

OBLEA: A New Methodology to Optimise Bluetooth Low Energy Anchors in Multi-occupancy Location Systems

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Abstract: Nowadays, it is becoming increasingly important to understand the multiple configuration factors of BLE anchors in indoor location systems. This task becomes particularly crucial in the context of activity recognition in multi-occupancy smart environments. Knowing the impact of the configuration of BLE anchors in an indoor location system allows us to distinguish the interactions performed by each inhabitant in a smart environment according to their proximity to each sensor. This paper proposes a new methodology, OBLEA, that determines the optimisation of Bluetooth Low Energy (BLE) anchors in indoor location systems, considering multiple BLE variables to increase flexibility and facilitate transferability to other environments. Concretely, we present a model based on a data-driven approach that considers configurations to obtain the best performing configuration with a minimum number of anchors. This methodology includes a flexible framework for the indoor space, the architecture to be deployed, which considers the RSSI value of the BLE anchors, and finally, optimisation and inference for indoor location. As a case study, OBLEA is applied to determine the location of ageing inhabitants in a nursing home in Alcaudete, Jaén (Spain). Results show the extracted knowledge related to the optimisation of BLE anchors involved in the case study.

Keywords: Indoor location system, Bluetooth Low Energy, Fog-Cloud computing, Sustainable development goals

Categories: I.2.0, I.2.4, J.3

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1 Introduction

Location tracking systems offer a multitude of applications in different contexts, such as evacuation of people from subway areas [Demirkan and Duzgun, 2020] and enclosed spaces [García et al., 2020], energy optimisation in smart homes [Lee et al., 2011],

detection of natural disasters [Ramesh 2010], or even analysis of people's behaviour in fire drills [Chaiwongven et al., 2018]. One of the most important application areas is smart environments [Virginia et al., 2022, Rodrigo et al., 2021, Custodio et al., 2012].

Smart environments [Espinilla et al., 2018] are spaces equipped with intelligent devices that capture the interactions that take place within them with the aim of extracting knowledge. Given the privacy advantages of environmental sensors over vision sensors, these are widely used in the health sector for activity recognition in homes. However, environmental sensors, such as presence, motion or opening/closing sensors, have the disadvantage of not distinguishing who performs a certain interaction (for example, who is opening a door or entering the kitchen) [Liming et al., 2012]. In this scenario, the indoor location system plays a fundamental role in the recognition of daily human activities and anomalous events [Lee et al., 2018, Özdemir, 2016], providing a solution to certain outstanding challenges like multi-occupancy [Razzaq et al., 2020] by locating the inhabitants.

Different methods [Albín et al., 2021, López et al., 2019] have been proposed to obtain the location of the inhabitant when performing daily activity recognition in multi-occupancy contexts. However, each method presents a methodology with a fixed configuration for a single case study that is difficult to transfer to another smart environment. This fact presents a challenge that needs to be addressed: how to optimise the configuration of a BLE multi-occupancy location system that can be transferable in a flexible way.

The OBLEA (Optimisation of Bluetooth Low Energy Anchors) methodology for indoor location systems is proposed to address this issue. OBLEA, based on a data-driven approach, considers multiple variables for the configuration of BLE anchors (BLE protocol, number of anchors, size of the time window for aggregating anchor values and classifier algorithms) to obtain the best performing configuration with a minimum number of anchors in multi-occupancy indoor spaces. This methodology includes: i) a flexible framework in the indoor space to represent all the components involved in locating the inhabitants; ii) the architecture to be deployed according to the framework (this architecture considers the received signal strength indicator for the BLE anchors and aggregation processes by time windows); and, finally, iii) the optimisation and inference for indoor location to obtain the best performing anchor configuration that facilitates transfer with a minimal learning stage.

As a case study, the optimisation of the location indoor system in a nursing home with elderly people in Alcaudete, Jaén (Spain) has been analysed. Locating elderly people in a nursing home is crucial to guarantee their safety [Sadoughi et al., 2020, Fraile et al., 2010]. Finally, the proposed methodology is evaluated taking into account the Sustainable Development Goals (SDGs) established in the 2030 agenda by the United Nations [United Nations, 2021]. This type of assessment is essential to further compliance with the goals and objectives of the 2030 agenda.

The rest of the paper is organised as follows: Section 2 reviews recent literature on technologies for indoor location and location detection using BLE technology. Section 3 presents the OBLEA methodology in the context of multi-occupancy. Section 4 evaluates the OBLEA methodology to optimise the indoor BLE location system configuration in a real case study. Section 5 evaluates the alignment of the proposed methodology with the SDGs and, finally, the conclusions are presented in Section 6.

2 Related Works

In this section, we review recent literature on indoor location technologies and the foundations of location detection using BLE technology.

2.1 Indoor Location System Technology

In the literature, indoor location systems (ILS) use different types of technologies with multiple features. The most popular are the mechanical, acoustic and radio frequency technologies reviewed in this section and illustrated in Figure 1.

