BLE channel model analysis for SARS-COV2 location and tracking applications

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***Abstract*—Mutual proximity and exposure time can provide critical information to assess the risk of propagation of highly contagious viruses such as SARS-CoV2. To this extent, Bluetooth Low Energy (BLE) represents the best candidate in the low range communication technologies to estimate the proximity distance between smartphones by means of ranging algorithm based on Received Signal Strength Indicator (RSSI) measurements. Although promising, the high variability of the radio propagation channel for ISM-band technologies suggests that a deep analysis of BLE is needed in order to isolate the different propagation factors. In this paper we show, through extensive measurements, the fluctuation of BLE channel in various environments and provide a ray tracing model to fully capture the BLE channel behavior. Results show how unpredictable BLE measurements become at increasing distances and under different positioning configurations, leading to *misleading* detections for contact tracing apps. A possible solution could be to introduce the use of mathematical models to capture core aspects of population mobility in order to estimate realistic exposure information.**

Keywords—RSSI, BLE channel model, ray-tracing model, path loss, AP, Broadcast transmission

I. INTRODUCTION

Since the appearance of the SARS-COV2 pandemic, there has been a controversy in the research community about the use of smartphones to develop contact tracing apps to contain the spread of the pandemic, due to the low accuracy of proximity information of low range technologies integrated in the personal devices. With this focus, recent studies have concentrated on the accuracy issue of the contact information [1], [2], [3]. The use of Bluetooth Low Energy Technology (BLE) has proven to be a powerful tool to determine the proximity of other smartphones by using the RSSI (Received Signal Strength Indicator) measurements. Other technologies, such as movement profiles obtained through cellular base stations, WLAN access points or geolocation services such as Global Navigation Satellite Systems (e.g. GPS, Galileo, etc.) are far too inaccurate to correctly identify possible infection contacts [4]. Hence, the soundness of contact tracing applications is strictly related to the accuracy of the "*contact*" information where, according to the WHO [5] indications, a "*contact*" occurs when two persons are: at mutual distance less than ***2 meters;*** and maintaining such distance for a period time more than ***15 minutes***.

The use of RSSI measured to infer periods of close contact between persons is strongly dependent on propagation conditions under which user devices are found. RSSI can be influenced by several factors such as human body shape, different types of indoor environments, relative orientation of mobile handsets as well as interference factors of other technologies operating in the ISM band. Consequently, the RSSI detected values do not always directly correspond to specific distance among user devices. To this extent, we aim to perform a suitable contact estimation by conducting an advanced channel model evaluation supported by extensive experimental results. We show, through comprehensive measurements, the fluctuation of BLE channel in various environments and provide a ray tracing model to fully capture the BLE channel behavior. Moreover, a dedicated smartphone app has been developed for Android smartphones for testing's sake. Lastly, we provide useful insights to isolate different statistical components of BLE channel model in order to characterize various propagation behavior and reduce the distance estimation uncertainty. Through extensive measurements it is possible to observe that only RSSI-based estimations do not provide a sufficient contribution to lower the number of misleading estimations and ultimately provide a reasonable epidemic control system. The main goal of our analysis is to investigate the connection aspects by providing preliminary evaluations regarding people mobility models and connection graphs. Hence, a connected people connection analysis is provided to study the problem from a systemic standpoint, assuming several distance contact thresholds with emphasis on showing the impact in terms of number of people infected. This aspect is not trivial and further evaluations are needed to refine the connectivity model.

The remainder of this paper is organized as follows: a description of the theoretical model of BLE channel is reported in Section II by exploiting the different factors that could impair BLE propagation; description of a BLE tracing app is provided in Section III; extensive experimental results aboutdistance estimation by RSSI are described in Section IV and V; a preliminary contact analysis is reported in Section VI to indicate the effect assumed by the social distance threshold, and finally the main conclusion are drawn in Section VII.

