Distributed Social Medical IoT for Monitoring Healthcare and Future Pandemics in Smart Cities

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Abstract
Urban public health monitoring in smart cities focuses on the control of conditions and health challenges in urban environments. Considering the rapid spread of diseases and pandemics, it is important for health authorities to trace people carrying the virus. In smart cities, this tracing must be interoperable and intelligent, especially in indoor surfaces characterized by small distances between people. Therefore, to fight pandemics, it is necessary to start with the already-existing digital equipment of the Internet of Things, such as connected objects and smartphones. In this study, the developed system is employed to provide a social IoT network and suggest a strategy which allows reliable traceability without threatening the privacy of users. This IoT-based system allows respecting the social distance between persons sharing public services in smart cities without applying smartphone applications or severe confinement. It also permits a return to normal life in case of viral pandemic and ensures the much-desired balance between economy and health. The present study analyses previous proposed social distance systems then, unlike these studies, suggests an intelligent and distributed IoT based strategy for positioning students. Two scenarios of static and dynamic optimization-based placement of Bluetooth Low Energy devices are proposed and an experimental study shows the contribution and complementarity of the introduced contact tracing strategy with the applications on smartphones.
Keywords:
BLE prototyping, indoor social IoT, smart health monitoring, Moth Flame Optimizer.

1. Introduction

Health monitoring is an important issue to be considered in smart cities. Smart Health monitoring can take advantage of connectivity, which is an essential element in building the infrastructure of smart cities. Connectivity allows easier interaction and subsequently more efficient collection of medical data for better control of public health. Indeed, in smart cities, the IoT allows to coordinate the communications between smart devices and sensors for the early detection of health problems through patient observation and data collection [1]. In the future, IoT gadgets used in personal health assessment will revolutionize health and pandemic monitoring in smart cities. After the collection of data, its pre-processing, analysis, and interpretation should be correctly achieved. For this purpose, artificial intelligence (AI) mechanisms are involved. In smart cities, AI can also perform tasks such as the automatic processing of medical records and the data transfer between the different services (care, payment, insurance, etc.).

However, nowadays, the problem of the technological gap between the different population classes remains an issue to resolve for facilitating the use of smart services provided to citizens.

Countries have been racing to support scientific research for the development of a COVID-19 vaccine in few months. But the major problem was: How to control a future pandemic situation if the vaccine cannot stop the spreading of the disease? The schedules for vaccines are also shown that after more than 30 years scientists identified the Human Immunodeficiency Viruses (HIV), there is no vaccine for it. To answer the question about when a pandemic disappears, Larry Brilliant, a researcher who led the World Health Organization (WHO) smallpox eradication program, said that COVID-19 "will still be" [2]. Hence, how will we live with a viral future pandemic? The other reason for the ineffectiveness of the strategy of waiting for a specific vaccine to fight a potential future pandemic consists in the huge number of existing but unknown animal viruses (about 1.7 million). Indeed, the more humans introduce changes in nature and modify wildlife (by deforestation for example), the more viruses appear [3]. In this context, new technological solutions are necessary to prevent future pandemics. Scientific community must quickly think about a more realistic deconfinement strategy after

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pandemics. To progressively get out of confinement without putting the health of the smart city citizens at risk, the use of personal data anonymously, coupled with intelligent algorithms and Bluetooth Low Energy (BLE) tools will offer a secure and efficient solution. Indeed, faced with an unprecedented pandemic, intelligent and innovative methods combining communication technologies, AI and Big Data can provide the most effective models and scenarios for deconfinement. These techniques are based on simulating and predicting the spread of the pandemic or the contact tracing to identify and isolate infected persons and the ones recently contacting them. In this regard, to prevent a health problem from turning into an economic crisis, a collaborative strategy between different stakeholders is applied in this study. This strategy uses a social IoT (SIoT) network for tracing contacts in public spaces (public transport, universities, hospitals, shops, or stadiums, etc.) in which contagion is highly possible. IoT is a powerful technology which, by collecting data, contributes to the development of several fields such as deep learning [4], big data management [6] or even [7]. In this regard, SIoT, a variant of IoT, and contact tracing, described below, are two fundamental concepts in our study.

The SIoT [8] is one of the recent advances in IoT networks. It is the result of interaction between IoT and social networks. It allows accessing the interactions and social relationships between the objects of the network [9]. Its aim is to distinguish people from things and to allow to things have their own "social" networks. SIoT networks guarantee a better sharing of information, services, networking solutions and applications using a network of social friendly objects while protecting people's privacy.

On the other hand, the contact tracing process is generally applied to identify the potential infected persons by analysing the history of their social contacts and visited places. Indeed, manual contact tracing is a classic tool used to fight infectious diseases in the past decades, but it was never used for rapid-spreading pandemics given the enormous need for human resources to track infected people and their associates. A more efficient solution is to automate this process by using smartphones and BLE devices to reinforce the social distancing in education, transport, and sport spaces.

Different applications, discussed in section 2.2, involved the use of big data mechanisms to manage the data of millions of users, which makes them technologically expensive in terms of computing resources and data storage. Besides, they require a smartphone and the installation of an application on the user side, which is not applicable in numerous regions and countries.

Different communication technologies used in contact tracing applications were developed. In what follows, we illustrate these technologies and their suitability in our application context: Despite Global Positioning System (GPS) is a famous localization tool, it is inefficient in identifying close collocation of persons, especially in overpopulated indoor environments for different reasons. Furthermore, although most of the recent studies dealing with indoor positioning have focused on radio frequency identification (RFID) and Wi-Fi, there is no common customer implementation of these technologies like the GPS navigation for end-users using smartphones [10]. This shortcoming is due to the difficulty of the direct use of RFID and Wi-Fi positioning technologies in smartphones having different hardware specifications. Recently, different studies such as [11] have investigated the application of short-range communication technologies for indoor positioning systems. Indeed, the BLE positioning technology is a promising positioning method thanks to its easy implementation and availability in mobile phones.

The usefulness of the proposed system in our paper lays in the fact that there is no need for smartphones and applications to be installed and managed by the user for health monitoring during pandemics. In fact, after getting the devices in the entrance of a store or a stadium, users will receive messages indicating their locations or seat numbers in the space without using their smartphones. Since the location of connected objects does not indicate directions, especially indoor, these locations must be statically located and numbered in advance. This numbering is already done or easy to do in most of the targeted spaces such as seats in lecture halls, stadiums, buses, or trains.

The originality of the deconfinement strategy we propose is that it does not depend on the use of smartphones, which simplifies the user-side network architecture, makes the space configuration easier and minimizes the costs of placement of devices. Furthermore, the privacy issue does not arise since the user's data is not recorded or manipulated. A real prototyping is achieved in this study without applying a training process. Indeed, to determine the number and positions of persons, we only consider the dimensions of the space to specify the number and positions of persons. Thus, the space should be discrete, which is the case of the most targeted workplaces such as transport vehicles and stadiums.

The rest of sections of the paper are organized as follows: Section 2 investigates the existing contact tracing applications, scientific studies and its differences compared with our system. Section 3 illustrates the suggested system based on two scenarios of ensuring social distancing. Section 4 highlights numerical and experimental results and discusses the efficiency and behaviour of the introduced system. Section 5 summarizes the findings of this research work and its perspectives.

2. Related works and applications

Several works have been suggested to simulate the spread of the Covid-19 pandemic using mathematical models or AI methods. Other medical research studies have shown the danger of removing the lockdown without taking precautions to gather people without respecting the two-meter social distance [12]. Moreover, various applications have been proposed to track places already visited by infected people using smartphones. In the following sub-section, we detail the main scientific studies and the applications proposed in this context:

2.1 Scientific studies for preserving the contact tracing

At the beginning of the COVID-19, German authorities succeeded in slowing-down the pandemic propagation by manually tracing contacts, then quickly quarantining the infected persons [13].
Indeed, automatic contact tracing was first proposed in [14]. This system collects the data of users by scanning the surrounding environment using Wi-Fi. Then, the scan data are uploaded to a server. Pairwise matching scores between the database and the user data are achieved periodically to determine contacts. Subsequently, an encryption process is used to guarantee the private interrogation of the database in the server by the users.

In [15], authors suggested a decentralized BLE protocol to position nodes without any training preceding the placement of nodes. It is the anchor node that automatically execute the training. This protocol relies on a signal-to-distance reference list to accurately assess the real distance between nodes. Although the proposed application is efficient in localizing people in indoor spaces, its average error is about 1,5 to 3 meters, which makes it inappropriate for the COVID-19 context of localization where two meters should be respected in social distance. Furthermore, smartphones (and not simple BLE nodes) must be employed in this system, which makes the positioning process complex.

Authors, in [16], proposed a tracing contacts strategy to contain the spread of the COVID-19 pandemic by identifying and tracking suspected peoples. However, there is no implementation or given technical details about the evaluation results to assess the efficiency of the suggested system with different strategies. Besides, the design of the used localization protocols should be specified to guarantee the interoperability of the suggested system. Moreover, the theoretical introduced model is dedicated only for iOS and Android systems, which may implicate additional costs, compared to the simple placement using BLE nodes.

In [17], authors suggested a mobile application named "digital Ariadne" to locate and track personal devices. Although the authors affirmed that their system guarantees anonymous access, the use of mobile devices raises several issues regarding data privacy, data interoperability and the cost of implementation. Moreover, the study did not present experimental results; it is only a theoretical investigation.

