A Real-Subject Evaluation Trial for Location-Aware Smart Buildings

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***Abstract*—The increasing demand for smarter yet more efficient indoor spaces necessitates moving towards advanced technologies, such as Internet of Things architectures, to allow further integration to our physical world. In this work, we introduce a Bluetooth Low Energy-based infrastructure for location-aware buildings, along with a full-scale real-subject trial. The trial was undertaken with students in our engineering building at NC State, under IRB approval. Our focus is on showing a proof-of-concept of deploying location-aware infrastructure through experimentally collecting data able to facilitate building management and user localization. We examine a multi-floor environment installation and analytically prove how viable and economic our solution is to equip future intelligent facilities.**

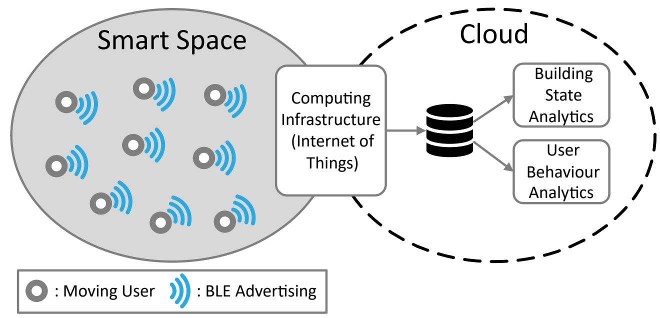

Fig. 1. Location-aware intelligent building model

I. Introduction

In the past, as long as a building was appropriately cooled or heated and sufficiently secure, it was considered to fulfill its purpose; however, that is no longer the case. Nowadays, the limits are pushed beyond managing temperature, door-locks and general security, to go as far as reducing energy costs, preventing physical disasters, asymmetric threats and improving the life quality of occupants. To accomplish that, buildings must become smarter, especially in the sense of being able to monitor location and movement inside the facility.

Intelligent spaces are physical environments equipped with computational infrastructure and sensing capabilities that exhibit a high form of interaction [1]. Such smart spaces should be able to autonomously acquire knowledge of their users and use it to improve their overall experience in the space. ”Smart” is defined not only by the various services offered but also by the broad use of various sensing systems located around the area. Such sensing capabilities refer to collecting space state data such as environmental conditions, as well as the ability to track the user's physical location, identity and preferences. Therefore, in order for a smart space to be productive, it must support the two rising trends of the digital age: connectivity and big data analytics, focused inwards to ensure efficient operation.

Heading towards this world of smarter spaces, the Internet of Things (IoT) is essential in this transformation of enterprise and residential facilities into ”intelligent” ones. The Internet of Things is defined as the ability of objects (things) to be interconnected through the Internet [2]. One of the services an IoT-equipped building has to offer is microlocation, which is the precise localization of an entity [3]. Many approaches concerning microlocation have been developed.

Infrastructure-less microlocation solutions do not require any pre-installed equipment on the facility. These systems utilize signals from inertial measurement units (IMUs), namely accelerometers, gyroscopes or magnetometers to estimate the user's position [4], [5]. On the other hand, infrastructure-based solutions rely on wireless technologies such as WLAN, Bluetooth, Radio Frequency Identification (RFID), or ultrasound. Such systems aim to use the building's existing infrastructure to estimate the user's microlocation using wireless signal strengths and triangulation techniques [3], [6]. Most of these solutions incorporate systems where the moving user carries equipment (e.g. a smartphone) that acts as a scanner receiving signals from fixed transmitters [7], [8]. However, the inverse strategy that uses a movable-beacon fixed-scanner approach is also encountered for case-specific applications [9], [10]. Despite the numerous approaches proposed, each one of them comes with several challenges that make the indoor localization problem far from solved [3], [11].

