A User-enabled Testbed Architecture with Mobile Crowdsensing Support for Smart, Green Buildings

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Abstract

We present an IoT testbed architecture for Smart Buildings that enables the seamless and scalable integration of crowd-sourced resources such as smartphones and tablets. The purpose of this integration is dual. First, the embedded sensory capabilities of the resources provided by the crowd are combined with the sensing capabilities of the building for efficient smart actuations. Second, the system is able to interact with its users in a direct, personal way both for incentivising them to provide sensory data from their devices and to receive feedback on their preferences and experienced comfort. The above are exposed to the experimenter as a set of services thus providing great agility on developing and evaluating a broad range of use case scenarios. We demonstrate this flexibility by deploying a testbed in the premises of a building and by evaluating several crowd incentive policies in the context of a smart luminance scenario. The scenario is based on Participatory Sensing principles to create live luminance maps, aggregate user preferences and accordingly adjust the luminance units.

I. INTRODUCTION

Technological advances during the past decade in the field of embedded systems have driven the rise of the Internet of Things (IoT) paradigm. The constantly increasing adoption rates of truly portable hand-held and wearable smart devices have paved the way for the Mobile Crowdsensing Systems (MCS) that seek to exploit the embedded sensory capabilities of these devices and their intrinsic mobile nature. Between the first stage of conceiving a new paradigm, by laying down its theoretical foundations, and the final stage of rolling out at full scale a new technology, there lies an intermediate phase where small scale, experimental systems are putting the vision to the test, thus providing valuable feedback. Such testing facilities bridge the gap between abstract assumptions, necessarily present when theoretically analyzing a concept, and implementation-specific limitations that emerge due to technological dependencies and real-life limitations. Various challenges regarding the design of such testbed facilities have been widely highlighted and relevant desired properties have been identified (e.g. see [1], [2] for IoT testbeds). Among these properties, the realism of experimentation environment, device and service heterogeneity and efficient service composition during the experimentation life cycle are important aspects to improve upon existing testbed facilities. Increased realism implies matching the experimentation conditions as close as possible to the typically operating situations where the final solutions are expected to be deployed. This way design flaws or imperfections can be earlier detected and evened out, thus reducing the cost of roll out and maturation time. Device and service heterogeneity offers experimenters with more experimentation options and better captures how technological environments are expected to mature at later deployment stages. Efficient service composition is thus a key requirement for efficient testing facilities. Therefore, mechanisms to control and exploit realistic experimental conditions during the evaluation phase are necessary.

Our contribution. We present an IoT testbed architecture for Smart Buildings that enables the seamless and scalable interaction of crowd-enabled resources provided by the end-users of the facility. This integration increases the awareness of the facility both in terms of sensory capabilities as well as in terms of users’ preferences and experienced comfort. Combined with smart actuation, IoT communication and networking technologies, the experimenter is provided with an agile experimenting platform. The facility exposes its operations as services thus greatly facilitating the definition and evaluation of diverse use-case scenarios. In order to demonstrate the use of the facility we design and evaluate several incentive policies in the context of a smart luminance scenario based on Participatory Sensing. First the end-users are incentivised to provide access to their hand-held devices from which data on the ambient environmental conditions are collected and aggregated into live luminance maps. Then, the indoor lighting units are dynamically adjusted based on the luminance maps and the feedback provided by the users to the system on their personal preferences and experienced comfort.

II. RELATED WORK

There have been numerous testbed facilities using wireless sensor networks as the main component of their backbone infrastructure. For instance in [3] the authors present Syndesi, a framework for creating personalized smart environments using wireless sensor networks. This framework, among other services provided, is able to identify people and take personalized actions (such as control of electrical devices) based on their personal preferences. As a proof of concept, authors present a
Fig. 1: High-level architecture

real-world deployment, where two use-case scenarios are implemented in the premises of a building. In [4], the authors present PhoneLab, a smartphone testbed that provides access to smartphone users incentivising them to participate in experiments while simplifying experiment data collection. Three selected results from a usage characterization experiment are presented. A more diverse approach is presented in [5], where the testbed deployment is focused on smart buildings, a key building block for cities of the future. The presented system combines heterogeneous IoT devices such as a programmable experimentation substrate in a real life office environment while making feasible the experimentations with real end users. Authors present the architecture of the facility and underline the considerations that motivated its design. Using several recent experimental use cases they demonstrate the usefulness of such experimental facilities for user-centric IoT research.