The research work of [18] introduced a new strategy to manage different heterogeneous IoT devices in indoor spaces controlled using BLE technology. Despite the relevance of the proposed approach in ensuring the interoperability of devices, the number of managed IoT devices is few and does not give an idea about the performance of the suggested method when using a higher number of devices.

The study in [19] presented a decentralized strategy for contact tracing based on peer-to-peer communication between devices. A blind process of signature was used to ensure the privacy and protection of the users' data. Although the idea is interesting, it presents only the theoretical concepts of the proposed framework without prototyping and real application.

In [20], authors developed a system providing alerts to users who were close to regions already visited by infected peoples. Although the system guarantees the anonymity of users and does not collect their location history or personal data, the interpretation of the results of the system is not provided.

Another study, in [21], provided a large-scale proximity tracing system, while ensuring the security and privacy of stored information, to determine persons contacting infected ones. For more efficiency, the system records the countries visited by the users. The data collecting process can be either automatic, based on the GPS data location, or manually done by the user. The tracing process relies on a backend server sharing information with the application installed on smartphones. However, the criteria given by authors to assess the security and privacy aspects of proximity tracing was not accurate. The study in [22] suggests an intelligent model to determine the configuration of repartition of students on the seats in a classroom. Unlike our study, the experimental tests are based on Arduino sensors and Raspberry units to collect and store data. The aim was to verify the degree of respect of the social distance between the students sitting in the classroom. Moreover, it was mentioned, but not explained, how the privacy of personal data is ensured by the implemented system.

Regarding the experimental tests and the used methodology, the study in [23] uses the same type of M5StickC nodes [24] we used, but the methodology and the experimental scenario of testing were very different: [23] proposed three standard optimizers (Genetic Algorithm, Ant Colony, and Particle Swarm) as a methodology while in our study, we suggest a method based on a much more recent optimizer called MOTH which was hybridized with Multi-Agent Systems (MAS) to increase the efficiency of the algorithm for monitoring the social distance. Moreover, the number of students was limited to 20 in the simulations in [23], while our tests rely on experimental tests with a greater number of persons. Another difference was in the evaluation metrics since [23] used networking measures such as the amount of transmitted data, and the standard deviation, while our tests rely mainly on the average distance and the number of reconciliations between persons.

The authors in [25] propose a survey on the different techniques of monitoring used for maintaining the social distance between persons, especially in indoor spaces.

In [26], the authors suggest a survey to review the role and use case of different scenarios of social distancing. Numerous wireless technologies were tested to highlight their advantages and drawbacks. An investigation of previous recent studies was given to evaluate the methods of designing dans developing social distancing wireless-based technologies which allows a better preparation for future pandemics.

The study in [27] illustrates a Deep Learning algorithm to control the respect of social distance in public places. Humans are identified in the taken videos via a YOLOv3 recognition approach. The detection process relies on a pre-trained layer of overhead human data. A threshold is set, and an approximation of the distance is computed to measure the distance between persons. A tracking algorithm identifies persons violating the fixed threshold. The accuracy of the system is enhanced by a transfer learning paradigm. The results of testing the system confirm an effective recognition of people who do not apply social distancing measures. However, privacy concerns should be guaranteed in such systems using live video and location information of persons.

Authors in [28] introduce BeepTrace, a Blockchain system for contact tracing with privacy maintaining. The Blockchain technology in the proposed system links the user with authorities in a decentralized way without violating the user's locations and identities.

The study in [29] enumerate the possible use cases of the Blockchain to fight against COVID-19. For this purpose, three Blockchain models are proposed to help authorities to better manage the increase of urgent cases. This study confirms the usefulness of using Blockchain in the field of health crisis management.

In [30], authors suggest resolving the problem of securing localization systems using a distributed Blockchain model. This model, which aims to reliably locate both things and people, was called

Internet of Entities (IoE). It is compatible with the existing networking infrastructure and focuses on respecting privacy which is one of the drawbacks of classic localization systems. The study also confirms the benefits of the use of distributed Blockchain models in real contexts.

2.2 Comparison of implemented contact tracing applications with our proposed system

Our solution is essentially based on ranging rather than localization. Indoor BLE devices are used to evenly distribute people across the available space. The Wi-Fi is used for an application network need. To distinguish our proposed solution and its novelty, we discuss, in what follows, the different implemented applications:

BlueDot [31] is a Canadian application implemented to make the users aware about the risky places even before the authorities classified them as “risky”. The applied algorithm uses a machine learning mechanism to collect information and guess the status of the locations according to numerous parameters such as the population density, the accessibility, and the neighborhood of the location.

Covid-IA [32] is a French initiative proposing a map to simulate the spread and evolution of the pandemic in France according to several deconfinement parameters such as the infection rate, the movement of persons, the population density, and the possibility of displacement between cities.

StopCovid [33] is another application introduced by the French authorities to follow-up the infected contacts. It is independent of mobile phone platforms. Its goal is to break the chain of transmitting the COVID-19 in gathering places and public transport to prevent a second wave of this disease.

In [34], a system, called WeTrace, was implemented to provide crowdsourcing for COVID-19 data. The proposed method is scalable since it involves data collected from hundreds of thousands of people.

PEPP-PT [35] is a European initiative introduced to enhance the strategy of fighting the COVID-19. The developed application broadcasts the IDs from the history of infected persons while protecting the identity of infected persons.

Another application, named Trace-Together [36], was suggested by the authorities in Singapore to automatically trace the contact of users, scan their environment and broadcast their IDs using Bluetooth. The history of scan is locally stored, and the used IDs are uploaded to a server. Indeed, when a person is identified as infected, the authorities ask for or force the upload of this history to their servers to notify other persons and to identify individuals recently being in contact with COVID confirmed persons by searching their IDs in the history.

Moreover, researchers from MIT university proposed a privacy-focused solution named Private Kit [37] to hide the user’s locations for privacy protection. This application uses Bluetooth and GPS. It involves both health authorities and citizens. It privately identifies and updates the location data of users then locally stores this information each five minutes.

Covid-Watch [38] is a system implemented after a collaboration between the US health authorities and Stanford University. It is a cell-phone application representing a more distributed variant of the Trace-Together method. This distribution aspect is based on sending out and looking for signals (random and anonymous IDs) using Bluetooth. These IDs are locally stored, change periodically (kept for only one month). Once a person using the application is infected, the application will alert other users by sending the list of his/her stored IDs. The system is compatible with Android and iOS devices and the development of the backend infrastructure for storing and validating data is achieved with Python.

DP-3T [39] is a decentralized proximity tracing application preserving people’s privacy. It was suggested by the Swiss health authorities. It includes a backend SDK and a demo application for Android and iOS. This system is compatible with the solutions proposed by Google and Apple.

Table 1 illustrates the characteristics and the differences between the implemented applications and tools used to trace and track the COVID-19.

Table 1 Comparative analysis of COVID-19 contact tracing applications

APPLICATION	DATA STORAGE	COMMUNICATION TECHNOLOGY	COLLECTING INFORMATION TECHNOLOGY	PRIVACY	USE	LICENSE
BlueDot	Distributed	BLE	GPS	Anonymous data	IA prediction strategy	Open source
WeTrace	On user's device, shared if detection of infection	BLE	GPS and timestamp	Encrypted and anonymous data, public key generation	Developed and supported by authorized institutions	Open source
PEPP-PT	On user's device, shared if detection of infection	BLE	From near devices using P2P Bluetooth communications	Cryptography of data	Recognition of IDs achieved on device	Partially open source
Trace-Together	Local on user device, distributed	BLE	From near devices using P2P Bluetooth communications	Encrypted collected BLE data	Infrastructure maintained by contributors (developers)	Commercial software
Private Kit	Local on user device	BLE	GPS	Encrypted user's locations	User's details are not all disclosed	Open source
Covid-Watch	Local, decentralized	BLE	GPS with anonymous data	Encrypted and anonymous data, public key generation, GDPR	Public common database	Open source
DP-3T	Local, distributed	GPS, GSM, BLE, triangulation	GPS and timestamp	GDPR, Hash functions	Notifications broadcasted. Supported by authorized institutions	Open source
StopCovid	Local, distributed	BLE	Bluetooth	Encrypted user's locations	Developed and supported by authorized institutions	Open source

Numerous countries and universities proposed different, but isolated and identical efforts to fight the spread of the COVID-19 using mobile Bluetooth devices. The suggested mobile applications store the information in local databases to guarantee the preservation of data privacy. The aim of these applications is to slow down the propagation of the COVID-19 without increasing the surveillance of users.

However, although these studies focused on the respect of social distance in public services, very little effort was made to manage the crowds of people using BLE devices after confinement.

3. Research Design

3.1 Mathematical modelling

Mathematically, our problem may be considered as a *Set Cover Problem* having an NP-complete complexity [40] [41]. The *Set Cover Problem* can be summarized as follows: Considering a set ***A*** and an element ***e***, if ***e*** belongs to ***A***, it is considered as covered by ***A***. If we have a set ***U***, and a set ***S*** composed of subsets from ***U***, the objective of the *Set Cover Problem* is to cover all the elements ***U*** with the smallest subfamily from ***S***.