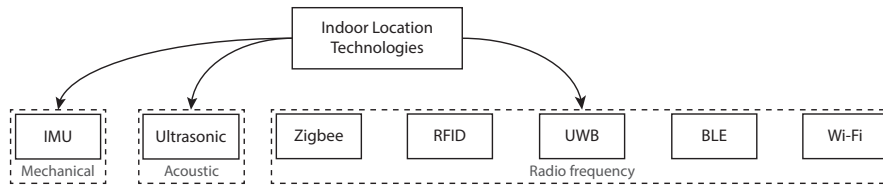


Figure 1: Technologies proposed in indoor positioning systems.

In mechanical sensors, inertial measurement units (IMU) such as accelerometers or gyroscopes are used. These sensors determine movement in terms of position and angle, respectively, on the basis of an initial position, an angle and a velocity. Although this technology was initially designed for outdoor applications, it has subsequently proven to be effective for indoor use [Lee et al., 2021, You and Wu, 2021, Pham et al., 2021, Khan et al., 2020, Han et al., 2018, Yao et al., 2017, Faragher et al., 2012] due to its high accuracy and efficient energy management [Pham et al., 2021]. However, most systems that rely on this type of technology are invasive and obtrusive because of the need to be attached to the target. In addition, due to drift and cumulative error, it is necessary to implement the approach using filtering methods such as Kalman filtering [Lee et al., 2021].

ILS systems can also be based on ultrasound technology. This technology uses the propagation of acoustic pulses transmitted by an audio generator to other fixed or mobile client devices deployed inside an enclosed space, allowing position mapping [Esslinger et al., 2020, Carter et al., 2018, Qi et al., 2018, Jordaan et al., 2017, Medina et al., 2013]. Ultrasound technology has the main advantages of guaranteeing low penetration into the wall and being low cost, but with the drawbacks of low range and costly deployment in large indoor spaces.

Finally, radio frequency-based location systems have been the most widely used in the last decades. Within this field there are several options: Wi-Fi, BLE, ZigBee, Ultra-Wide Band (UWB) and Radio Frequency Identification (RFID). The most popular radio-frequency options are reviewed below.

- **WLAN or Wi-Fi** [Zhao et al., 2021, Pichaimani and Manjula, 2021] is a standard communication technology for wireless data transmission operating in the 2.4 GHz-5 GHz frequency band of the electromagnetic spectrum. The effective range is very

wide, covering from about 50 to 100 metres, and the location accuracy is within a few metres in an environment with dense Wi-Fi coverage. The main problem is that the target entity must carry a Wi-Fi enabled device, e.g. a smart phone.

- **BLE** [Zhao et al., 2021, Albin et al., 2021, Pinto et al., 2021] is similar to Wi-Fi in terms of transmitting radio signals in the same frequency and using the same location principles. In this case, it operates at 2.4 GHz (unlicensed frequency band), ensuring it is always available, and allows collaboration with other network services. This feature, combined with its low cost, makes it a widely used technology. However, unlike Wi-Fi, its range of 1 to 5 metres makes it less effective for applications that require a larger area.
- **ZigBee wireless communication** [Chen et al., 2020, Athira and Babu, 2019, Tan et al., 2018, Han et al., 2018, Konings et al., 2017, Liu et al., 2017, Konings et al., 2017] is a standard designed for short-range coverage. It operates in multiple bandwidths and the signal range is up to 100 metres, but in actual indoor environments it is typically between 20 and 30 metres. Thus, this technology is limited to short range and low data rate applications.
- **UWB technology** [Yang et al., 2021, Brovko et al., 2021] is based on interactions between the electromagnetic field and matter. It uses images obtained from the scattering of electromagnetic waves within the environment, generating detailed geometry. It operates on a very large bandwidth of more than 1.5 GHz. However, this wide bandwidth causes interference with other devices. Therefore, it is necessary to resort to power limitation, which makes it impractical for many applications. Finally, the cost of deploying UWB systems is currently high compared to other systems like BLE, which significantly reduces their deployment potential.
- **RFID technology** [Nazari and Shirmohammadi, 2020, Pereira et al., 2019, Wang et al., 2019, Shamseldin et al., 2018] consists of tags, a reader, and a server equipped with RFID middleware. The tags can be passive or active, needing a battery in the second case, and are unique. RFID identification is very popular and useful for a wide range of applications, but has several limitations: the standardisation of operating frequencies, the invasive nature, the additional infrastructure needed for proximity identification, and the high computational cost when multiple tags are used to achieve higher accuracy.