Early after the first smartphones were introduced, research teams started investigating the combined usage of their embedded sensory capabilities. In [6] authors recognize the opportunity of fusing information from populations of privately-held sensors as well as the corresponding limitations due to privacy issues. In this context they describe the principles of community based sensing and they propose corresponding methods. In more recent works, the authors in [7] use the notion of Participatory Sensing (PS). They consider the problem of efficient data acquisition methods for multiple PS applications while taking into consideration issues such as resource constraints, user privacy, data reliability and uncontrolled mobility. They evaluate heuristic algorithms that seek to maximize the total social welfare, via simulations that are based on mobility datasets consisted of both real-life and artificial data traces. Finally, in [8] the authors propose a utility-driven smartphone middleware for executing community-driven sensing tasks. The proposed middleware framework considers preferences of the user and resources available on the phone to tune the sensing strategy thus enabling the execution of tasks in an opportunistic and passive manner.

III. Testbed Architecture

Fig. 1 presents an overview of the IoT testbed architecture. The architecture consists of Control Cubes for converting electrical devices into IoT smart objects, a networking device operating as a network protocol bridge, Android enabled smartphones and NFC tags. The testbed also runs auxiliary services such as an indoor localization service and a Crowd Server. Below we discuss in detail the components of the architecture.

a) Control Cube: The Control Cube ( [9], [10]), is a device that enables every-day, conventional appliances and automations to join the IoT vision. By combining Future Internet Technologies (like IPv6, CoAP and the IPSO Application Framework) and off-the-shelf electrical and electronic components into an open and modular architecture, Control Cube is a low cost, easily deployable, plug-n-play solution that extends the IoT paradigm. Each Control Cube is able to provide meta-data including information on the type of the device, its state and the supported operations. Furthermore, the embedded sensors of the Control Cube are used to monitor ambient environmental conditions (i.e. temperature, relative air humidity and luminance levels). The testbed consists of four Control Cubes that control: a) four indoor light units each one controlled independently b) two electric curtains each one controlled independently c) one air-conditioning unit with support for temperature and fan control d) one ventilation unit with support for fan direction and speed control. The supported devices and sensors of the testbed and their representation are shown in Table I.

b) M2M communication: The testbed combines a diverse set of communication interfaces in order to support different classes of devices. The Control Cubes form an M2M, ad-hoc network, running the IEEE802.15.4 at the physical and MAC layers,
IPv6 protocol over 6LoWPAN and CoAP. On the other hand, Android devices carried by the users utilize the IEEE802.11 at the physical and MAC layers, the IPv4 and CoAP (Californium library, [11]). In order to enable the devices for direct communications with each other without the need for intermediate webservices, we developed a networking device that acts as a protocol bridge. This device is built around a Raspberry Pi micro-computer equipped with a USB wireless card and a TelosB sensor mote. Its role in the testbed is to set-up both a wireless sensor/actuator network and a local Wi-Fi while providing connectivity with the Internet. Consequently, by relaying traffic between the two radio interfaces and performing IPv4-to-IPv6 translation, the protocol bridge enables the ad-hoc communication among the smartphones and the Control Cubes.

\( c \) Indoor localization service: The testbed facility also provides a service for indoor localization for Android smartphone users. The service is based on four Bluetooth beacons [12], deployed at the corners of the deployment space, that act as anchor points. This way, the space is virtually tessellated into tiles [13]. Each smartphone is able to estimate its distance from each beacon via the Android Beacon Library [14] at a refresh rate of 1Hz. Then, it is able to triangulate its position inside the space and identify which tile it occupies.

\( d \) Crowd server: This component is the core of the Mobile Crowdsensing System of the testbed as it implements the Participatory Sensing functionalities. By utilizing the Socket.Io websockets [15] the Crowd server maintains a connection with the smartphones that are present in the testbed in order a) to be aware of their distribution via the indoor localization service b) to interact with the smartphones and their users in order for them to declare their preferences on desired luminance and to offer them incentives which they can either accept or reject and c) to collect ambient luminance sensor readings from the smartphones of the users that have accepted the incentive they were offered. Based on these readings, the server constructs detailed luminance maps and combines them with the user preferences in order to adjust accordingly the light units. The main functions of the Crowd server are described below.