In this paper we present a Bluetooth Low Energy (BLE)-based infrastructure for location-aware smart buildings, along with a large scale realization of the system inside the NC State University's ECE building. While a lot of published work is focusing on moving-scanner fixed-transmitter systems, we present and test a system that inverts this logic. Our proposed system consists of fixed scanners deployed on the intelligent

TABLE I
DIFFERENT COMPONENTS AND THEIR FUNCTIONALITY

Component	Functionality
Gimbal Beacon Series 10	BLE Beacon packet transmitter
Raspberry Pi 3	BLE Beacon scanner, Internet accessability
Server	Data Management, MQTT Broker, Web Application Host
Database	Data storage
Web Application	User Interface, Raspberry Pi Management, Data Analytics

building while moving users are equipped with beacons that constantly transmit BLE advertisement packets fingerprinting their location. The general aim of this project is to describe an easily deployable and practical smart building infrastructure able to generate data that can be used not only for tracking the behavior of a specific user, but also detecting the state of the facility at any given time.

Figure 1 presents our schematic model for such a location-aware building. In this work, we also present a series of preliminary results that utilize the data collected by the one-month-long IRB trial. Most existing work on microlocation experiments have been conducted in restrained environments and on a small scale. We consider our large scale deployment of scanners and BLE beacons in a living environment, such as a university, as an attempt that can be the beginning for further research.

This paper is organized as follows: Section II presents an overview of the proposed system. Section III describes the large scale experiment conducted. Section IV discusses system's signal strength performance and range. The preliminary results are presented in Section V. Finally, we discuss future work in Section VI and conclude this paper in Section VII.

II. SYSTEM OVERVIEW

A. Approach

Our proposed design aims for an easily deployable smart building infrastructure able to generate data that can be used to provide facility management and microlocation. To that end, our solution's goal is to be cheaply scalable with minimal infrastructure changes.

As discussed previously, the dominant approach in most relevant works is moving-scanner fixed-beacon systems that require a scanner for each user. In most cases these devices are smart-phones already equipped with BLE and Internet connectivity. While this seems a widely accepted solution, it has a significant impact on device power autonomy.

On the contrary, the moving-beacon fixed-scanner approach that we propose allows stationary low-cost scanners plugged into a power source, unconfined by any battery life standards. Access to WiFi on the building's secure network is guaranteed and the provision of BLE beacons to the masses is considered a small cost. A realization of this system is also possible using smart-phones acting as beacons. This would require a less

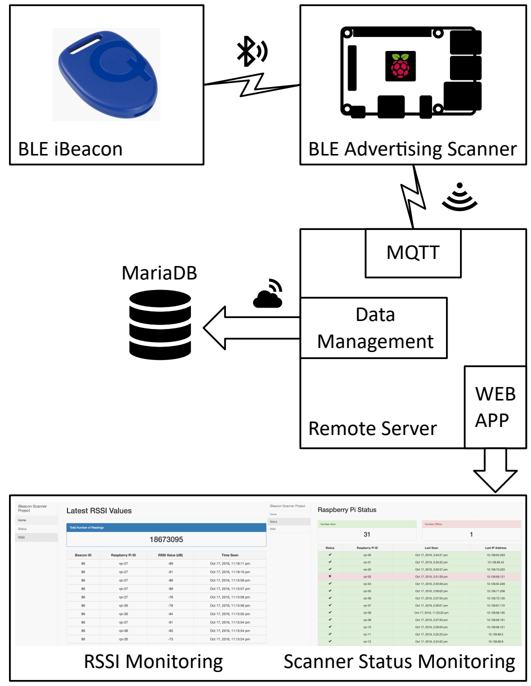

Fig. 2. System Architecture

resource-demanding phone application with minimal impact on battery life.

In our movable-beacon fixed-scanner system, primary cost factors arise from scanner devices, BLE beacons, data transmission and analytics. In regards to scanner devices, two product lines were compared due to their cost similarities: Raspberry Pi and Intel Edison. While both devices provide similar capabilities, we found the Raspberry Pi 3 to be superior due to lower costs per device and on-board WiFi and Bluetooth Low Energy modules. As long as the beacon provided reasonable accuracy, allowed iBeacon configuration, and provided a one-month battery life, it was considered a feasible solution. Gimbal Beacon Series 10 and Estimote iBeacon products were compared, with Gimbal showing to be a much more cost effective solution.