II. Bluetooth Low Energy Channel model

The development of proximity detection applications for user devices are often based on RSSI evaluations for distance estimation by considering the propagation model characteristic with all factors that influence the received signal [4]. This approach leverages the periodical transmission of advertisement broadcast packets containing the *ID* and the calibrated $RSSI_0$ value at reference distance of d_0. Such value allows to determine the distance between two devices based on the well-known BLE channel model, expressed as the following equation:

$$RSSI_{|dBm} = \underline{RSSI_{o|dBm}} - 10*\alpha*\log_{10}(d_{|m} / d_{0|m}) + \widetilde{W} \quad (1)$$

Where $\underline{RSSI_{o|dBm}}$ is the mean value of a random variable that represents the received power at reference distance of d_0, usually assumed as *1 m*. Usually, such value is not constant due to channel propagation variability and impairments. The parameter α represents the propagation factor, strictly related to the morphology of the surrounding environment ($\alpha = 2$ for LOS and $\alpha > 2$ for NLOS respectively). Finally, $\widetilde{W}$ is a random variable that takes into account propagation channel fluctuations (both long term and short term variabilities). From (1) it is possible to derive an estimated distance starting from RSSI measurements. Such distance can vary with respect to the real distance of the devices due the fluctuations of the BLE channel as follows:

$$d_{est|m} = 10^{\frac{\left(\underline{RSSI_{0|dBm}} + \widetilde{W} - RSSI_{d|dBm}\right)}{10\alpha}} \quad (2)$$

It is straightforward how the accuracy and efficiency of distance estimation (and thus the location estimation) depends heavily on both the accuracy of the measured RSSI values and the model used to derive and calculate the distance significantly influenced by the surrounding environment, by considering different factors that could impair BLE channel model.

A. Bluetooth Low Energy theoretical model

We can distinguish the following main components that influence the BLE radio channel behavior:

- ***Two-ray propagation effect***: RSSI fluctuations values are a combination of two different components of the received signal: direct path and reflected path. This behavior is graphically depicted in Fig. 1.

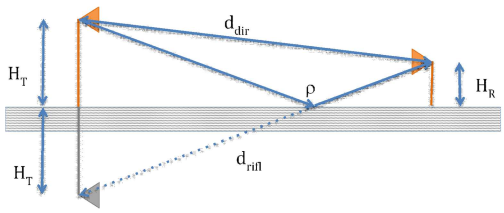

Fig. 1. Two rays propagation model.

Where the path Tx-Rx can be expressed as:

$$E = E_{dir} + E_{rifl} = E_{dir}\,[1 + E_{rifl} / E_{dir}] =$$
$$E_{dir}\,[1 + \rho \exp\{j\,\beta\,(d_{rifl} - d_{dir})\}] \quad (3)$$

Where d_{dir} is the direct path and d_{refl} the reflected path respectively. ρ is the reflected coefficient.

Additional absorption factors due to different materials in the surrounding environment may contribute to the model. As they provide a negligible contribution in the overall received signal, they are not considered in our propagation estimation model.

- ***BLE channel:*** the broadcast channels in which the "*advertising*" signaling occurs are three according to the IEEE802.15.4 WPAN indication [5]. Specifically, BLE standard was designed to use channels *37*, *38*, and *39* for advertisement. Each of these 3 channels undergoes the effect of the 2-ray model and, during a transmission, it is no possible to univocally distinguish among their contributions. As a consequence, their RSSI values even at the same distance could vary due to the uncertainty of the propagation channel condition for all duration of the transmission. The effect of RSSI fluctuation in different BLE channels is depicted in the Fig. 2 for different distance.
- ***Interference on other 2.4 GHz ISM band technology:*** The presence of Wi-Fi in the same environment could impair the RSSI measured values for the same distance during the exposure estimation process. The high variability may be due to the effect of WI-FI impacting on all three BLE carrier frequencies (see Fig. 3).

- ***Antenna Characteristics:*** the majority of modern smartphones are equipped with Planar Inverted-F antennas (PiFa). The antenna gain strongly impacts the emitted and received power. With PiFa antennas the radiation happens away from the ground plane (i.e. towards the rear of the phone) and the energy is directed away from the head. Hence, the antenna gain could vary according to different smartphone brands, with different gains, that can usually vary from *G = -2.5 dBi to 1.1 dBi,* and have different connector losses. These introduce additional variability in the propagation model.