Join. The Crowd server listens for “join” messages from the smartphones that are willing to participate. The join message contains the location of the device and the lighting preference of the user.

Send incentives. The server calculates the incentives depending on the policy that is defined, according to the devices that have already joined. Then, the server sends the calculated incentives to the corresponding devices.

Accept. The server listens for “accept” messages from the devices that have accepted the offered incentive. The users can accept the offer during a specific time window.

Decline. The server listens for “decline” messages from the devices that have declined the offered incentive. In the cases where users will not respond to the offer within the available time window they are considered to have declined it.

Start. The server sends a “start” message to the devices that have accepted the incentive offer in order to start sending their sensor values.

Revoke. The server sends a “revoke” message to the devices that have declined or not responded to the offer. Those devices are now waiting for the next round.

SensorValues. The server listens for “sensorValues” messages. Those messages contain the light level that each device measures. The server calculates the average light for each tile and acts on the average preference of the users in this tile.

Stop. The server sends a “stop” message to the devices that were participating in this round in order for them to stop sending their sensory data. All the devices are now waiting for the next round.

The testbed also provides an easy and transparent way to the user in order to set up her smartphone and start interacting with the testbed. The user simply needs to read an NFC tag or scan a QR code in order to install the application. Then, the user will be able to declare her preferences on ambient conditions, receive and reply to the incentive offers and provide information regarding her location as well as sensory data from her smartphones embedded light sensor. In the cases where no user is present in the premises of the testbed or no user is connected to it through the application, the ambient conditions of the area are set at a default level defined by the testbed itself based on the history of usage. Furthermore, the architecture of the testbed and its design makes it easily expandable both in terms of network size and in the diversity of measured parameters.

IV. MOBILE CROWDSENSING

The aforementioned architecture enables the embedded sensory infrastructure of the facility to be opportunistically augmented by integrating any available smart devices located in its area of operation. Since such devices are carried by people, the system initially incentivises their owners to provide access to their embedded sensors, as well as to provide feedback to the system. This way the facility raises its awareness on the actual conditions in the building, as well as on the comfort levels the end-users are experiencing.

A. A crowd-enabled scenario for efficient indoor lighting

In order to demonstrate the capabilities offered by the described architecture, we developed a smart luminance scenario that incorporates Participatory Sensing mechanisms. In this scenario the system tries to optimize the operation of indoor light units in terms of energy efficiency and user satisfaction via Participatory Sensing practices. Consider a planar area of interest \( S \) that abstracts a smart room. \( S \) is virtually tessellated into sub-regions or tiles each denoted by \( S_i, i \in \{1, 2, \ldots, |S|\} \). In general we assume that each tile is illuminated by one light unit which may have a binary on/off state or a dimming function. Inside the area of interest \( S \), there is a set of mobile agents \( A \) abstracting people carrying smart devices (smartphones, smart-watches, etc).
TABLE I: Smart automation and sensing devices and their URI representation.