B. Architecture

There are five different components in our system as shown in Table I and Figure 2. At a configured rate, iBeacons [12], transmit unique packets. Depending on the transmission power configuration of a beacon, it can transmit data to further distances dependant on the obstacles within the environment.

The beacons within the system are configured to broadcast under the same 16-byte universally unique identifier (UUID) [13]. Each beacon is distinguished by a 4-byte identifier embedded in the iBeacon advertisement packet. Beacon transmission rate was set to 1 Hz, transmission power to 0 dBM, and our antenna was set to propagate in an omni-directional manner. These settings provide best propagation results and are befitting for a one-month battery lifetime usage.

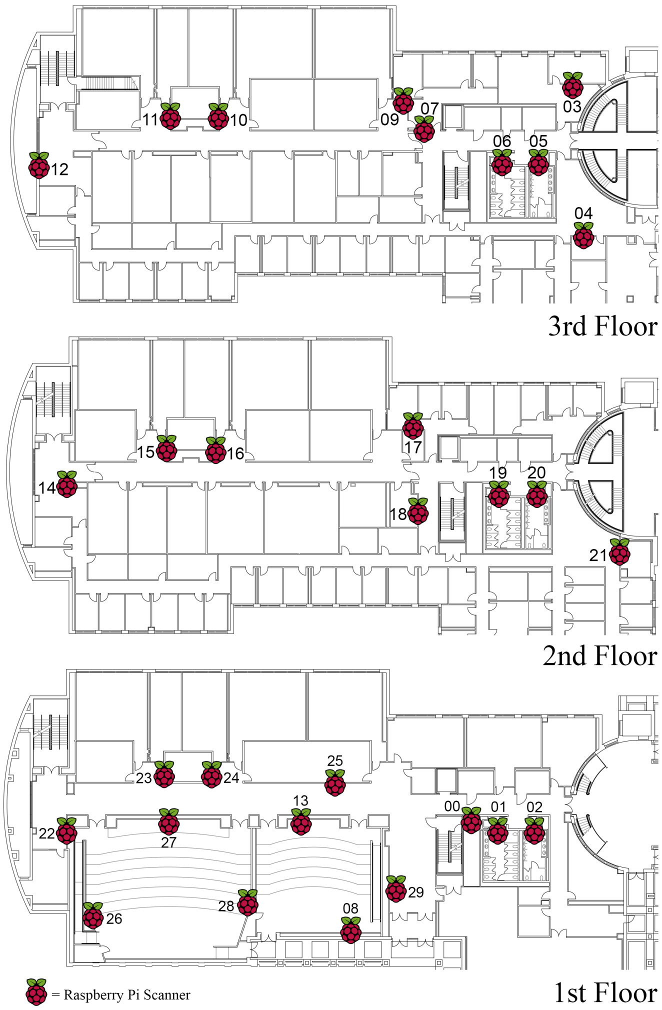

Fig. 3. BLE scanner locations in multiple floors

The Raspberry Pi is essentially the back bone of our system; the device scans for BLE beacons carried by various users. On top of this, it is programmed to correctly scan only for our iBeacons such that no other beacon or BLE advertising packets are accepted. Raspberry Pi development also includes functionality to promote facility management and self-sustained system reliability checks.

After processing of incoming beacon packets, Raspberry Pis forward the information to the local Linux server for further processing and storage via a secure WiFi network. Utilizing the MQTT (Message Queuing Telemetry Transport) protocol as discussed in [14], Raspberry Pi devices are programmed as clients to the MQTT broker hosted by the server. MQTT is a secure, lightweight M2M communication protocol which is efficient for IoT applications. The server, along with hosting the MQTT broker service, performs data management processing on the incoming data; namely, data is validated and stored into the various tables in the MariaDB SQL database.