In order to verify effects of the main factors described, an extensive experimental activity has been carried out as reported in the following sections.

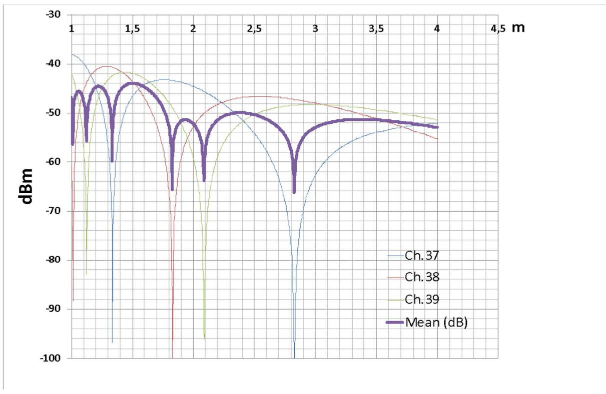

Fig. 2. RSSI values for the different channel BLE vs. distance by assuming ray-tracing model with two devices positioned at the same height of *43 cm*.

III. DEVELOPED APP

The proposed app was developed using the React Native framework, specifically the react-native-ble-manager library [10] for Scanning with a custom native *BLE Advertising library*. **Advertising** is the activity that each BLE service performs in order to notify other devices in close proximity that a BLE service is available. **Scanning** is the activity performed by a device that looks for *Advertising packets* to eventually initiate a BLE connection. In most contact tracing apps, an actual connection is not needed as only the *Advertising-Scanning* paradigm is sufficient to estimate proximity and exposure.

The app was designed to run the BLE Advertisement service of a specific *UUID* (*Universally Unique Identifier*) at launch and simultaneously scan for packets with the same UUID. The Scanning process would last *5 seconds* with *1 second* pause to avoid packets queuing in older smartphones. Each advertisement packet would contain the information about the transmission power (*txPowerLevel*) and is logged for statistical purposes. A screenshot of the app is depicted in Fig. 3.

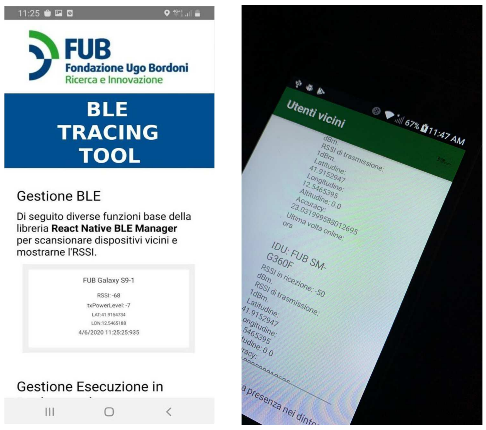

Fig. 3. BLE Tracing tool: home page (left), BLE RSSI value detected (right).

IV. EXPERIMENTAL SETUP

To identify and support a suitable theoretical model through real COTS devices, field measurements of received signals were conducted. The selected testing scenarios were indoor and outdoor. The indoor scenario is deemed representative of an environment where signals can bounce off furniture and walls (e.g. a meeting room, an apartment). The outdoor scenario is considered representative of an open-air environment with some buildings around (e.g. a street, a courtyard). The app was tested on 5 different Android smartphones of varying vendors and price range and it was observed that results weren't varying across platforms. Therefore, most of the measurements were performed using two Samsung S9 smartphones. A fine tuning of BLE settings regarding Advertising and Scanning was crucial in order to implement an efficient testing environment. In particular, to collect large amounts of data to analyze, the Scanning mode was set to *LOW_LATENCY* to feature the highest duty cycle obtainable. As for the Advertising, the mode was set to *LOW_LATENCY* as well, corresponding to a transmission every *100 ms*. A set of different transmission power parameters were tested: *HIGH_POWER* (corresponding to *1 dBm*); *MEDIUM_POWER* (corresponding to *–7 dBm*); *LOW_POWER* (corresponding to *–15 dBm*); *ULTRA_LOW_POWER* (corresponding to *–21 dBm*).