As an example, we have ***U*** with five elements to cover ***U*** = {1,2,3,4,5} and four subsets: ***u1*** = {1,2}, ***u2*** = {3,4}, ***u3*** = {4.5} and ***u4*** = {1,2,3}. The aim of this problem is to cover all the elements of ***U*** with the subsets ***u1***, ***u2***, ***u3*** and ***u4***. A possible coverage is ***u1***, ***u2***, ***u3*** because each element from ***U*** exists in at least one subset. However, this coverage ***u1***, ***u2***, ***u3*** does not use the minimum number of subsets. On the other hand, ***u3 and u4*** use the fewest subsets, which makes the latter coverage the best one.

The decision problem corresponding to the *Set Cover problem* may be defined as follows: A finite set ***U***, an integer ***k*** and ***S*** (a subset of *U*), are defined as inputs to the problem. To resolve this decision problem, it is sufficient to find, if it exists, a subset ***T*** from ***S*** with a size less than ***k***, such that the union of the elements of the subsets of ***T*** is equal to ***U***.

This problem can be transformed into an optimization problem to minimize the used number of subsets. We associate to this problem a weight ***c(S)*** for each set ***S*** to minimize the sum of weights.

The most appropriate optimization modelling for this problem is a linear integer optimization: If a variable x_s is considered for each subset, the linear program of the problem will be as follows:

$$\text{Minimize } \sum_{s \in S} x_s,\ x_s \in \{0,1\} \quad \textbf{(1)}$$

such that: $\sum_{s \in S} x_s \geq 1, \forall e \in U, \forall s \in S$ **(2)**

The objective function (1) aims at minimizing the number of subsets such that x_s is either covered (x_s = 1) or not covered (x_s = 0). The constraint (2) indicates that all elements must be covered.

The *Set Cover problem* is in relation with other algorithmic problems, among others:
- The *Exact Coverage Problem* which considers that the items must be covered more than once.
- The *Vertex Coverage Problem* is a special case of the *Set Cover problem* applied to a graph.
- The *Maximum Coverage Problem*.

*** Modelling our problem as a *Maximum Coverage Problem***: This problem is a variant of the "*Set Coverage Problem*" aiming to cover the maximum number of elements (individuals or students in our case) with at most ***k*** available subsets (e.g. places to occupy in the lecture hall or in the bus).

The input to the *Maximum Coverage Problem* is an integer ***k*** representing a set of elements and a list of subsets from that set. The aim of the latter problem is to identify the ***k*** subsets while guaranteeing the maximization of, at least, one of these subsets. Each element is assumed to be covered if and only if it belongs to one selected subset.

Our *Maximum Coverage Problem* is formalized into an integer linear optimization problem as follows: In classic coverage, the objective of this problem is to cover the maximum space by using the minimum number of nodes. In our case, we try to distribute a specific number of nodes over the discrete space (possible positions known in advance) while guaranteeing the maximum spacing between them. Thus, we consider ñ nodes in indoor space. Hence, $\sum_{p \in \Omega_1} \xi_p^i \geq ñ, \forall i \in \Omega_4$. Consequently, the following function is proposed:

$$\text{Maximize } \sum_{\hat{g} \in \Omega_3} \left(\sum_{p \in \Omega_1} \xi_p^i - ñ\right), \forall i \in \Omega_4 \quad \textbf{(3)}$$

such that ξ_p^i is 1 if a node ***i*** covers the position ***p*** with a minimal rate of power, 0 otherwise.

The cost of repositioning a node ($i \in \Omega_4$) depends on the number of movements needed after adding **ñ** nodes. This number of movements should be minimized to respect the social distance and minimize the contact between people (nodes) while moving.

$$\text{Minimize } \sum_{p \in \Omega_1} \sum_{t \in \Omega_2} \eta_t^p K_{\hat{g}}^{\mu}, \forall i \in \Omega_4, \hat{g} \in \Omega_4 \quad \textbf{(4)}$$

η_t^p is equal to 1 if a site $p \in \Omega_1$ contains a nomad sensor of a type $t \in \Omega_2$, 0 otherwise.

$K_{\hat{g}}^{\mu}$ is the cost of hardware needed to move a sensor $i \in \Omega_4$ positioned at a site $\hat{g} \in \Omega_3$.

Ω_1 corresponds to the sites in which nodes can be placed.
Ω_2 denotes the types of nodes.
Ω_3 represents the targets to be detected.
Ω_4 designates the nodes having sites in Ω_1 and types in Ω_2.
such that:

$$\sum x_i \leq k \quad \textbf{(5)}$$

$$\sum_{j \in \Omega i} x_i \geq y_j \quad \textbf{(6)}$$

$$R = \frac{\sum_{p \in \Omega_1} \xi_p^i \,/\, ñ}{ñ} \quad \textbf{(7)}$$

$$y_j \in \{0,1\} \quad \textbf{(8)}$$

$$x_i \in \{0,1\} \quad \textbf{(9)}$$

The aim of the objective function (3) is to increase the number of covered items. The objective function (4) indicates that the objective is to reduce the number of movements of persons which reduce the number of old nodes used to reposition in new positions after adding new nodes. Constraint (5) shows that ***k*** subsets must be selected. Constraint (6) specifies that if y_j is strictly positive then, at least, one subset $\mathbf{e_j} \in \Omega_i$ must be selected. Constraint (7) describes the relation between the communication radius $\boldsymbol{R}$, the total area and the number of individuals. Constraint (8) reveals that e_j is covered if y_j is equal to 1and e_j is not covered if y_j is equal to zero. Constraint (9) indicates that Ω_i is selected if x_j is equal to 1 and Ω_i is not selected if x_j is equal to zero. Being NP-complete, the *Set Coverage Problem* can be solved using different approximation algorithms such as optimization algorithms and meta-heuristics.

3.2 Distributed strategy for BLE positioning

*** Operation of the used BLE devices**: To assess the operational feasibility of distance measurements between connected objects and to evaluate their performance, a testbed using 22 sensors was modelled in a wireless mesh network topology to concretely validate the ranging between pairs of BLE objects. Several nodes, such as smartphones, tablets, laptops, and communication nodes, such as "M5StickC ESP32-PICO Mini IoT Development Kit" [24] which can be worn on the wrist or put in the pocket, are used. The second type may be utilized by people who do not have a smartphone. In fact, smartphones have a BLE transmitter/receiver, a GPS receiver, and an IP connection to the internet in Wi-Fi and 3/4G. M5StickCs nodes are programmed with a BLE ranging protocol as it is the case for smartphones that need to install a similar BLE ranging application. The ranging protocol is as follows: regularly and typically, every second (or less), a small random time value is generated to desynchronize any collisions between competing transmitters. Then, the equipment sends a BLE frame carrying the identifier of the transmitting node.

Each BLE receiver is also capable of receiving frames if it is within the radio range of a transmitter which is typically around ten meters in free field, i.e., in Line of Sight (LOS). We verified the maximum radio ranges by performing several tests on different types of BLE nodes. Due to the power of the signal received from the sent BLE advertising frame, the receiver deduces if the distance between the two nodes is less than one meter if the power of the signal received from the sent BLE is a predefined range (set between -50 and -70 dBm in our experimental scenarios). To achieve this, the received radio power was converted into distance using the *Fris* Formula and knowing the transmission power, the characteristics of the transmitting and receiving antennas and the gain of the radio receiver. A calibration phase can be performed for each type of radio node or even for each type of radio pair. The objective of this study is not to obtain a very high accuracy of distance measurement, but a rather rough estimate at ten cm of accuracy (For greater precision, the Ultra-wideband (UWB) technology can be used). But unfortunately, this technology associated with the evaluation of radio flight time is still very little present on Smartphones. Hence, BLE is sufficient to determine a contact distance of one meter or more. The duration of the "contact" was subsequently evaluated and stored in the M5StickC node, then transmitted to the next encountered M5StickC node or smartphone. The latter can utilize its IP connection to transmit this information to the central computer where the positioning algorithm was implemented. Smartphones will also implement this BLE ranging protocol by transmitting both their own ranging and the ranging derived from another M5StickC node. Smartphones can also use their GPS to locate themselves, but with relatively low accuracy of around 15 meters which is not appropriate in our application context.

This network architecture is illustrated in Fig.1. Twenty-two M5StickC nodes were used to form a mesh Wi-Fi network based on a hierarchical tree without a loop starting from the identifiable root node at the bottom of Fig.1. These nodes also serve as a gateway to an IP network via a Wi-Fi connection. All Wi-Fi links, whether real between the access point and the M5StickC gateway client or point-to-point links on the mesh part, must be on the same 802.11n Wi-Fi channel. This type of Wi-Fi link does not force the gateway node to change the channel between the two parts of the network. For the mesh part, a library inspired by “painlessMesh” [4] was used. This library works for ESP32 and ESP8266 nodes.

