presented CrowdSenSim, a simulation platform for MCS systems. CrowdSenSim is tailored to assess sensing activities in large-scale realistic urban environments and is designed to output results on participant recruitment, data generation and the cost sustained for sensing and reporting from the users point of view. We also demonstrated the suitability of the simulator for analysis of smart city services with a case study on public street lighting. CrowdSenSim is distributed as public available software.[4]

For future work, we plan to validate simulation results CrowdSenSim generates with experimental data obtained from existing crowdsensing platforms. Future development directions are twofold. First, we plan to implement a more sophisticated and accurate communication model to analyze in more details the networking aspects of MCS systems. Second, we plan to develop a function to allow researchers to define directions of user movements on individual basis. Future research directions will exploit CrowdSenSim to investigate other important city services such as smart waste management and extend the simulator to operate in vehicular environment, where vehicles contribute to the process of data generation in addition to mobile devices. The current trend sees automotive companies to increase on-board equipment of vehicles with storage, computing capabilities and a growing set of sensors. Data collected by these sensors is not only beneficial for the operation of the vehicles and monitoring of their status, but is projected to become a precious source of information for municipalities as well.

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