<table>
<thead>
<tr>
<th>Device type</th>
<th>States</th>
<th>Control Cube resource</th>
</tr>
</thead>
<tbody>
<tr>
<td>4-bits 2 curtains</td>
<td>left up / 01XX</td>
<td>gpio/dout/0</td>
</tr>
<tr>
<td></td>
<td>left down / 10XX</td>
<td></td>
</tr>
<tr>
<td></td>
<td>left stop / 00XX</td>
<td></td>
</tr>
<tr>
<td></td>
<td>right up / XX01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>right down / XX10</td>
<td></td>
</tr>
<tr>
<td></td>
<td>right stop / XX00</td>
<td></td>
</tr>
<tr>
<td></td>
<td>both up / 0101</td>
<td></td>
</tr>
<tr>
<td></td>
<td>both down / 1010</td>
<td></td>
</tr>
<tr>
<td></td>
<td>both stop / 0000</td>
<td></td>
</tr>
<tr>
<td>1-bit light</td>
<td>on / 1</td>
<td>bio2/dout/x</td>
</tr>
<tr>
<td></td>
<td>off / 0</td>
<td>where x is 0,1,2,3</td>
</tr>
<tr>
<td>4-bits ventilation</td>
<td>off / 0000</td>
<td>gpio/dout/0</td>
</tr>
<tr>
<td></td>
<td>blinds open / 0010</td>
<td></td>
</tr>
<tr>
<td></td>
<td>airflow out / 0011</td>
<td></td>
</tr>
<tr>
<td></td>
<td>airflow in / 1010</td>
<td></td>
</tr>
<tr>
<td>Air-conditioning unit</td>
<td>on/off / 0001</td>
<td>gpio/pulse/0</td>
</tr>
<tr>
<td></td>
<td>temperature up / 0010</td>
<td></td>
</tr>
<tr>
<td></td>
<td>temperature down / 0100</td>
<td></td>
</tr>
<tr>
<td>Ambient sensors</td>
<td>sensor value</td>
<td>sh, st, sv</td>
</tr>
</tbody>
</table>

Each agent is denoted by $A_j$, $j \in (1, 2, ... |A|)$. Due to the indoor localization capabilities of the testbed, at each given time the tile in which each agent is present is known to the system. Based on how often and for how long each agent is present in the testbed area, we categorize her either in the set of regular agents that have a long and concise record of presence or in the set of visiting agents that their presence tends to be more ephemeral. Furthermore, each agent demonstrates a level of trustworthiness towards the system in terms of actually fulfilling her commitment to provide access to their smartphone and meaningful data when agreeing to do so in return for an incentive. The system maintains for each agent $A_j$ a corresponding indicator $f_{ame}^j$, and initially each agent is equally trusted by the system. Then, depending on whether each agent fulfills her commitment to provide access to her smartphone or not, the system adjusts this indicator. In particular:

$$f_{ame}^{j+1} = \begin{cases} f_{ame}^j - \gamma, & \text{if the agent participates and does not fulfill her commitment} \\ f_{ame}^j + \gamma, & \text{if the agent participates and fulfills her commitment} \\ f_{ame}^j, & \text{if the agent does not participate} \end{cases}$$

where $f_{ame}^{j+1}$ and $f_{ame}^j$ denote the value of the indicator for two consecutive rounds (see next paragraph) and $\gamma$ denotes the adaptation constant. Finally, we assume that the smartphone device of each agent is characterized by an accuracy factor $q_j$, capturing the quality of sensed data.

The system discretises time in rounds. At the beginning of each round each agent declares to the system her preferred value of ambient luminance denoted by $l_{ux_j}$. Then, the system computes the average desired luminance at each tile based on the individual preferences of the agents that are present on this tile during this round. Based on the average desired luminance and the ambient light values collected from the smartphones, the system tries to adjust the ambient light conditions to the preferences of the agents by turning the corresponding light units on or off. In order to incentivise the end-users, the scenario follows a gamification approach by using virtual coins. During each round the system has a budget $B$ of virtual coins to distribute as an incentive to the agents; we denote by $I_j$ the incentive offered to $A_j$ on a particular round.

B. Incentive policies

1) The Flat Incentive: This is a naive strategy used as a baseline in the evaluation of the other strategies in which the system equally distributes the available budget over the set of agents. In particular each agent $A_j$, currently located in tile $S_i$ is offered:

$$I_j = \frac{B}{|A|}$$

2) Presence/Location-aware Incentive: As the system is constantly aware of the location of each agent inside the room, in this strategy, the system equally distributes the budget first over all non-empty tiles and then over all agents of each tile. In particular each agent $A_j$ is offered:

$$I_j = \frac{B}{|\sigma||A_{S_i}|}$$

where $|\sigma|$ denotes the number of non-empty tiles and $|A_{S_i}|$ denotes the number of agents located in tile $S_i$. 
A variation of this strategy also takes into account the accuracy $q_j$ of each agent:

$$I_j = \frac{B_j}{|\sigma[A_j]|} \sum q_j$$  \hspace{1cm} (4)