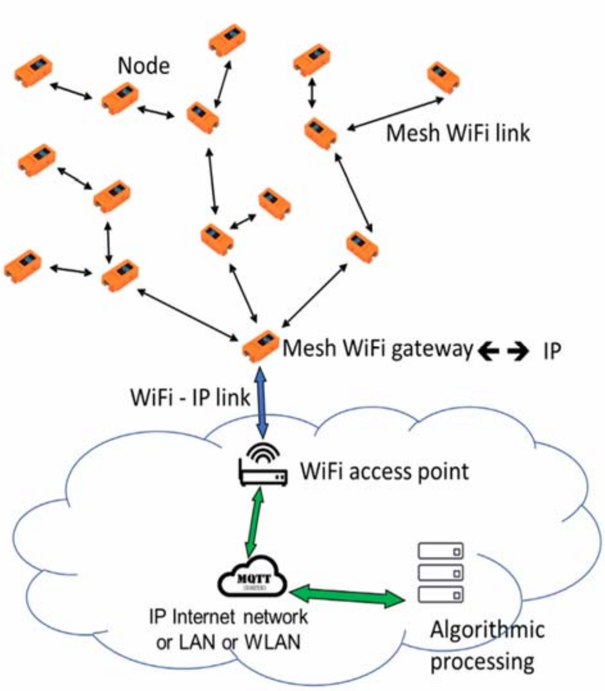


Figure 1 Proposed network architecture

The gateway node receives broadcasted messages from all nodes in the mesh network and propagates them to the Wi-Fi access point using the Message Queuing Telemetry Transport (MQTT) protocol and a "Publish" primitive. It is necessary to implement an MQTT broker on the IP network (Wi-Fi, Ethernet, or even Internet via routers). For our testbed, we implemented this broker in a Linux machine using Mosquitto. Then, we employed a machine (in the IP network) to run the optimization algorithms. By performing a "subscribe" adapted to the MQTT topics published by the gateway, this algorithm allows obtaining the input data useful for its algorithmic processing. This data is composed of the information directly sent by each node of the mesh network, with several fields in each frame: the source address of the sending node, the address of the node with which the source has just detected a contact less than one meter, the time of the beginning of contact (the "painlessMesh" library ensures the implementation of a protocol for synchronizing the clocks of the nodes of the mesh network) and the duration of the contact.

3.3 Design of the distributed positioning algorithm

To respect the social distance, the challenge is that only a percentage of the global space should be usable according to the WHO spacing recommendations [42]. This percentage of available space is related to numerous parameters such as the number of involved persons, the obstacles existing in this space, the desired social distance, and the momentary need to use this space (for multi-function spaces).

Indeed, when leaving the choice of placement to people, they often choose a single part of the space (the part having the easiest access, the most comfort or simply the closest to them). The proposed system allows an automatic and uniform distribution of people in space according to the above-mentioned parameters. The system was used, in the performed experiments, to compute the new configuration of the locations and automatically, dynamically, and gradually install the maximum number of people in the space. In this regard, we admitted two scenarios:

3.3.1 Static scenario for the placement

In this scenario, the number of people is known in advance, hence there is no need to apply an optimization algorithm. Fig. 2 highlights the operations of the algorithm, as follows:

- Uniformly distributing people over the locations: calculating the number of possible locations and determining them.
- Allocating the positions to people: Sending messages to BLE devices. In fact, each message contains the location allocated to the concerned person.
- Confirmation by the person: sending a standard feedback message to the central computer once the person reaches his/her place.
- Verifying the respect of social distance: the central computer measures the distance separating each device from its neighboring devices.
- Sending the results tests to the concerned device to check if the social distance is respected or not.

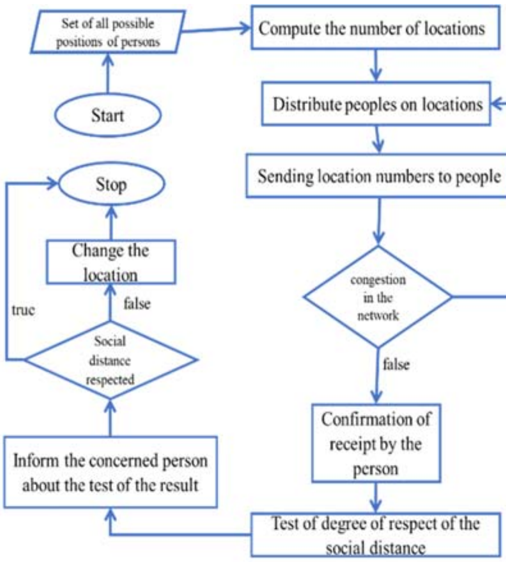


Figure 2 Flowchart of the static positioning scenario

Algorithm 1 presents the steps of the static positioning algorithm.

***Algorithm 1* Static positioning algorithm**

1. Begin
2. Set social_dist_threshold
3. Set nb_locations
4. Distribute_peoples_on_locations()
5. Send (nb_locations, people)
6. congestion = False
7. Verif_congestion_state()
8. If (congestion == false)
9.   Confirmation_receipt(person)
10. End if
11. If (social_dist > social_dist_threshold)
12.   Change_location()
13. End if
14. End

3.3.2 Dynamic placement scenario: A hybrid MFO-MAS optimization algorithm

In this scenario, the total final number of people is not known in advance, which is the case of buses, trains, and stadiums.

A maximum threshold of the estimated number of people can be set to return to the static scenario. However, this dynamic scenario has another objective different from that of the static scenario: keeping people as far away as possible from each other. This objective is necessary to contain the viruses as some studies [43] have claimed that the viral viruses may stay in the air for hours and the social distance should be between 7 and 8 meters.

Therefore, the proposed algorithm explained in Fig. 3 can be described as follows:

- Performing a scheduling such as that presented in scenario 1 without using an optimization algorithm and according to an estimated maximum threshold of people.
- If this threshold is exceeded, a new threshold is set, and a hybrid optimization algorithm will be used to launch a repositioning process to redistribute people with two objectives: "maximizing the coverage of the surface to separate individuals from each other as much as possible" and "minimizing the number of the movements of individuals who have been installed".
- If the threshold s_i is reached, the last step will be repeated, the repositioning process will be achieved and a new threshold s_{i+1} will be set.
- Applying a stopping condition which may be either the maximum execution time of the algorithm or the maximum number of people accepted by the space while respecting the smallest authorized social distance.

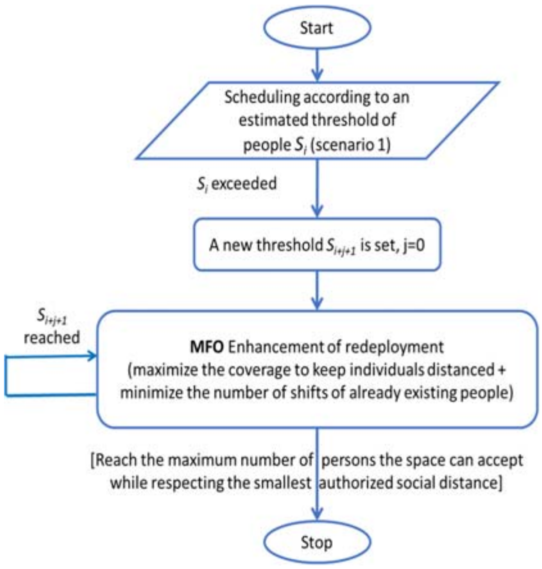


Figure 3 Dynamic repositioning process

Algorithm 2 illustrates the steps of the Dynamic repositioning algorithm.

***Algorithm 2* Dynamic repositioning**

1. Begin
2. $S_{actual} = 0$
3. Schedule (S_{actual} ,S_i)
4. NbPersons = 0
5. While (NbPersons < MaxNbPersons)
6. If ($S_{actual} > S_i$)
7. set a new threshold S_{i+j+1}

8. j=0
9. While (j < S_{i+j+1})
   MFO()
   maximize the coverage
   NbShifts = NbShifts-1
   j=j+1
10. End while
11. End if
12. NbPersons = NbPersons+1
13. End while
14. End

A multi-agent system was used simultaneously with the Moth-flame optimization (MFO) algorithm to effectively manage the interactions between the actors of the system. In this hybrid MFO-MAS system, the optimization was carried out by MFO at the level of each agent. An agent represents a BLE node showing the possible location in the region of interest (RoI) and occupies the space to be covered by a person. Following the execution of the MFO at the level of the agent nodes, the controlling agent receives the proposed solutions, chooses the best solution, and sends a message to all nodes to update, if necessary, their positions to ensure applying the best-found solution. According to the objective functions, the aim is to reduce the displacement of existing nodes with a maximum distance separating the nodes.

*** Application of the Moth-flame optimizer:**
MFO is a swarm-based optimization algorithm, first proposed in [44]. It is based on imitating the behavior of moths when moving at night. These movements are based on exploiting the moon light by adopting the "transverse navigation guidance" mechanism, which is based on the principle of the moth's flight at a fixed angle toward the moon light. This technique enables to fly in a straightly if the source of light is far away (such as the moon). However, the artificial lights distract the moths trying to fly on a flight angle around this nearby light. Consequently, the latter loses its flight path and enters in deadly circular flights following the artificial light or around flame light.

The MFO, illustrated in Fig. 4, randomly generates a set of moths dispersed on the search space. Then, it computes the positions of the moths using the fitness functions to mark the best position with a flame. To identify the best flame positions, the moth positions are updated using a spiral motion feature and by new individual best positions. This process of updating or proposing novel locations is repeated until fulfilling the stopping conditions.