Bluetooth beacons appeared on the market with the adoption of the Bluetooth 4.0 standard (commonly called BLE or Bluetooth Low Energy), and have become increasingly popular. A BLE beacon is a simple piece of hardware that emits BLE packets on a constant basis [Tabbakha et al., 2021, You and Wu, 2021, Bucheli et al., 2020]. Smartphones and other devices can detect these packets, measure their signal strength (RSSI) and determine their location. BLE beacons present the following advantages over other technologies [Misal et al., 2020, Du and Xiong, 2020, Konstantinos and Orphanoudakis, 2019, Stavrou et al., 2019]:

- Bluetooth beacons are typically low-cost, small and unobtrusive (a few centimetres wide), can be installed almost anywhere (glued or screwed to the wall), and can run on batteries or be plugged in.
- Both Android and iOS devices have great BLE support, allowing several BLE readings per second and decent signal strength stability. This allows computing location per second, ideally providing good navigation.

- The BLE beacon parameters (transmit power, transmit frequency, etc.) can be easily configured, being flexible to support different modes of operation and to create multiple alternatives.

The main issue with indoor location systems based on BLE beacons alone is that, to achieve good accuracy, it is necessary to deploy several beacons (e.g. one every few meters) in the enclosed space. However, considering their low cost, this issue can be easily overcome.

2.2 Location Detection with BLE Technology

Since our proposal is based on BLE technology for indoor location, this section reviews the basic aspects.

Location detection using BLE technology is based on measuring received signal strength indicator (RSSI) strength [Karoui et al., 2021, Long et al., 2021, Zeng et al., 2021, Lee et al., 2021, Chen et al., 2020, Li et al., 2020, Yao et al., 2017]. This feature is intrinsic to any wireless technology and uses a unit of power expressed in decibels relative to a milliwatt (dBm or $dBmW$). RSSI provides information on signal strength between two devices with the same type of Bluetooth connection. Strength values are usually expressed as negative values and typically range from 0 dBm to -100 dBm . A strength value close to 0 dBm would indicate a good connection between the two devices, whereas negative values would indicate a weakening connection. In the context of ILS, RSSI gives an approximate distance between two BLE devices. Figure 2 illustrates how the RSSI signal strength is read.

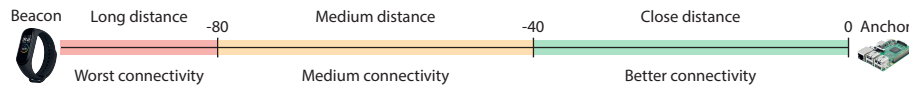


Figure 2: Interpretation of RSSI values.

Therefore, two types of BLE devices are proposed to locate the inhabitant: anchor and beacon. The beacon is a wearable device that is carried at all times by the inhabitant. The beacon's unique purpose is to provide a BLE connection which is scanned by the anchor elements at all times. The anchor scans nearby devices with a BLE connection at each time instant t . These elements are filtered by the MAC address of the target beacons (monitored inhabitants) and their RSSI value is collected. This type of device must be distributed throughout the monitored area and together they enable the inhabitant (beacon) to be located in real time.

3 OBLEA: Optimisation of Bluetooth Low Energy Anchors in Multi-occupancy Location Systems

In this section, we present the OBLEA methodology, along with its benefits compared to other methods.

3.1 OBLEA Methodology

In this section, we present OBLEA, a new flexible methodology for the Optimisation of Bluetooth Low Energy Anchors in multi-occupancy location systems, which facilitates transferability to different indoor spaces with a minimal learning stage.

The main steps of the OBLEA methodology are as follows:

1. Establishment of a flexible framework for indoor location.
2. Deployment of architecture in the indoor space.
3. Location inference method based on a data-driven approach.

The following sections describe the OBLEA methodology in detail.

3.1.1 Flexible Indoor Location Framework

In this methodology, first the special characteristics of the indoor environment, S , where it is necessary to locate multiple inhabitants are defined.

1. Relevant location areas $\{A_1, \dots, A_j, \dots, A_J\} \in S$ in an indoor space.
2. A set of inhabitants $\{H_1, \dots, H_k, \dots, H_K\} \in S$ and a set of mobile location beacons $\{w_1, \dots, w_k, \dots, w_K\}$, such as activity wristbands. Each beacon w_k is directly associated with a single inhabitant H_k and is identified by its MAC address $\overline{w_k}$. Specifically, in our proposal, the Xiaomi Band 3¹ activity wristband model was selected as a beacon. This device was chosen due to the high battery life (approximately 30 days) and its small size (17.9 x 46.9 x 12mm) and weight (20g). It is equipped with version 4.2 BLE connection.
3. Each relevant location area A_j has an associated set of location anchors $\{sbc_1^j, \dots, sbc_l^j, \dots, sbc_L^j\} \in A_j$. Each anchor can only be associated with one area $A_j \cap A_i = \emptyset$. In our proposal, a single-board computer (SBC) with high computational power and a DC power supply is required. The model we selected was a Raspberry Pi 4B². This SBC has a small size of 85 x 56mm which has a minimal impact on the environment and an idle power consumption of 500mA. Although this model has BLE connection, it has been equipped with two nano USB adapters with two different versions: version 4.2³ and version 5.0⁴.
4. Beacon as fog node $\overline{sbc_l^j}$ responsible for collecting RSSI data through the MQTT protocol, and subscribing to the set of anchors covering the entire enclosed space $\{sbc_1^1, \dots, sbc_l^j, \dots, sbc_L^J\} \in S$.