3) Behavioral-aware Incentive: Following this strategy the system maintains an indicator $fame_j$ for each agent based on which her commitment and trustworthiness is rewarded; e.g. how many times has the agent contributed in the past and whether the agent has fulfilled her commitment. In particular each agent $A_j$ is offered:

$$I_j = B_j \frac{fame_j}{\sum_i fame_i}$$  \hspace{1cm} (5)

4) Mobility-aware Incentive: Following this strategy the system favors the agents that frequently move inside the room as they are able to provide data corresponding to different subregions. Here each agent $A_j$ is offered:

$$I_j = B \frac{\Delta S_{A_j}}{\sum_i \Delta S_A}$$  \hspace{1cm} (6)

where $\Delta S_{A_j}$ denotes the distance covered by agent $A_j$ (measured in tile-units) since last round.

5) Mixed Incentive: As the composition of the crowd may change in time in terms of size, distribution in space, willingness to participate, sensor accuracy or mobility the system may need to adapt its incentive strategy. The mixed incentive strategy constitutes a probabilistic combination of the aforementioned "pure" strategies that enables the system to implicitly capture such changes in the crowd. Initially, the system chooses uniformly at random which strategy to follow. If the chosen strategy has been positively accepted by the crowd then the corresponding probability is reinforced over the rest of the strategies and vice versa. This scheme enables the system to dynamically adapt its behavior and eventually converge to an equilibrium among the "pure" strategies that achieves the highest acceptance ratio by the crowd. To summarize, the mixed strategy follows the following procedure:

a) For the first round choose u.a.r. among the “pure” incentive strategies.

b) For the next round, adjust the corresponding probability of the chosen strategy $I_c$ based on its acceptance ratio $a_{I_c}$ as follows:

$$\Pr[I_c]_{t+1} = \begin{cases} 
\Pr[I_c] + \delta & \text{if } a_{I_c} > 60% \\
\Pr[I_c] & \text{if } 40% < a_{I_c} < 60% \\
\Pr[I_c] - \delta & \text{if } a_{I_c} < 40%
\end{cases}$$  \hspace{1cm} (7)

c) Accordingly, for the next round, adjust the corresponding probabilities of the rest of the strategies $I_r$

$$\Pr[I_r]_{t+1} = \begin{cases} 
\Pr[I_r] - \frac{\delta}{3} & \text{if } a_{I_r} > 60% \\
\Pr[I_r] & \text{if } 40% < a_{I_r} < 60% \\
\Pr[I_r] + \frac{\delta}{3} & \text{if } a_{I_r} < 40%
\end{cases}$$  \hspace{1cm} (8)

d) Return to step (a) but use the newly adjusted probability distribution.

The reason for choosing the $a_{I_c} > 60%$ is because in this scenario we wanted the testbed to be "smooth" while transitioning from one incentive to the other. Lower values of $a_{I_c}$ will result to more even distributions over the “pure” incentives.

V. Experimental Evaluation of the Incentive Policies

In this section we describe the experimental evaluation of the incentive policies and the gains on the energy consumption by initially monitoring the conventional use of the testbed facility and then by engaging its smart automations and Mobile Crowdsensing capabilities.

A. Evaluation Metrics

For the performance evaluation of the various incentive policies and the efficiency of the overall system, we utilize several performance metrics that capture different aspects of the IoT and MCS components of the testbed facility.

Social Welfare: This metric evaluates the satisfaction and comfort that the end-users (agents) are experiencing while using the smart room. In particular, social welfare measures the average difference of luminance over all agents inside the smart room measured from the preferences of each agent and the final luminosity achieved by the system. For each round, the system computes the following quantity:
where \( \text{lux}_{A_j} \) denotes the preferred luminance by each agent \( A_j \) and \( \text{lux}_{S,A_j} \) denotes the achieved by the system luminance at the tile that agent \( A_j \) occupies during this round.

Energy consumption: For each incentive policy we measure the energy consumption of the smart room coming from the indoor light units. This metric is used in order to evaluate the energy efficiency versus the user comfort trade-off for each policy.