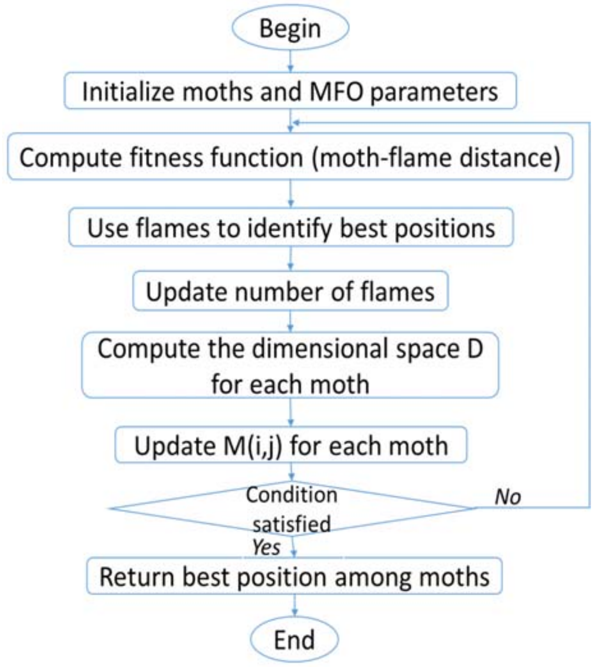


Figure 4 Flowchart of the used MFO algorithm

Algorithm 3 shows the steps of the MFO algorithm.

***Algorithm 3* MFO algorithm**

1. Begin
2. Initialize(moths_ params, MFO_params)
3. If (NON(MFO stop conditions))
4. computeFitness(moth_flame_dist)
5. For each flame fi
6. IdentifyBestPosition (fi)
7. End for
8. updateF(nbFlames)
9. For each moth mt
10. computeDSpace(mt)
11. updateM(M(i,j))
12. End for
13. End if
14. Return bestPosition(mt)
15. End

*** MAS: Justification of the hybridization and the use of MAS**

The hybrid MFO-MAS algorithm allows to integrate the learning capacities of MAS into the MFO.
In the proposed multi-agent modelling, each agent represents a BLE node that knows its position and the positions of the other nodes. It also searches for a new optimal distribution of all nodes by running the MFO algorithm.
The collaboration between agents allows developing a “society” to achieve their local and global objectives [45]. This collaborative decision-making process is compatible with the nature of the problem of repartition of people

according to a set of specific criteria. Therefore, the proposed hybrid MFO-MAS algorithm is generally used to resolve real-world complex problems such as social distance monitoring. However, a perfect resolution of these complex problems requires an accurate specification of the behaviour of the agents, the way of interaction between them, their perceptions of the environment and their knowledge. The latter depends on the agent capabilities of enhancing the local search of self-locating in the search space, and its capability of learning from the environment or from other agents.

*** Modelling of the multi-agent architecture and interactions between agents:**

The proposed multi-agent architecture includes two types of agents: controller agent (*agCtrl*) and BLE node agent (*agBLE*). *agCtrl* attribute, for each *agBLE*, its neighbors and its first position in the space of the problem. Afterwards, each *agBLE* agent should find an optimal solution using MFO until reaching a sufficient quality of solution or number of iterations.

The architecture and the intentions of agents using the CNP are as follows:

* ***agCtrl***: The structure of the environment is two-dimensional as most surfaces where persons can meet. Indeed, each agent can occupy only one point in the environment. The **agCtrl** gives additional information to other agents about the problem and the environment, whereas agent **agCtrl** has the parameters:

- n : the dimension of the problem space.
- L : the population size.
- P : set of the visited points $p.\in.P$ in the problem space.

p={d_1x d_2 x … x d_n, *used*} is a "point" in the n dimensional space. *Used* has a Boolean value reflecting if the current location was used or not.

* ***agBLE***: Each ***agBLE*** identifies a position in the search space which is a configuration of the repositioning problem. Thus, its position in the search space is not a position of a node in the 2D surface to be covered. ***agBLE*** agents may collect information from the environment or request it from the ***agCtrl*** or from other ***agBLE*** agents. Among its tasks, we can mention requesting the actual positions of other agents in the search space and communicating its position to other ***agBLE*** agents.

4. Proof of concept on a real testbed

To assess the efficiency of the two placement scenarios using BLE nodes detailed in the last section, a real prototyping is suggested. Thus, the proposed solution was implemented in a practical context with experimental scenarios performed on a testbed composed of 22 BLE sensors.

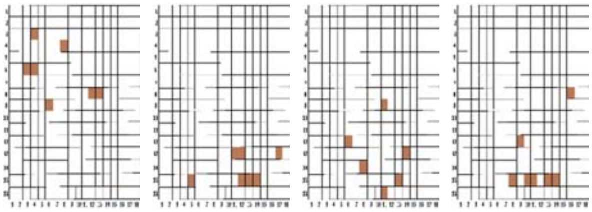
4.1 Testbeds setting

An i7-9700K 3.6 GHz computer was utilized as a server receiving information and managing the relations between BLE nodes. The double physical layers use Wi-Fi / BLE 2.4 GHz. The experiments are set as follows: 7 to 22 BLE nodes were disseminated in a region of 352 m2. The transmission range of nodes was 20 meters. The integrated antenna was a part of an ESP32 transceiver. The power of transmission of BLE and Wi-Fi was 100mW. Since optimization algorithms are of probabilistic aspect, 25 experiments were executed to obtain the averages values presented in the figures 7-11. The used M5StickC ESP32 Mini IoT nodes were equipped with a 4MB Flash memory, an IR transmitter, a grove port, a 2.4G antenna, a microphone, a watchband, and wall mounted for Arduino Micro-Python, a UI-Flow programming, a color LCD screen display, and an extendable socket. These nodes, shown in Fig. 5, were easily handled, and managed using Arduino libraries containing different network protocols. Regarding the latency of the network, which indicates the communication delays in the network, in milliseconds. Regular pings were used to determine the average network latency. The latency in our tests was 40.51. Indeed, an acceptable latency rate should be generally less than 100. The optimal rate is generally between 30 and 40.

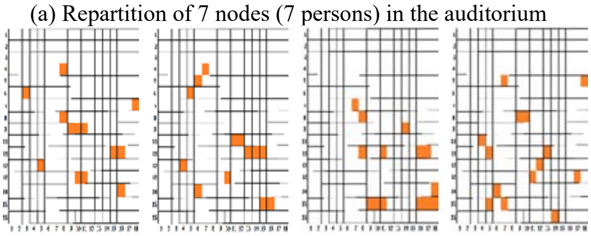
Figure 5 The used M5StickC ESP32 Mini IoT nodes

4.2 Simulations of random movements

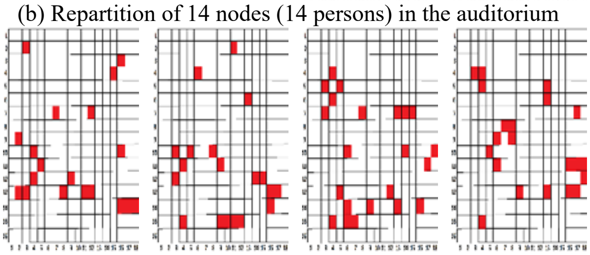
To evaluate the two static and dynamic scenarios, we simulated the movements of people randomly entering and positioning themselves in the used space. The simulations were performed to avoid a real placement of people in the period of containment (from March 2020 to May 10th, 2020). The chosen space is an auditorium with a maximum capacity of 352 seats (16 rows, 22 places per row, one meter separates the adjacent seats). To compare the obtained results in the two scenarios and since we had 22 available BLE nodes, we simulated the movements of 22 people who would enter and choose their places on the 352 seats. Fig. 6 illustrates a random simulated distribution of BLE nodes for 7, 14 and 22 people.



(a) Repartition of 7 nodes (7 persons) in the auditorium



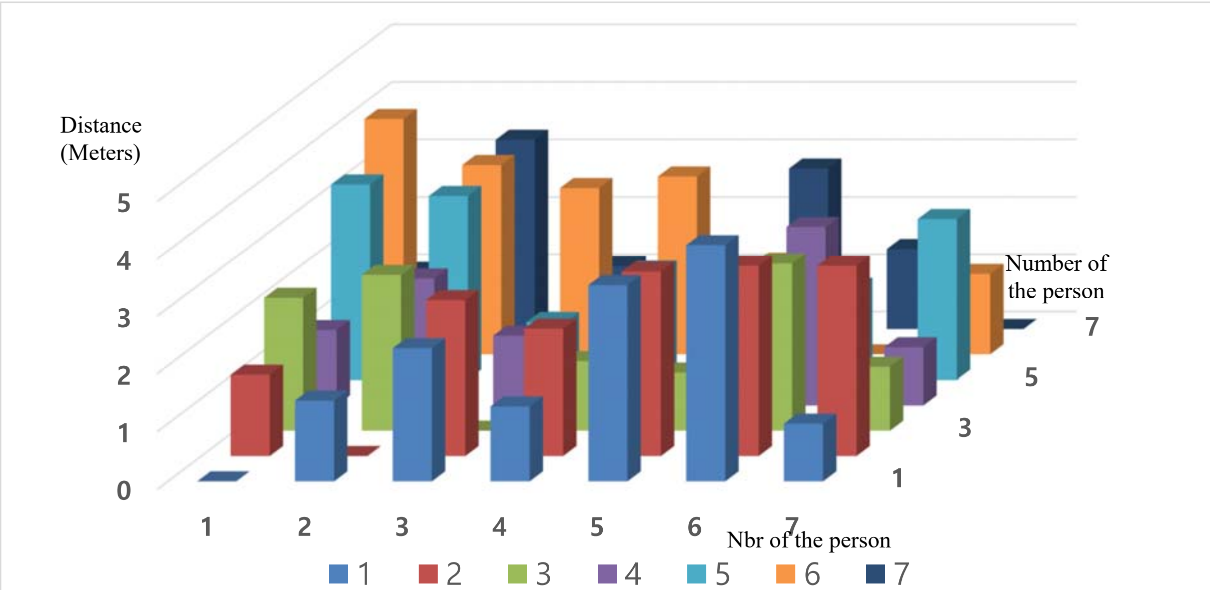
(b) Repartition of 14 nodes (14 persons) in the auditorium