Starting from *API level 26*, Android offers the possibility of additional levels of transmission power by means of the *AdvertisingSet class.* That requires smartphones to have at least Android 8.0, substantially limiting the pervasiveness of contact tracing apps. In our testing, we used *API level 21* to keep the requirements as low as Android 5.0.

Devices are positioned at the same height on the same orientation at *43 cm* from the ground and three experiments were conducted: *LOS* (where phones were in a Line Of Sight configuration); *NLOS* (where a phone was positioned on a chair and the other was handheld by a person obstructing the LOS); *NLOS-Blockage* (where a phone was positioned on a chair and the other was kept inside a pocket of a user).

V. ANALYSIS AND EVALUATION RESULTS

In this section the evaluation results are shown. We concentrated in the analysis of experiment results for the case LOS outdoor with the transmitted power of *Ptx= -7 dBm.* For each measurement point, different RSSI values are detected during each of the tests. In particular, in Fig. 4 and Fig. 5 the RSSI test evaluations from *1 m* to *2.44 m* (i.e. canon social distances) with 12 cm steps (i.e. the corresponding wavelength λ of BLE carrier frequency), to isolate different factors in the BLE propagation model definition, are presented. By figures, it is noticeable how the RSSI fluctuates due to the variability of the radio channel. This behavior is confirmed by the standard deviation calculated for each measurement point.

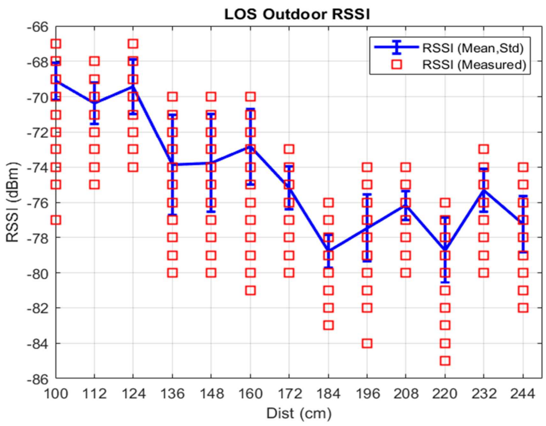

Fig. 4. Mean and Standard deviation values (left) of RSSI measured (right) vs distance (*1 m to 2.44 m*).

It is possible to note that the RSSI values, for outdoor LOS scenario, to estimate *1 m* of distance are around *-75÷ -70 dBm*, while are around *-75 ÷ -80 dBm* for *2 m*. This means that there is no overlapping area between the two values. On the other hand, the estimation values for distance more than *2 m* experiment overlapping zones that could produce uncertainty. We found that for levels between *-70 dBm* and *-75 dBm* we can assume with a fair level of confidence a distance estimation lower than *1.5 m*, while for level lower than *– 75 dBm* we can estimate a distance higher than *1.80 m*. To better investigate the effect of BLE radio channel propagation, we consider the frequency at which measured RSSI values occur for each position. It is possible to observe that in all cases, some levels are detected with higher frequency with respect to others. This behavior suggests that it is possible to isolate a few effects that contribute to impair the propagation.

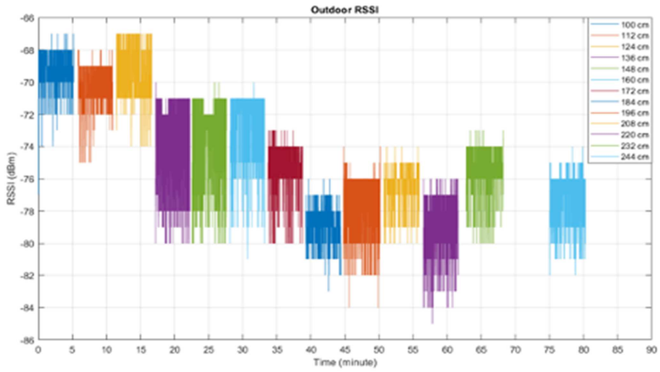

Fig. 5. RSSI values for each position vs test period time (*1 m to 2.44 m*).