Moreover, a web application is provided for a dashboard-like view into real-time system updates including Raspberry Pi status and recent incoming readings. This web application can be further developed to host real-time facility management applications.

C. Operation

Data path and data management in such a system surely affects its real-time ability, performance, and features. In our design, we followed two approaches for data processing.

The first approach is to consistently forward all the received signal strength indicator (RSSI) values received by beacon scanners to our central server. While this approach is intuitive, it requires high data throughput to the cloud. This RSSI Report approach in data management allows the possibility of our two main required functionalities: facility management and user microlocation.

Our second implementation rather utilizes local processing power to manage data, while also yielding less network traffic. We followed a Check-In/Check-Out approach where each beacon scanner device manages a list of current beacons that are in its vicinity. On a beacon's initial entry of the scanner's vicinity a 'time-in' timestamp is attached. While a user maintains their locality to the beacon scanner, a 'last-seen' timestamp is continually monitored and updated. As a user exits the beacon scanner's area, and packets no longer are received by the beacon scanner, an event packet is finalized and sent off to the cloud. Here, a time period of thirty seconds is used such that the user exit event is assured. A downfall of this Check-In/Out approach is that it inhibits precise microlocation functionality, as RSSI values are no longer sent to the cloud.

III. IRB Trial - Experiment

In order to present a realization of the proposed solution in realistic conditions, we performed an extended real subject experiment. The trial was approved by both the NC State Department of Electrical and Computer Engineering, and the Institutional Review Board for the Protection of Human Subjects in Research (IRB).

Regarding the deployment of our system, thirty Raspberry Pi scanners were attached in three floors within NCSU Centennial Campus - Engineering Building II, as shown in Figure 3. The goal was to distribute beacon scanners symmetrically throughout the building and according to their estimated covering range, as discussed in Section V. However, restrictions due to power outlet locations limited our choices and enforced final scanner location. Moreover, due to building regulation restrictions, some scanner devices were placed approximately 2 feet from the ground. To achieve an unobstructed signal propagation in overcrowding cases we propose placement of scanners near or attached to ceilings.

While abiding by IRB privacy rules, we were able to gather basic participant information including gender, age, major, and year of education. Although students accounted for most of the participants in our trial, faculty and staff also took part. For beacon distribution, each user attached their beacon to their backpacks or keys, whichever they had on their person more often. The trial lasted from September 15 until October 17, 2016 and we successfully recruited 46 participants.

IV. MEASUREMENTS

Before the full-scale live-subject trial of the system at the ECE department's spaces, we conducted a series of experiments in order to model the received signal strength performance of our configuration as well as examine possible interference events due to RF signal characteristics. In fact, we wanted to estimate the radius covered by each BLE-scanner and examine the possibility of BLE advertisement packets being picked up by scanners positioned in other floors.

The first experiment investigates the relation between RSSI and distance. Theoretically, the signal propagation model commonly used to relate RSSI to distance, *d*, is the log-distance path loss model:

$$P_d = P_{d_0} - 10\,\gamma\,\log(\frac{d}{d_0}) \tag{1}$$

where:

- P_d is the RSSI (dBm) at distance d from the source
- P_{d_0} is the RSSI (dBm) at the reference distance d_0 from the source
- γ is the path loss exponent which depends on the propagation channel

Therefore, when unknown, d can be calculated using the expression:

$$d = d_0 \cdot 10^{\frac{P_{d_0} - P_d}{10\,\gamma}} \tag{2}$$

Reference distance d_0 is selected such that it belongs to the antenna's far-field.

The experimental setup consists of a single iBeacon along with a single Raspberry Pi scanner mounted on a hallway wall at the height of approximately 1.6 meters. Measurements were executed at 32 different user-scanner distances varying from 0 to 10.5 meters by averaging all RSSI values received by the scanner over a period of 30 seconds. During the first test, we examined beacon performance in an unobstructed line-of-sight (LoS) between the scanner and beacon, while varying transmission power configurations. Figure 4 shows the RSSI values received at different distances for beacon transmission powers of 0, -6 and -12 dBm. For transmission powers lower than 0 dBm we observed the intermittent loss of advertisement packets after 9 meters, so in order to expand the reach and reliability of an iBeacon BLE packet, we used TX power of 0 dBm for all beacons in the trial.