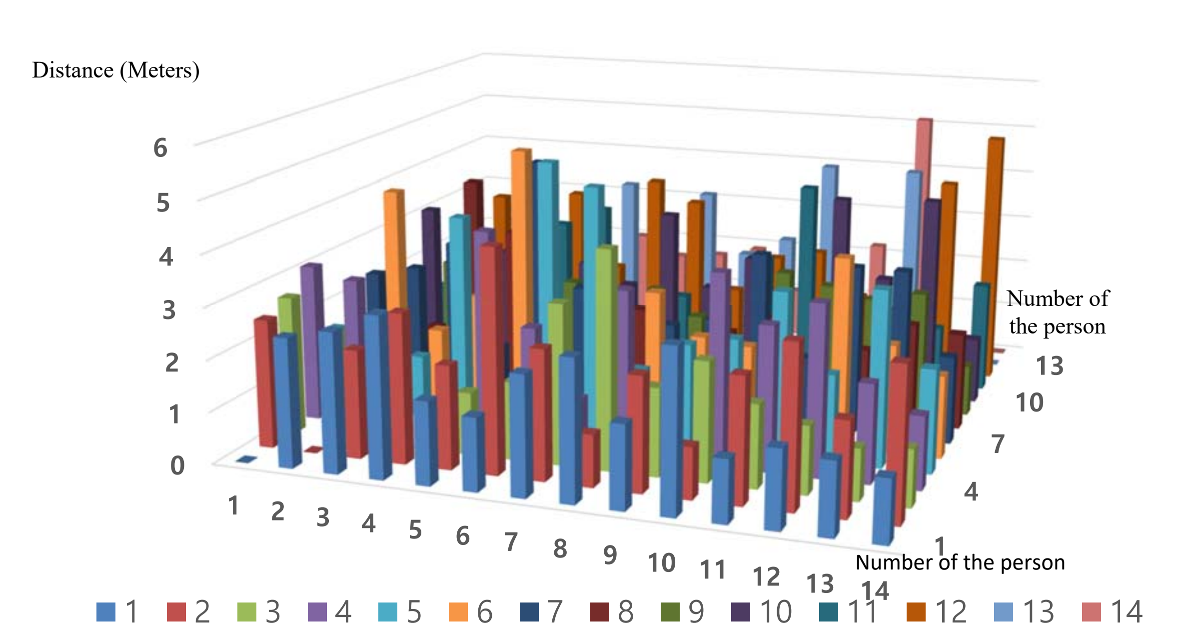
(c) Repartition of 22 nodes (22 persons) in the auditorium

Figure 6 Examples of random distributions of people in the 16x22 meters auditorium (from March 2020 to May 10th, 2020)

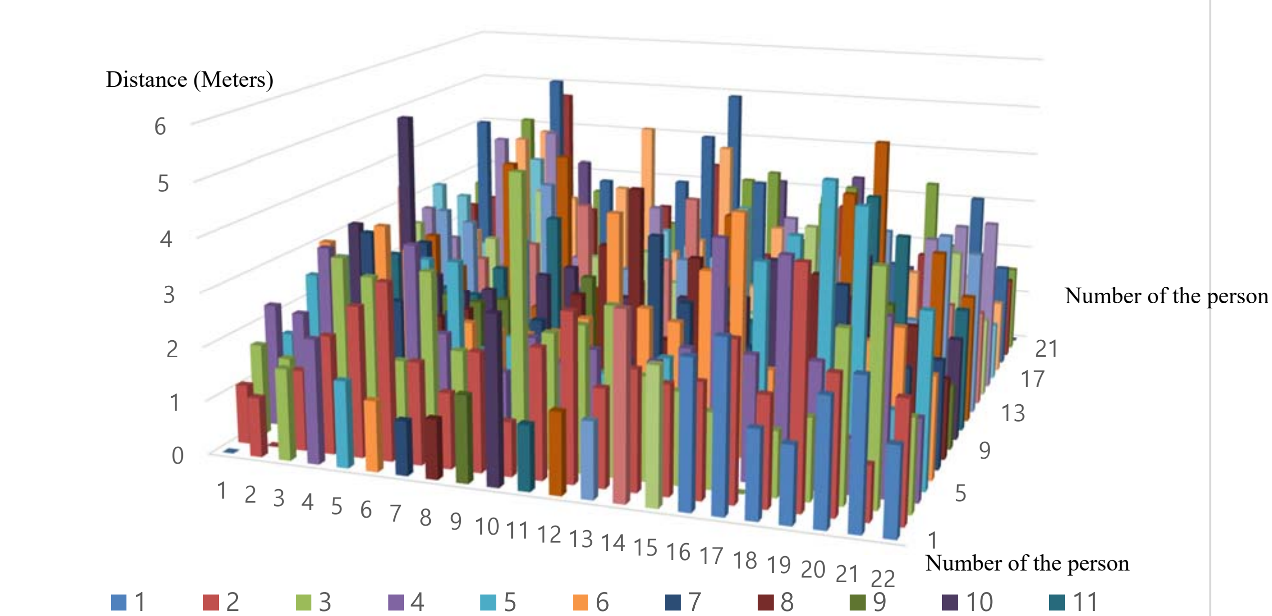
The simulation scenario is as follows: 7 people entered the auditorium followed by 7 other persons after 30 minutes and 8 persons after one hour. The average results of 25 runs, measuring the average distances between placed people, are shown in Fig 7. The closeness (the minimum recorded distances) between people were measured during the movement and the displacement. Fig. 7 shows that, if we let people stand freely, most of the distances between people are less than two meters. This distance decreases especially if the number of people increases from 7 to 14 and to 22. This observation can be explained by the social relations between people preferring to stay together in groups of two, three or more.



(a) Average distances between 7 persons



(b) Average distances between14 persons



(c) Average distances between 22 persons

Fig, 7 Average distances between people in simulations achieved from March 2020 to May 10th, 2020

Fig. 8 illustrates the number of times in which the distance separating each couple of persons is less than two meters in the random simulations. Theoretically, this distance was assumed to be zero for the static and dynamic scenarios since the movements of persons were guided and limited.

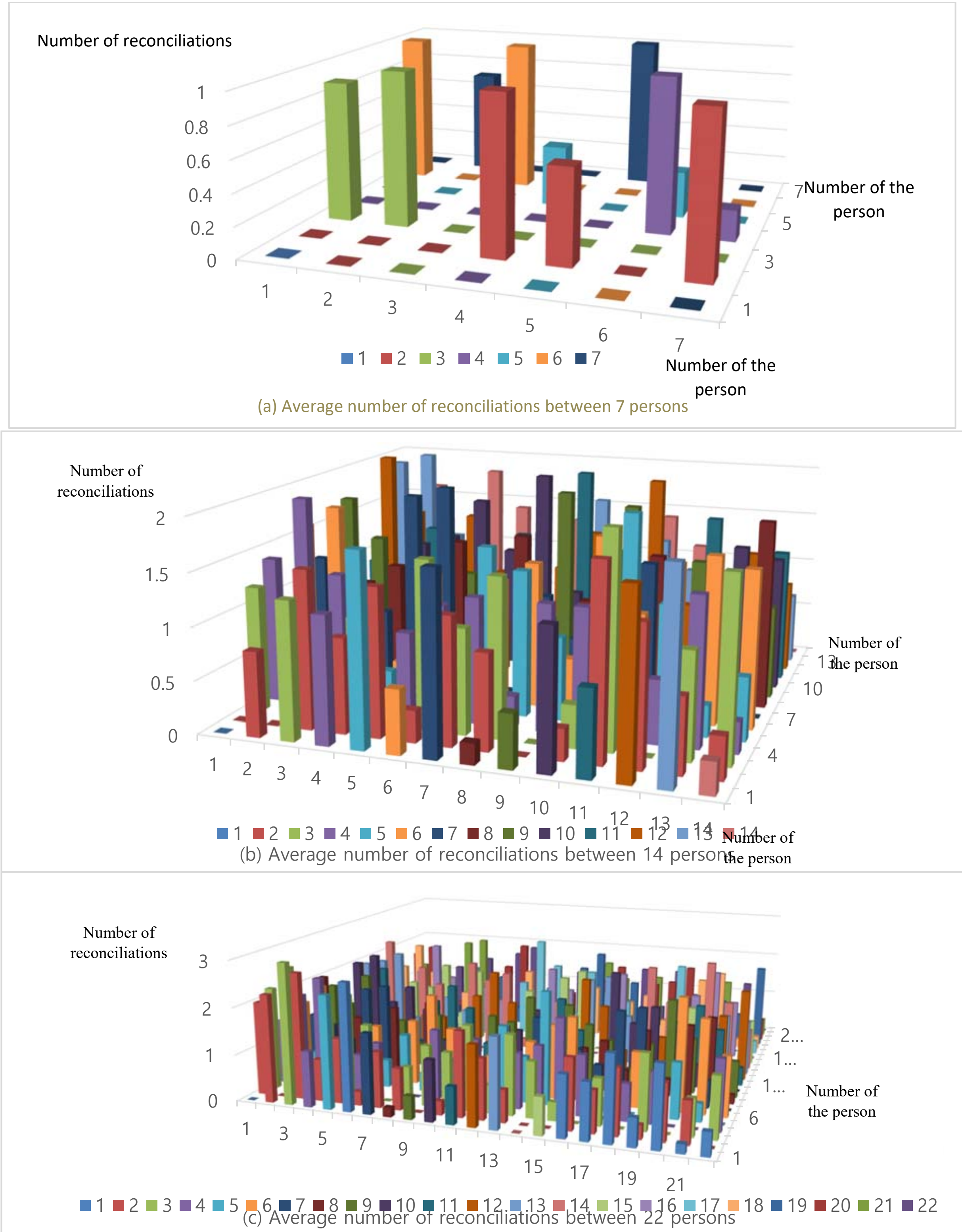


Fig. 8 Average number of times of reconciliations between people in the simulations achieved from March 2020 to May 10th, 2020