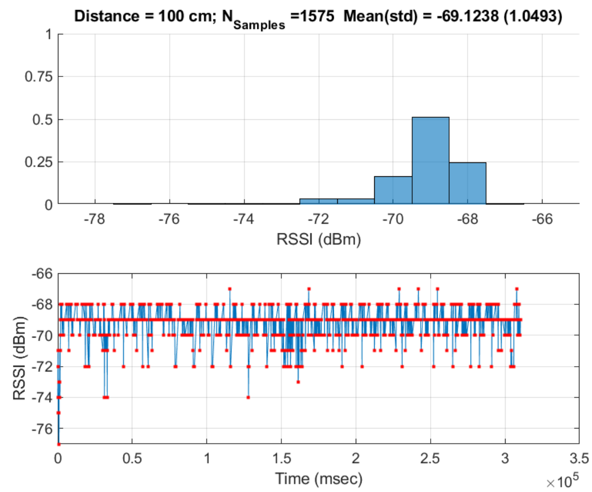

Fig. 6. RSSI measured values probability distribution (upper) and values during the test period time (lower) @ *1m*.

A clear exemplary case is depicted in Fig.s 6, 7 and 8, where details of selected distances are reported. We omit additional figures for brevity's sake, as similar trends were also noted in measurements of other distances. Specifically, in Fig.6 it is possible to observe a RSSI gaussian-like distribution around the RSSI mean value. In Fig.7-8 however, the RSSI distribution probability can be observed around two main values. This suggests the presence of plural effects that impairs the BLE propagation behavior. The observed trend confirmed the theoretical analysis presented in the previous sections, where the main effect can be described by the ray-tracing propagation model. The RSSI fluctuations experienced even in LOS outdoor conditions (i.e. best case) pushes the need to consider additional information to obtain a more realistic contact tracing indication, such as people mobility models. For this aim, our preliminary results are briefly described in the following.

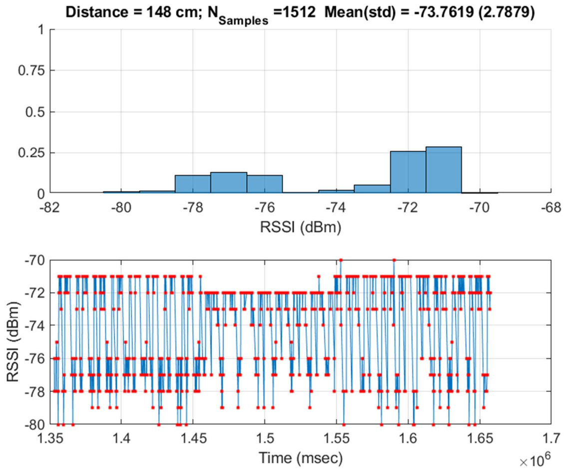

Fig. 7. RSSI measured values probability distribution (upper) and values during the test period time (lower) @ *1.48 m*.

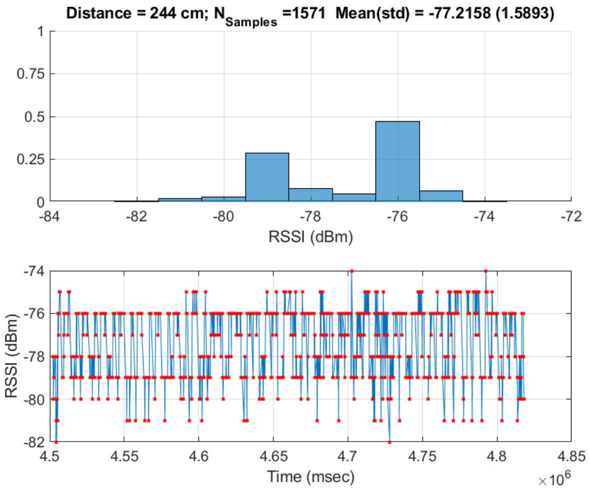

Fig. 8. RSSI measured values probability distribution (upper) and values during the test period time (lower) @ *2.44m*.