3.1.2 Architecture for BLE Indoor Location Systems

The flexible framework proposed in this methodology is designed to be deployed in a new architecture, illustrated in Figure 3 and described below.

Each BLE anchor sbc_l^j generates an output stream $St_{RSSI}(sbc_l^j) = \{m_l^{ju}\}$, where each measure is a tuple composed of three components:

¹ <https://www.mi.com/global/mi-band-3/specs/>

² <https://www.raspberrypi.com/products/raspberry-pi-4-model-b/specifications/>

³ <https://www.tp-link.com/es/home-networking/adapters/ub400>

⁴ <https://www.asus.com/us/Networking-IoT-Servers/Adapters/All-series/USB-BT500/>

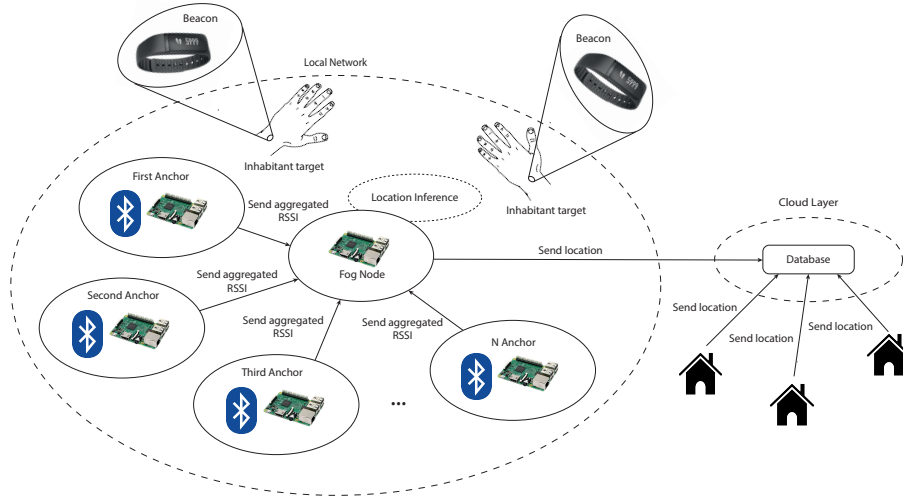


Figure 3: BLE indoor location system architecture.

1. Timestamp t_l^{ju} .
2. The MAC address $\overline{w_l^{ju}}$ of the scanned beacon that is associated with the enclosed space S : $w_l^{ju} \in \{\overline{w_1}, \dots, \overline{w_k}, \dots, \overline{w_K}\}$.
3. RSSI value v_l^{ju} of the beacon at timestamp t_l^{ju} .

For each beacon sbc_l^j , the RSSI value v_l^{ju} generated in the output stream is the result of applying a time window to the data stream. Each time window is defined by the size Ez . Therefore, the time window is computed in a time space $\Delta(t) = [t - Ez, t]$. This size can be dynamically modified according to the space and the monitored area.

The aggregate value of RSSI computed over the time window given a time instant t_0 is defined by the following equation:

$$TW \left(St_{RSSI}(sbc_l^j), Ez \right) = \{t_l^{ju} \in m_l^{ju} | t_l^{ju} \in \Delta(t_0)\}$$

This value is collected by the fog node $\overline{sbc_l^j}$, which applies a fixed time window Ez to avoid empty values over a period of time. Furthermore, a main element is defined as a fog node. This device is another SBC, presented in Section 3.1.3, which implements part of the inference method in order to estimate the location of the monitored inhabitants. To reuse resources and to improve energy efficiency, it has been included as one of the anchor elements.

Each of these devices is interconnected through a local network and uses the MQTT network protocol for communication. The main element performs the inference method for indoor inhabitant location and sends out all the information to a node in the cloud to store it persistently in a database.

3.1.3 Optimisation and Inference for Indoor Location

In this methodology, a model capable of optimising BLE anchor configuration is proposed. To do so, first of all, a dataset⁵ with the maximum number of anchors in the indoor environment is generated. From this dataset, training and testing of the different configurations is performed, with the objective of selecting a configuration that reaches a balance between a low number of anchors and high accuracy.

This model is optimised using the best performing configuration with a minimum number of anchors and time window size to aggregate the RSSI values in the anchors. The steps are summarised in Figure 4 and are described below:

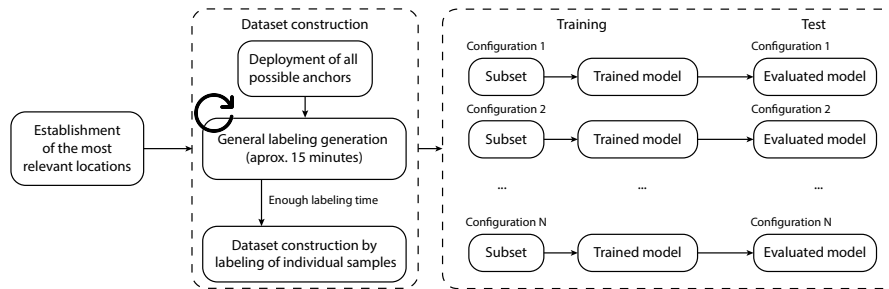


Figure 4: Steps involved in indoor location optimisation and inference.