Nb of the person

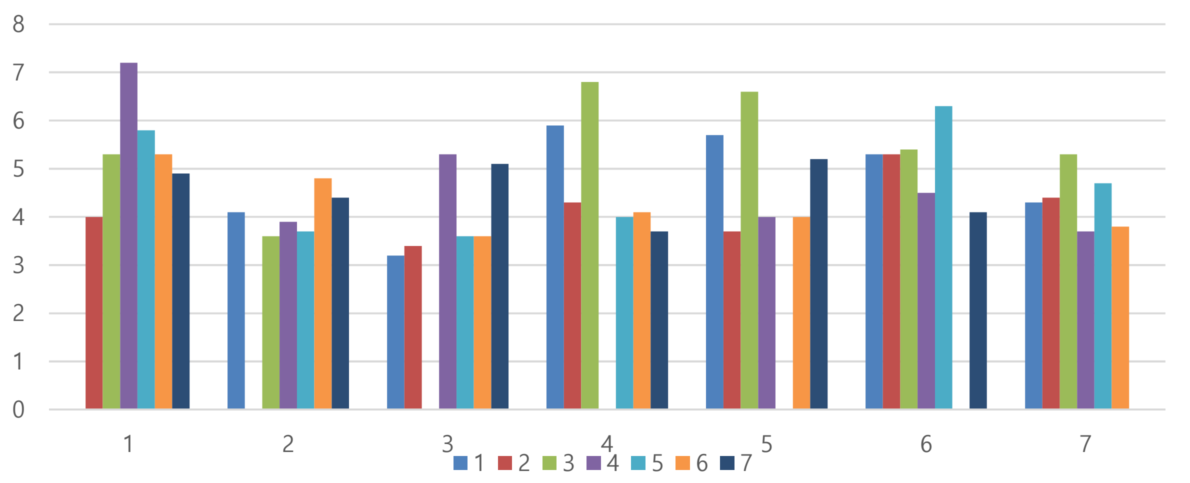
Fig. 8 indicates also that reconciliations of less than two meters between people were recorded between half of the number of people because it is in that distance that people moved and changed their locations.

4..3 Comparisons of simulations with real experimental tests

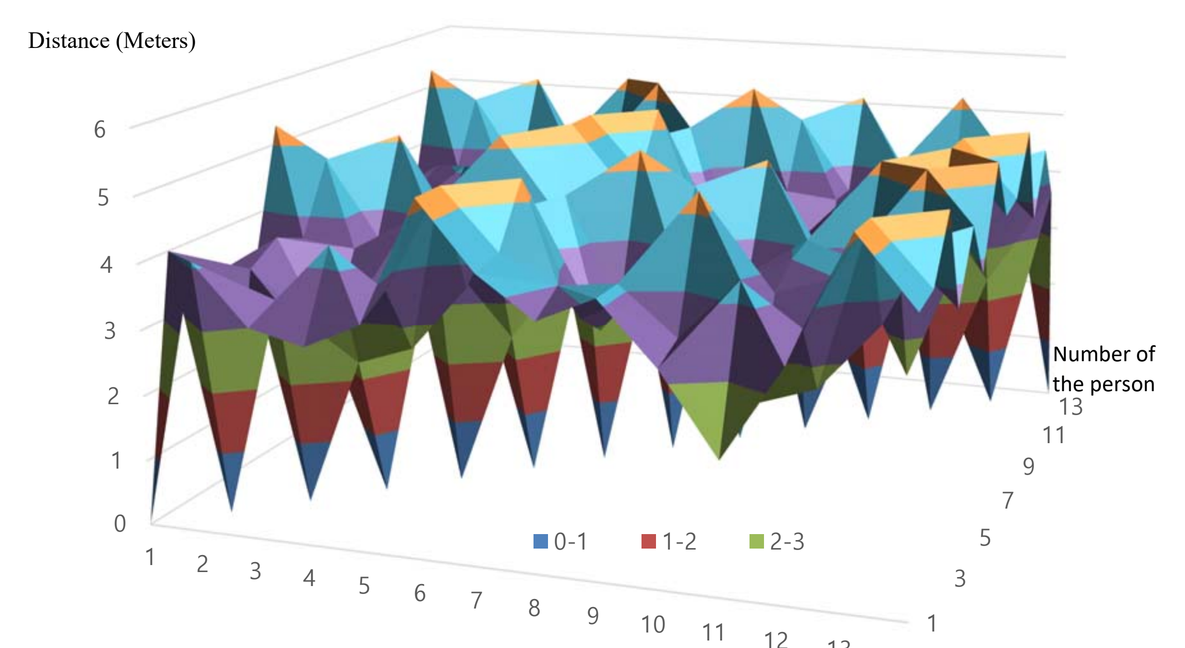
In the following, we compare the results of reconciliation and distances between the simulations (random placement) and the positioning using the static and dynamic scenarios, with an execution average of 30 times. The real experiments were achieved from Mai 15th 2020 to June 30th, 2020, in the lecture amphitheaters of the IUT of Blagnac in the University of Toulouse, just after canceling the lockdown due the first COVID-19 confinement on Mai 11th 2020.

- **Random scenario vs static scenario:**

Fig. 9 illustrates the average distances between people in the static experimental scenario.



(a) Average distances between 7 persons



(b) Average distances between 14 persons

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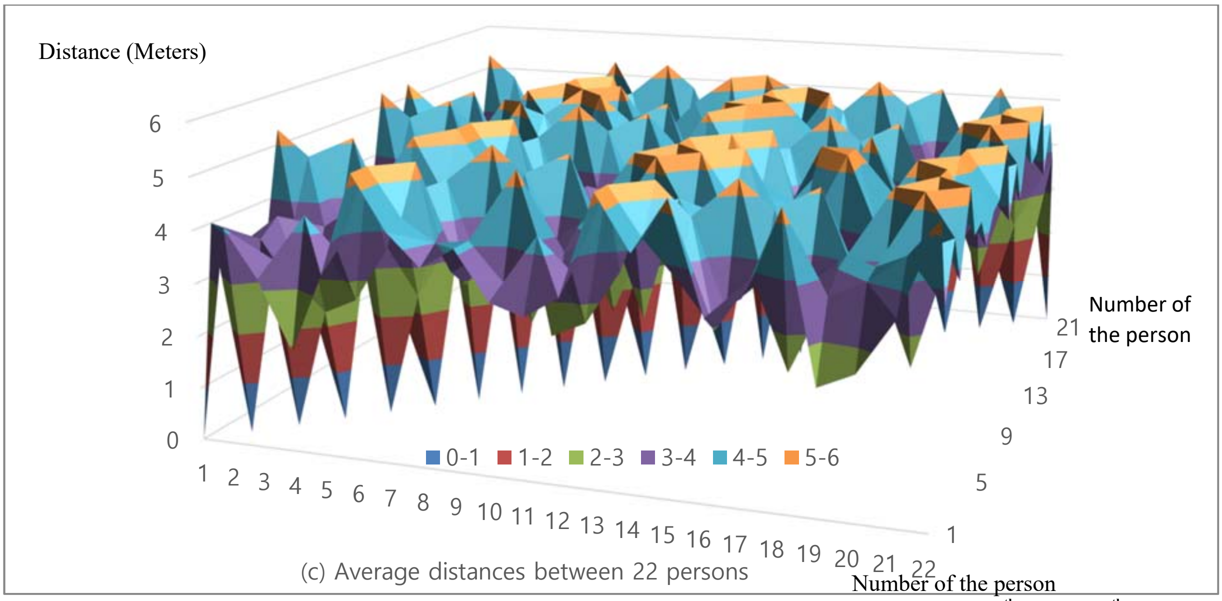

Fig. 9 Average distances between persons in the static experimental scenario achieved from May 15th to June 30th 2020

Fig. 9(a) illustrates that all persons were positioned while respecting the distance of, at least, three meters which is greater than the needed social distance (two meters). Fig. 9(b) reveals that an average of 7 couples of persons were positioned within two meters. Fig. 9(c) demonstrates that more and more couples of persons were positioned with a minimal social distance equal to two meters, which indicates that the average distance between persons becomes smaller when the number of persons increases.