During the second test, the beacon produced advertising signals at 0 dBm transmission power, while the LoS with the scanner was obstructed by human bodies. Figure 5 shows RSSI values for this test along with a comparison with the case of unobstructed LoS at the same TX power level.

In both Figures 4 and 5, the distance and RSSI measurements were used to perform a curve fitting according to the propagation model described by Eq. 1. The results demonstrate that the log-distance path loss model is suited to describe BLE signal propagation in indoor environments. This analysis can also be used to determine optimal scanner placement inside a smart building in order to cover all spaces with a minimum beacon transmission power choice.

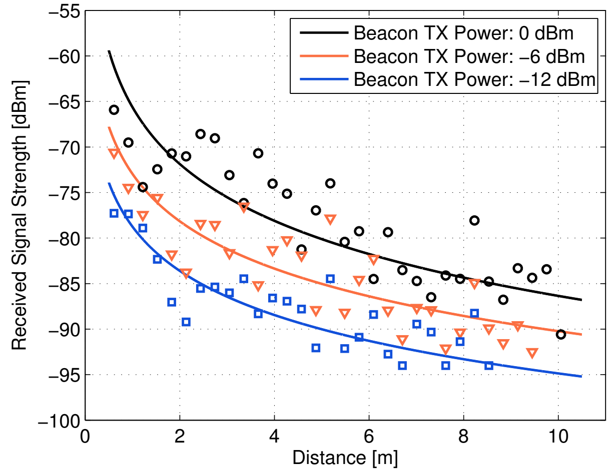

Fig. 4. Received signal strength vs distance - Line of Sight

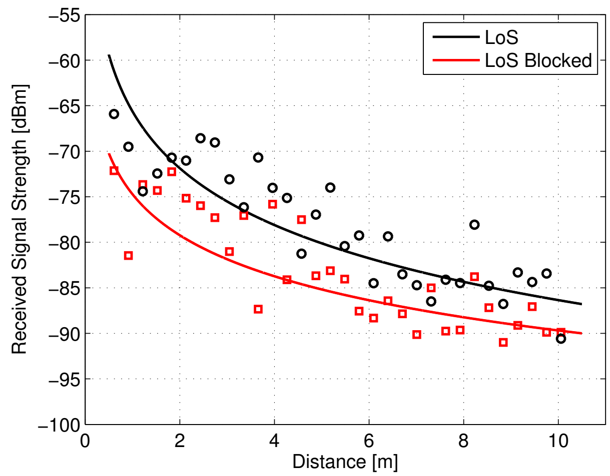

Fig. 5. Received signal strength vs distance - 0 dBm beacon TX power

TABLE II
FLOOR BLEEDING

		Percentage of advertising packets received [%]			
Test	**Test Floor**	**Floor 1**	**Floor 2**	**Floor 3**	**Total Floor Bleeding**
1	1	100	0.00	0.00	0.00
2	1	98.74	0.63	0.63	1.26
3	2	2.26	90.94	6.79	9.06
4	2	3.69	91.90	4.41	8.10
5	3	0.00	0.18	99.82	0.18
6	3	0.00	0.91	99.09	0.91
Average	–	–	–	–	3.25

The second set of experiments were performed by a user equipped with a single iBeacon, while moving in the building after all scanners were deployed and fully operational as shown in Figure 3. Test beacons were configured as described in Section III. For each test, a user followed a predefined point-A to point-B path. In many tests, we examined events where a scanner from another floor picked up the advertisement packet. We refer to these events as floor bleeding events. Table II shows the results of the aforementioned experiment.