1. Generating the dataset:
 - (a) Deployment of as many anchor elements as possible. The number of devices and their position is limited by the number of electrical outlets in the enclosed space.
 - (b) General labelling of the selected relevant areas at intervals of approximately 15 minutes (timestamp of entry and exit of a location).
 - (c) Each sample within the general labelling range is individually labelled.
 - (d) Data are unified into a single dataset.
2. Training and testing. According to the number of anchors, the different possible configurations are established (2^n , where n is the total number of anchors deployed). The subsets that have cardinality 0, 1 and 2 are eliminated, since these subsets are not suitable for calculating inhabitant location. Therefore, for each configuration:
 - (a) A subset of the dataset is extracted on the basis of the beacons used.
 - (b) The location model is trained and evaluated for each subset of the dataset.

Following the generation and evaluation of each of the models with the different configurations, the best configuration is selected based on the results obtained. To achieve this, the accuracy of each model is evaluated quantitatively.

⁵ <https://asia.ujaen.es/material/oblea-dataset/index.html>

3.2 Differences between OBLEA and Other Methodologies

The OBLEA methodology is related to past proposals in the literature. However, some key differences have been identified:

- To begin with, the objective of the OBLEA methodology is not to propose a location method under a static framework, as other methods do [Sun et al., 2021b, Duong and Dinh, 2019, Ok et al., 2019, Ai et al., 2021], but rather to optimise Bluetooth anchors in a flexible indoor location system. Our methodology provides flexibility to locate the anchors within real contexts. In this sense, it meets the challenge of optimising BLE anchors in terms of number, location and classifier.
- The methods proposed in [Albín et al., 2021, López et al., 2019] consider an architecture where the RSSI values are sent to a server where the raw RSSI values are processed, the model is trained and the location is inferred. However, it is not easily transferable. Meanwhile, the proposed architecture presents a fog layer composed of the BLE anchors and a fog node that includes short learning time, enhancing the transferability of the methodology to other applications. Our proposal computes the location of the fog node of an enclosed space and not on the server. This fact provides greater scalability in closed indoor spaces, and there may be different configurations for multiple closed spaces monitored in a same system.
- The purpose of our methodology is the optimisation of BLE anchors. Although the classification algorithm is considered as a variable within the experimentation, it is not a central variable as in other location methodologies [Thakur and Han, 2021, Sun et al., 2021a].
- In our methodology, the classification algorithms used to train the location model are not as computationally heavy, since they are deployed in the fog node (SBC) of each indoor space. Despite this, as we will see in the experimentation in Section 4.2, it achieves very good results. This differs from other methods that use heavier algorithms based on deep learning or convolutional neural networks [Thakur and Han, 2021, Sun et al., 2021a].

4 Evaluation of OBLEA in a Case Study

In this section, we present the evaluation of the methodology in a multi-occupancy case study. Specifically, on a floor of a nursing home with shared rooms. We have carried out a wide range of experimentation following the methodology and then the obtained results for analysis. Finally, the limitations of this approach described.

4.1 Case Study

The OBLEA methodology has been applied in a case study to a multi-occupancy context. Specifically, in a floor of a nursing home for elderly people in Alcaudete, Jaén (Spain), where it is vital to know the location of each inhabitant for safety reasons.

The floor of the nursing home was composed of 4 shared rooms and 7 inhabitants were monitored. Each of the rooms housed two elderly people and had of two clearly differentiated areas: a bathroom and a bedroom. The size of each room was approximately