- **Random scenario vs dynamic scenario with 3 thresholds:** Fig. 10 represents the average distances between 22 people in the dynamic experimental scenario.

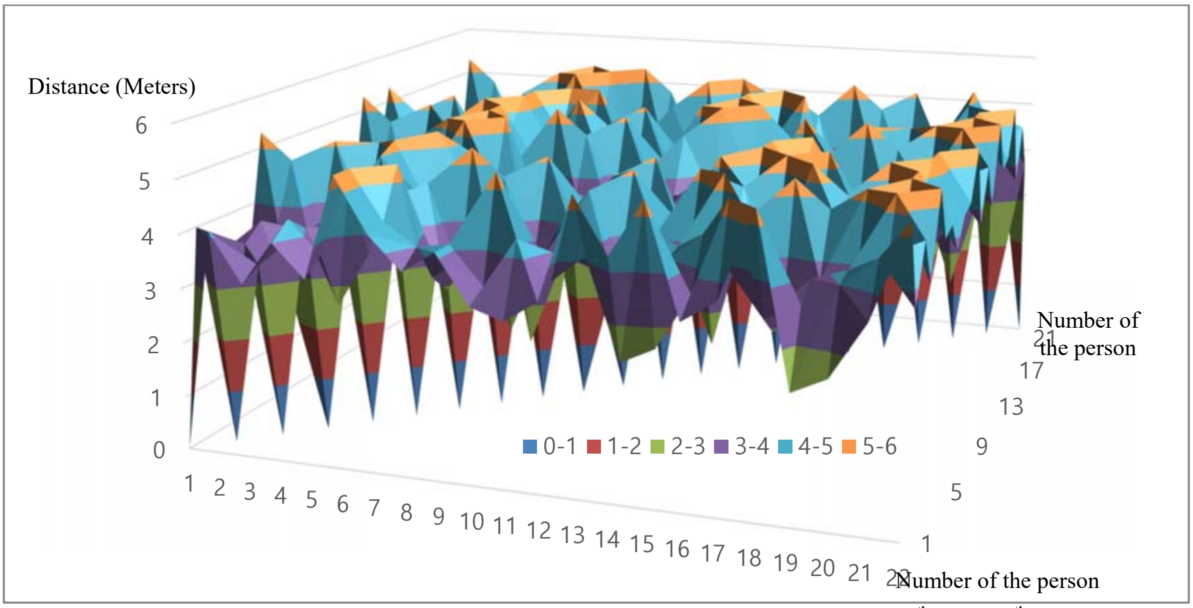

Fig. 10 Average distances between 22 people in the dynamic experimental scenario (May 15th - June 30th, 2020)

From Fig. 9(c) and Fig. 10, it is concluded that the dynamic experimental scenario allowed obtaining better average distances between people which implies the positive effect of the MFO-MAS optimization process used in the dynamic scenario. Although the number of reconciliations was assumed to be zero in the experiments, people have been found to overlap even though they knew their new positions. Fig. 11 shows the average number of reconciliations between 22 people in the dynamic experimental scenario.

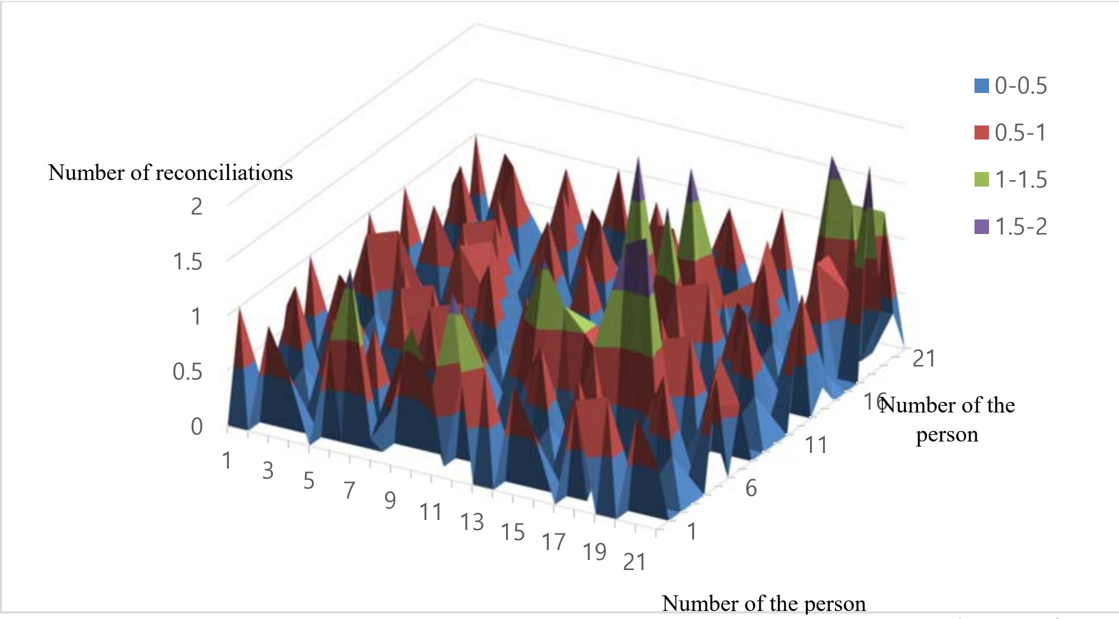

Fig. 11 Average number of reconciliations between 22 people in the dynamic experimental scenario (May 15th - June 30th, 2020)

The comparison of Fig. 8(c) and Fig. 11 shows that the dynamic experimental scenario gave better average number of reconciliations between people due to the efficiency of the repartition of nodes proposed by the hybrid optimization process based on MFO and MAS.

4.4 Discussion and interpretations

The proposed BLE-based positioning process was dynamically adapted (scenario 2). The communication strategy was applied to exchange the signal strength and location information values between BLE nodes by building a distance to signal reference set of nodes for more accurate estimation of the real distances between nodes. In this regard, several findings can be deduced from the performed experiments:

- The results are based on real operational testbed, which allows obtaining more precision to the deductions and approving the applicability of the proposed approach.
- The comparisons of simulations (Fig. 7 and Fig. 8) with prototyping (Fig. 9-11) reveal that the links of distances and reconciliations between some pairs of sensors (n_i, n_j) are not reciprocal. This means that the node n_i can see n_j while n_j cannot see n_i due to the existence of obstacles and the circumstances of placing nodes in a real prototyping environment.
- In addition to suggesting a spatial distribution of nodes, the proposed system determines the ranging (i.e., the calculation of the degree of contacts between devices) by measuring the distance, time, and duration of these reconciliations.
- The investigated application of social distance measurement requires a very high precision in calculating the locations. In the indoor experiments, BLE and Wi-Fi were used. The localization error was acceptable (about 10 centimetres) for the indoor tracking models and did not decrease its localization efficiency.
- The real prototyping validates the ability of optimization with multi-agent strategies to solve complex practical engineering problems.
- The issues of privacy regarding the COVID-positive individual were not encountered in the proposed application since the disclosure of user's identities was not necessary in this study.
- Regarding the possibility of transmitting COVID-19 by the BLE devices circulating from one person to another, a simple disinfection (by ultraviolet sterilization for example), after each use, will be sufficient.

5. Conclusions and perspectives

Compared to the application of Wi-Fi and RFID, the use of BLE devices in node's positioning applications is more beneficial given the low installation costs of IoT nodes and their independence from the restrictions required by data transmission and distribution platforms. In this context, a decentralized indoor positioning was proposed to guarantee the respect of social distance in public spaces and consequently to decrease the spread of pandemics after deconfinement. It was also noticed that the introduced BLE placement strategy creates a social IoT network to trace contacts and organize the positioning of persons in the space with the maximum distance between them, with full anonymity. A repositioning process is achieved if the number of people occupying the space increases. The latter process is based on a dynamic scenario using an evolutionary distributed optimization approach. Since tracking and forecasting pandemics is a global challenge, it is worth mentioning that, despite the proposed system is suggested for smart cities, it can be easily replicated and applied to normal cities, especially in developing countries.

Several research directions can be considered as future guidelines for this study:
- Developing an evacuation strategy for the exit of individuals from indoor spaces while respecting the distancing by automatically determining which person and how will exist first.
- Suggesting Machine Learning (ML) algorithms such as [46] [47] [48] [49] [50] to predict potential congestion: how to model the features of MLs (flow of people, schedules and peak dates based on the relevance of the space or service where people gather, etc.).
- More decentralization of the placement strategy of BLE IoT devices [51]: BLE nodes constitute a cooperative system to find the ideal placement without consulting a node or the central computer. In this context, a mechanism based on the concept of blockchains can be used to validate and accept the position of a node by other ones during the repositioning process.
- For long-term need and potential use of our system in future pandemics, the used BLE nodes can be redesigned to be incorporated into clothing where each citizen in the smart city can have its own connected BLE node that works upon entry into indoor spaces. This node can be easily moved from one garment to another.

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Conflicts of Interest: None.
Code and data availability: Code is available on demand. Experimental data and a video explaining the implementation and the use of testbed, can be downloaded from https://cloud.irit.fr/index.php/s/zm1sK7TjDIvVHRM
Author's contributions: All authors have contributed equally to this paper. All authors have read and agreed to the published version of the manuscript.
Ethics approval, Consent for publication, Consent to participate : validated by the authors.

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