V. Preliminary Trial Results

Based on the description of the proposed system in the preceding sections, it is obvious that the data generated by our system can be exploited in parallel for two basic smart building functions. The first function focuses on the building itself. The extracted data can be used to perform real-time facility management and monitor the smart building state at all times. The second function is user microlocation as the provided architecture can be used to locate a user within a confidence interval. In this section we focus on the building management utility of the proposed solution as it is practically demonstrated by the one-month-long real subject trial and the data yielded.

The first measurement that can be extracted from the system's generated data is building activity over time. As an activity metric we use the total amount of advertisement packets received by the Raspberry Pi scanners installed in the facility. Figure 6 shows a heatmap visualizing the overall building activity for each day of the experiment. Figure 7 compares the average building activity per hour over weekdays and weekends. We can observe that clear conclusions can be drawn regarding the differences in crowd activity during weekdays and weekends and between the respective hours of each period.

Apart from the chronological analysis of the activity, received advertisement packets can be used to extract the most visited places inside the facility. Figure 8 shows the mean and standard deviation of space activity during weekdays as captured by each Raspberry Pi scanner.

Finally, as discussed in Section III we implemented two approaches for processing the BLE advertisement packets received by each scanner. Figure 9 compares these two approaches in terms of total daily messages sent to the server by the BLE scanners. The RSSI Report approach generated a significantly larger amount of data than the Check In/Out