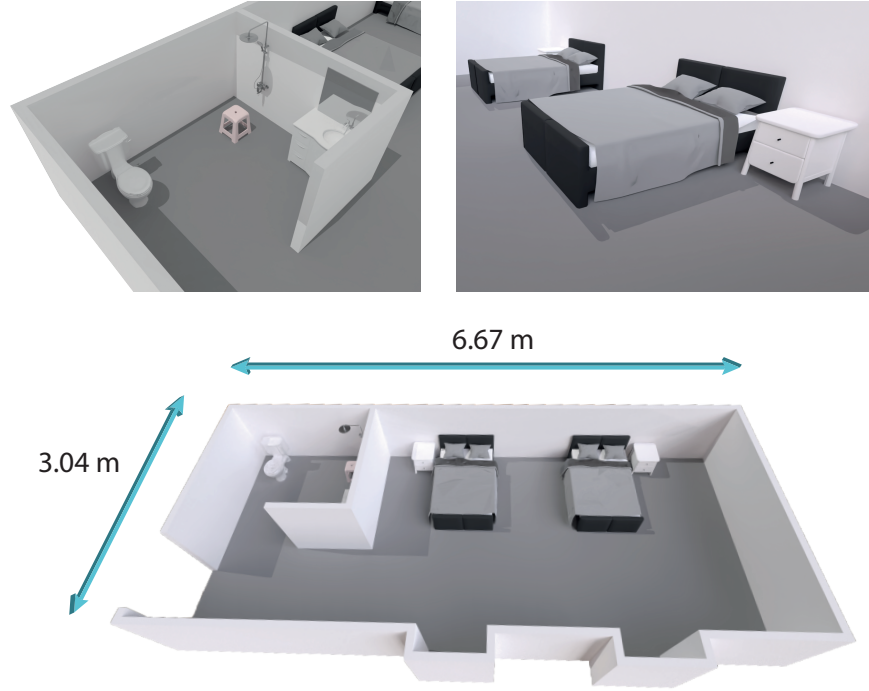


Figure 5: 3D recreation of the shared room. Starting from the top left corner: bathroom, bedroom and the entire room

6.7m x 3.04m, as illustrated in Figure 5. Each room had four power outlets, restricting the placement of location anchors to four devices, as shown in Figure 6.

Considering the relevant areas defined in Figure 6, our flexible framework was established as follows:

- The relevant location areas were selected $\{A_1 = \text{Bedroom}, A_2 = \text{Bathroom}, A_3 = \text{Outside}\} \in S$, S being a shared room.
- A set of two inhabitants $\{H_1, H_2\} \in S$ was given a set of 2 activity wristbands $\{w_1, w_2\}$ where H_1 was associated with w_1 and H_2 was associated with w_2 . Specifically, we used the Xiaomi Band 3⁶ activity wristband.
- A_1 had a set of 3 location anchors $\{sbc_1^1 = \text{Anchor2}, sbc_1^2 = \text{Anchor3}, sbc_1^3 = \text{Anchor4}\}$ associated with it, A_2 one location anchor $\{sbc_2^1 = \text{Anchor1}\}$ and A_3 no anchor. In our proposal, the Raspberry Pi 4B⁷ was selected as the BLE anchors. Each anchor had a program deployed to obtain the RSSI of the target inhabitants and aggregate the RSSI values in time windows according to the proposal presented in Section 3.1.2.

⁶ <https://www.mi.com/global/mi-band-3/specs/>

⁷ <https://www.raspberrypi.com/products/raspberry-pi-4-model-b/specifications/>

- Since *Anchor3* focused on the indoor space, this location anchor was selected as the fog node. A program was developed for this node to collect all aggregated RSSI samples and send them to the cloud layer.
- The cloud layer had a program developed to infer the current location of the inhabitants in real time, following the proposal presented in Section 3.1.3. In addition, this layer handled the persistence of the aggregated RSSI values in the time windows of each anchor and the inferred location.

It should be noted that, in order to improve optimisation, two BLE protocols (4.2 and 5.0) have been evaluated with the purpose of determining which one is the best performing. To do so, two Bluetooth Nano USB Adapters were connected to the Raspberry Pi 4B.

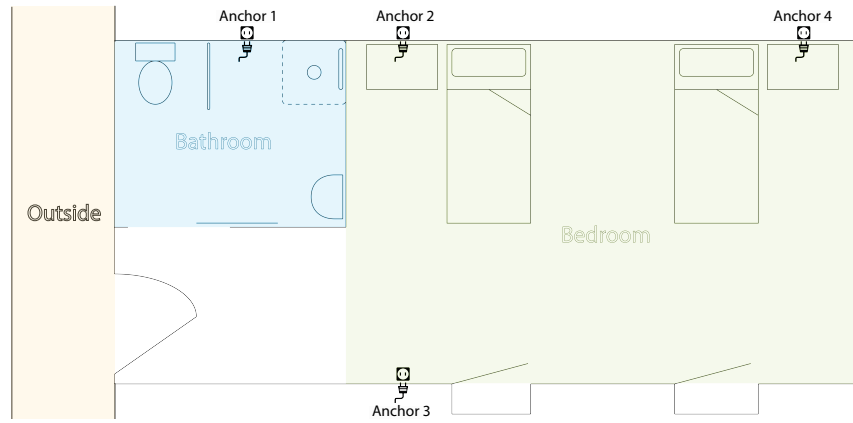


Figure 6: Room layout with sockets and relevant areas

4.2 Experimentation and Analysis of Results

In this section, an experiment with multiple configurations is described in which the following characteristics are evaluated:

- **BLE protocol version (PBLE)**: two BLE versions were tested: 4.2 and 5.0.
- **Time window size (SW)**: according to the amount of time covered, the system may respond better or worse: 1 second (without window), 5 seconds, 15 seconds and 30 seconds.
- **Set of anchors (SA)**: 4 possible subsets were evaluated, considering that sets with 1 or 2 anchors are not relevant. Therefore, the following possibilities were tested:

- $C1 = \{Anchor1, Anchor2, Anchor3, Anchor4\}$
 - $C2 = \{Anchor1, Anchor2, Anchor3\}$
 - $C4 = \{Anchor1, Anchor3, Anchor4\}$
 - $C5 = \{Anchor1, Anchor2, Anchor4\}$
- **Classifier:** different types of classifiers were proposed to identify the most suitable one. This was done because classifiers are highly efficient in training and evaluation, making them very suitable to be embedded in low-cost, low-computational-capacity IoT boards, enabling fog-edge location configurations. The following classifiers were evaluated: K-Nearest-Neighbour, Decision Tree and Random Forest.