Budget spent: For each incentive policy we measure how much of the available budget \( B \) the system has actually given to the agents. The various policies differ on how they incentivize the agents in terms of budget generosity as well as in terms of focusing on different aspects and using the available to the system information in different ways. For instance, the location-aware incentive focuses on the distribution of the agents inside the smart room while the mobility-aware incentive focuses on the changes of this distribution.

Acceptance ratio: For each incentive policy we measure how many agents have actually accepted the incentive offered. This metric captures the appeal of each incentive policy to qualitatively different sets of agents; different in terms of agent mobility, sensor accuracy, etc.

Area coverage: For each incentive policy we measure the number of different tiles that the system managed to collect smartphone sensor data from. For this metric, the mobility-aware incentive is expected to outperform all other policies.

**B. Experimental Study**

We deployed the testbed facility in an office room at the University of Patras premises. The room was virtually partitioned in 4 tiles, each one mapped to an on/off light unit. The Android application was used by 17 users (students, researchers and employees, all of them agnostic about the system). Each user, after accepting to join the experiment, was prompted periodically (each round lasted for 30 minutes) to provide light readings of his current location in exchange for some budget defined by the corresponding incentive policy. Note that the sensor readings were being sent during the entire 30 minute interval and the user’s smartphone consumed a percentage of its battery. If a user accepted an offer and for some reason did not succeed in providing useful data (e.g. the user kept her phone in her pocket and therefore no true ambient luminance measurements were collected), then the corresponding budget was not allocated. Apart from using the Android application for the lights actuation, users followed their daily office routine.

In Fig. 5 we see the evolution of the budget expenditure during the experiment. The total acceptance ratio over all agents for the entire experiment is shown in Fig. 2. Fig. 4 depicts the overall coverage for the 4 office tiles, i.e. how many tiles were covered\(^1\) throughout the rounds of the experiment. The total energy consumption for each incentive policy is shown in Fig. 3. In Fig. 6 we see the social welfare of the crowd for every incentive policy.

We observe that the acceptance ratio and the overall energy consumption follow a similar pattern (Figs. 2, 3). This is natural, since the more users that accept a budget offer, the more lights that are used for continuous time intervals. Regarding tile coverage (Fig. 4), low values of coverage indicate that either the specific tile was not selected by the users, or that users in it were not accepting the budget offer. When applying the mobility policy, the users were more confident in covering the whole office area, since the reward was higher. Consequently, mobility aware policy keeps good coverage levels in all tiles. We observe that all incentive policies lead to an increasing budget expenditure (Fig. 5). The mobility and the mixed incentive policies achieve higher budget savings, in contrast to the location aware incentive policy, which spends more of the available budget. In spite of the similarity of the two latter in the budget consumption rate, a closer examination of Figs. 2, 3 leads us to the conclusion that

\(^{1}\)Tile coverage refers to the spatiotemporal availability to collect sensory data via the users’ smartphones.
both mixed and location aware policies achieve similar acceptance ratios, but different overall energy consumption during the experiment. This fact makes clear that the location aware incentive policy exploits more efficiently the given budget during the experiment. It also achieves high area coverage, as shown in Fig. 4.

By comparing the impact of the various incentive policies, we conclude that the flat, mixed and location aware incentives, although spending lower budget than the mobility incentive, they result to an uneven coverage of the interest area in terms of measurements. For this reason, they also provide lower energy consumption, since at a given time only a portion of the office lights are on. The behavioral aware incentive policy has been proven highly adequate. It consumes relatively lower budget amounts compared to other policies and maintains fair coverage levels in all tiles (Fig. 4) and high social welfare (Fig. 6). This is a result of its adaptive nature which is based on the budget distribution according to the crowd’s location.
VI. Conclusions

In this paper we presented an IoT testbed for Smart Buildings following an architecture that enables and scalable integration of crowd-sourced resources. We demonstrated its agility via a use-case scenario in which the users first declare their preferences on the ambient luminance levels and then the system offers them incentives in exchange for access to the light sensors of their smartphones. Based on these readings the testbed constructs detailed luminance maps and is able to adjust the indoor lights to the user preferences. We evaluated several incentive policies taking into account diverse aspects of the crowd. For future work, we plan to extend the services provided by the testbed to also include privacy mechanisms as well as to implement more complex use-case scenarios.

References