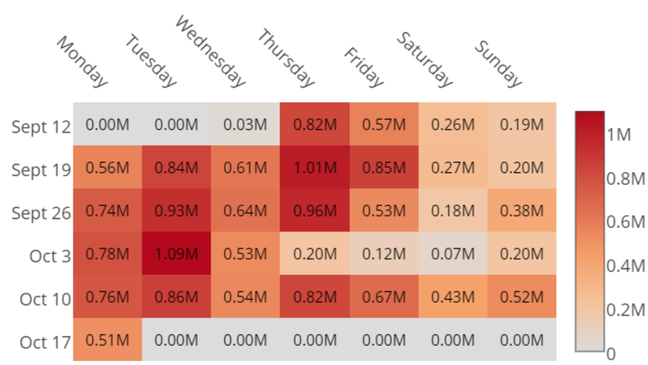

Fig. 6. Overall Building Activity Per Day

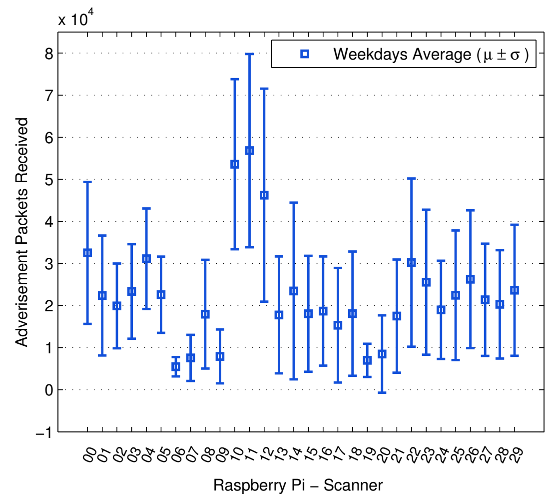

Fig. 8. Average Weekday Activity Per Raspberry Pi-Scanner

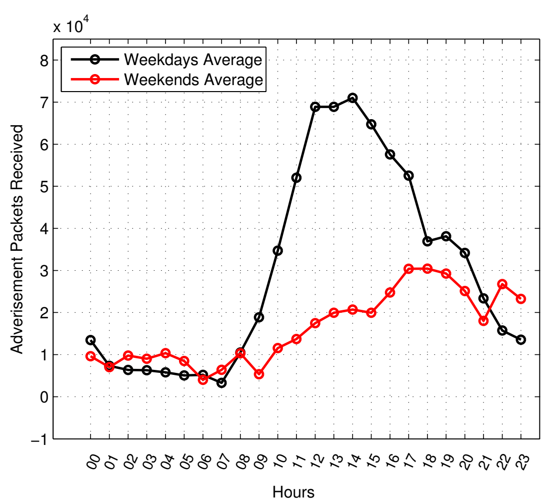

Fig. 7. Average Activity Per Hour: Weekdays vs Weekends

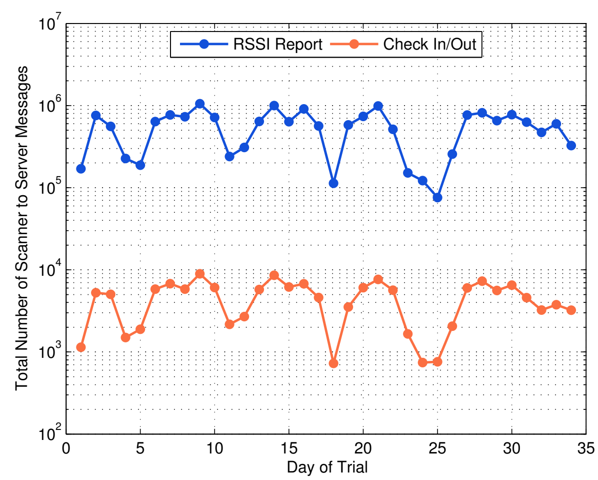

Fig. 9. Daily Comparison of Generated Traffic

approach and results to greater network traffic to over two orders of magnitude. Therefore, when only building management logic is required, the second approach is more efficient in terms of network resource management.

VI. Discussion and Future Work

As seen above, our proposed system can generate reliable facility metrics regarding user activity density and building space usage. Our preliminary system measurements characterize the BLE signal propagation. Such modeling can be utilized along with case-specific algorithms to estimate distances between beacons and scanners. Moreover, our measurements, after inspection of the data, revealed floor bleeding events where advertisement packets were picked up by scanners located in different floors in relation to the transmitting beacon. These events were limited to an average percentage of 3.25% whose main factor was found to be movements at the middle floor of the trial building, as suggested by Table II. These events can be averted by carefully adjusting the scanners' locations and performing RSSI calibration techniques. Also, an important variable to this phenomenon is the beacon TX power. A possible reduction of this setting to lower levels would result to a decrease of the floor bleeding phenomenon and consequently provide extra beacon battery life.

As future work, we consider developing a microlocation algorithm based on the system's overall moving beacon-fixed scanner approach. Extra care will be given to cases where users change floors using stairs with dedicated scanners located in predetermined positions. This user localization would allow them to interact with managed resources inside the environment. Moreover, this functionality would allow the smart space to efficiently use its power-based resources and even utilize user's microlocation to plan actions during emergency cases.

Concerns should also exist in terms of privacy for the facility occupants and security of the building itself. Even without a complex microlocation algorithm, anyone with access to the back-end system or anyone who can pick up the beacon broadcasts will be able to infer the location and activities of building occupants with fair accuracy. Plus, the presence or absence of BLE broadcasts can give insight into whether a building is occupied or not, raising security concerns. As future work, we consider developing security features and vulnerability countermeasures to mitigate these problems.

Finally, the installation of such a sizable system that hosts a substantially large number of people every given day, should take into account the impact on the facility's network performance. The architecture of the proposed system which is based on active moving beacons carried by each user, creates a significant amount of network traffic which is proportional not only to user's number but also to their location inside the building.

VII. Conclusion

In this paper we introduced a BLE-based smart space infrastructure. The system is based on a moving beacon-fixed scanner approach that can generate data to be utilized both for building management and user microlocation purposes. Moreover, we performed a large scale realization of the system via a real subject trial. Thirty Raspberry Pi-based BLE scanners were deployed on three floors of the NC State Engineering Building II, while 46 users were given a BLE iBeacon to carry with them for the one-month trial period. As a case study, this experiment was of particular interest as it yielded a large number of live data utilizing a BLE platform. We examined the system's response to the simultaneous three floor installation and presented the results. Finally, our preliminary results of the IRB approved trial yielded an accurate and useful building state analysis. These proved our proposed system to be a reliable solution able to equip a future smart facility. Our results can be used as a basis to further develop our solution and add extra functionality.

Acknowledgment

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