Experimenting with these features allowed us to evaluate 96 possible configurations (32 per algorithm). In Table 1, the 10 best results from the total number of experiments performed are presented. The overall results are presented in three different columns in Table 2. The accuracy of the algorithm is indicated for each combination.

Top	Classifier	PBLE	SA	Time window	Accuracy (%)
1	K-Nearest-Neighbour	v4.2	C1	30s	99.82
2	K-Nearest-Neighbour	v4.2	C2	30s	99.43
3	K-Nearest-Neighbour	v4.2	C1	15s	99.16
4	K-Nearest-Neighbour	v4.2	C3	30s	99.04
5	Random Forest	v4.2	C4	30s	98.56
6	Decision Tree	v4.2	C4	30s	98.53
7	K-Nearest-Neighbour	v4.2	C4	30s	98.41
8	K-Nearest-Neighbour	v4.2	C3	15s	98.35
9	K-Nearest-Neighbour	v4.2	C2	15s	98.32
10	K-Nearest-Neighbour	v5.0	C1	1s	97.6

Table 1: Top 10 results of the experimentation

K-Nearest-Neighbour				Decision Tree				Random Forest			
PBLE	SA	SW	Acc	PBLE	SA	SW	Acc	PBLE	SA	SW	Acc
v4.2	C1	1	0.9230	v4.2	C1	1	0.8864	v4.2	C1	1	0.9014
		5	0.9613			5	0.9221			5	0.9385
		15	0.9916			15	0.9319			15	0.9661
		30	0.9982			30	0.9524			30	0.9622
	C2	1	0.8981		C2	1	0.7966		C2	1	0.8814
		5	0.9484			5	0.8583			5	0.9329
		15	0.9832			15	0.9146			15	0.9607
		30	0.9943			30	0.9481			30	0.9598
	C3	1	0.9149		C3	1	0.8280		C3	1	0.9032
		5	0.9574			5	0.9115			5	0.9268
		15	0.9835			15	0.8660			15	0.9634
		30	0.9904			30	0.8505			30	0.9604
	C4	1	0.9047		C4	1	0.8768		C4	1	0.9070
		5	0.9484)			5	0.9365			5	0.9517
		15	0.9736			15	0.97			15	0.9745
		30	0.9841			30	0.9853			30	0.9856
v5.0	C1	1	0.9760	v5.0	C1	1	0.8186	v5.0	C1	1	0.8893
		5	0.9159			5	0.8416			5	0.8516
		15	0.8914			15	0.8475			15	0.7250
		30	0.9319			30	0.7625			30	0.7128
	C2	1	0.9567		C2	1	0.7736		C2	1	0.8110
		5	0.8888			5	0.7474			5	0.7515
		15	0.8458			15	0.7146			15	0.6983
		30	0.8670			30	0.7072			30	0.69
	C3	1	0.9561		C3	1	0.7784		C3	1	0.8501
		5	0.9150			5	0.8154			5	0.7579
		15	0.8859			15	0.7883			15	0.7131
		30	0.8916			30	0.7273			30	0.7156
	C4	1	0.9387		C4	1	0.9547		C4	1	0.9583
		5	0.8986			5	0.9066			5	0.9312
		15	0.8775			15	0.8800			15	0.9059
		30	0.90			30	0.8963			30	0.9167

Table 2: Percentage of accuracy achieved for each configuration

First, an analysis of the best BLE version is presented. For these experiments, it should be noted that two different versions were used: 4.2 and 5.0. From the results, it can be observed that 4.2 provides the best results in this case. In most of the configurations, the older version significantly outperforms the newer version, except for the configurations without time windows (one second), in which version 5.0 always achieves better accuracy.

Although version 5.0 gives us a higher coverage (quadruple the range), this can be a problem for the system. In the literature, BLE devices are often used with a range of just a few metres. This can be seen in Figure 7, where the results are shown in two line graphs: for KNN algorithm version 4.2 and KNN algorithm version 5.0.

As for the size of the time windows, in configurations using BLE 4.2, the accuracy obtained by the classifier improves as the time window increases. However, this is not the case for BLE 5.0. Figure 7 illustrates how the results in version 4.2 improve as the size of the time window increases.

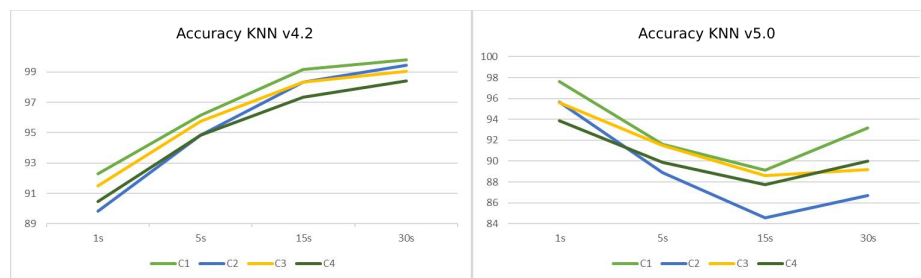


Figure 7: Graphs comparing the accuracy of the KNN classifier with different window sizes in each configuration: a) BLE 4.2 and b) BLE 5.0

The different location anchor configurations and classification algorithms have been evaluated. The best accuracy values are obtained for the options C1 and C4. As for the classifier algorithm, the strongest option is K-Nearest-Neighbour, which appears in 80% of the top 10 results.

Finally, the OBLEA methodology proposed in this paper provides an accuracy of 99.82% with BLE 4.2, configuration 1 (4 location anchors), 30-second time windows and K-Nearest-Neighbour. Although this combination has the best score, we can reduce the number of anchors to only three and cut costs by changing the C1 configuration to C2 with a loss of accuracy of only 0.39% (99.43%).

4.3 Limitations

Only time windows with a maximum size of 30 seconds were considered. Since this paper considers real-time location in a context where the safety of the elderly people is a priority, we considered it important not to use larger window sizes. In other contexts where immediacy is not a priority, window size could be extended and other configurations could be used for potentially higher accuracy.

Due to the need for immediacy in real-time location, the arithmetic mean operator has been used to aggregate RSSI values in the anchored BLEs across time windows. Other aggregation operators could be studied, although their impact will be related to the size of the time window (more than 30 seconds).

In this case study, the maximum number of anchors has been limited by the number of sockets available. A greater number of anchors could be included by using plug adaptors or external batteries. However, these options were not allowed by the nursing home because, on the one hand, there was a fear that the elderly inhabitants could trip over the extension cords and, on the other hand, the external batteries did not have the required autonomy.

Finally, it is noteworthy that this case study does not address possible failures within the network. To address this fact, the OBLEA methodology could be combined with the methodology proposed in [Espinilla et al., 2017].

5 Alignment with the Sustainable Development Goals

Technology and smart systems, such as the one presented in this paper, are crucial elements to achieve the highest sustainability standards. In this section, the alignment and compliance of our system with the SDGs are tested. To carry out the assessment, the 231 indicators and 169 targets have been analysed according to the taxonomy of the Global Indicator Framework Report for the SDGs and the 2030 Agenda for Sustainable Development targets [United Nations, 2021]. It is concluded that the SDGs particularly relevant to the analysis of this paper are:

1. Goal 3. Ensure healthy lives and promote well-being for all at all ages.
2. Goal 7. Ensure access to affordable, reliable, sustainable and modern energy for all.
3. Goal 9. Build resilient infrastructure, promote inclusive and sustainable industrialisation and foster innovation.
4. Goal 11. Make cities and human settlements inclusive, safe, resilient and sustainable.
5. Goal 12. Ensure sustainable consumption and production patterns.

Therefore, it can be assured that the presented system takes into account the requirements set by the United Nations for compliance with the SDGs.

6 Conclusions

The aim of this paper was to offer a new approach on how to optimise the configuration of BLE anchors in multi-occupancy location systems in a flexible and transferable way. This paper has presented the OBLEA methodology for the Optimisation of Bluetooth Low Energy (BLE) Anchors in indoor location systems, considering multiple BLE variables to obtain the best performing configuration with a minimum number of anchors.

To do so, first, a flexible framework for indoor spaces was proposed where the inhabitants to be monitored are equipped with wrist activity bracelets (beacon) and BLE anchors are deployed. Then, the architecture was presented, which includes all the elements of the framework, where the BLE anchors perform an aggregation process based on time windows and send the computed data to a fog node by MQTT. Finally, an optimisation and inference method for indoor location was presented. The inference method proposed is based on data-driven approach. First, a dataset is generated with the maximum number of anchors in the indoor environment. The different configurations

are then trained and tested based on this dataset. Finally, the configuration with the best balance between a low number of anchors and high accuracy is selected.

Furthermore, the proposed methodology was optimised and evaluated in a real case study in a nursing home in Alcaudete, Jaén (Spain) where an experiment was carried out with 7 inhabitants in four shared double rooms. As a result of the optimisation in this case study, it has been possible to locate the inhabitants in real time with 99.82% accuracy using a classifier based on the K-Nearest-Neighbour algorithm and aggregating the RSSIs in 30-second time windows.

Finally, the sustainable development goals that are aligned with the proposed methodology have been identified. Specifically, goals 3, 7, 9, 11 and 12 of the 2030 agenda set by the United Nations.

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