VI. CONTACT ANALYSIS FOR DIFFERENT POPULATION MOBILITY MODELS

The spread of an epidemic is strictly related to population proximity and its mobility. An important aspect of the outbreak containment phase is the contact tracing ability, as the concept of exposition is strictly related to the duration of the contact between two persons and the distance considered as minimum social distance. Based on these observations, we define the contact threshold ($Thresh_{Contact}$) as the maximum distance under which we can consider a contact occurred between two persons in a certain time t. In this section, our goal is to study the trend of the number of trackable contacts in a reference area for different values of a certain contact threshold. The purpose of this analysis is primarily to quantify the behavior of selected contacts in a certain geographic area and within a certain distance threshold given a certain pattern of user movement. Such evaluations have been repeated by considering two different types of mobility model: Brownian model and Manhattan model. In our simulations we assumed N persons deployed in a *Region of Interest* (*RoI*), represented by a square area, with side $L = 1000\ m$, and moving for a time interval $\Delta T = 1\ hour$. For each user, we assumed different moving parameters according to the following different mobility models:

- ***Brownian model***: RoI population density is *100 persons/km²* with $N=100$ persons whose initial position is obtained by a uniform distribution function within the whole RoI; walking speed v is an uniform random variable between $[0 – 2]$ *m/s*, while the movement direction ρ is a uniform random variable between $[0 - 2\pi]$.
- ***Manhattan model:*** RoI population density is 1 and *10 persons/km²* with $N=10$ persons whose initial position is obtained by a uniform distribution function along one of $N_{VE}=5$ vertical and $N_{HO}=5$ horizontal streets inside the RoI; during simulation, at time t a user in position P_t starts to move towards the crossroads X_t, that is randomly chosen among all crossroads closest to its current position P_t, with speed v_t, which is a random variable uniformly distributed between $[0.1 - 2]$ *m/s*.

Both models are characterized by a sampling frequency of users position equal to *1/sec*. We performed $N_{Run} = 100$ simulations for each scenario to obtain a statistical evaluation study. At simulation time, a contact event can be represented by a Boolean value equal to *1* if a contact is occurred between two users, *0* otherwise. Hence, we create a ***Contact graph*** as the graph obtained with *Nodes* that are the persons in the scenario and the *Edges* that are the *Contacts* occurred between them. Finally, we evaluate the impact of the considered social distance on the Contact graph with the two following performance metrics: the *number of Clusters of persons*, created in the scenario at the end of the simulation, and the related *dimension*. Briefly, a **Cluster** is the connected component of the Contact graph, while its dimension is the number of users composing it. Firstly, we create the Contact graph using the mobility simulation, and then we use the *Depth-First Search* (*DFS*) algorithm to determine the clusters and the above performance metrics. Each simulation is performed *100 times* and the related metrics are depicted in terms of weighted mean value and standard deviation. In Fig.9, the number of Clusters and the corresponding dimension for different threshold distance are shown, for the Brownian mobility model. We can clearly observe how increasing the threshold related to the social distance reduces the number of clusters created in the RoI, but subsequently increases their dimension. Moreover, the curves depict a clear trend of the contact graph: for higher threshold values, the graph is composed by a single big connected component containing almost all the nodes in the scenario. Similarly, in Fig. 10 the number of Clusters and the corresponding dimension for different threshold distance are shown for the Manhattan mobility model. In this case we observe the same trend in terms of number and dimension of Clusters, regardless of the distance threshold. This behavior is due to the high level of density of users per area in the Manhattan case as opposed to the Brownian case. Moreover, in the Manhattan case, the physical area allowable to users is smaller than the considered 2D geographic area (e.g. only streets in the area are permitted), while in the Brownian case the whole area is permitted. As the density of people increases, the saturation effect appears more quickly. The increasing density leads to obtaining a total connected graph after *1 hour* of simulation.

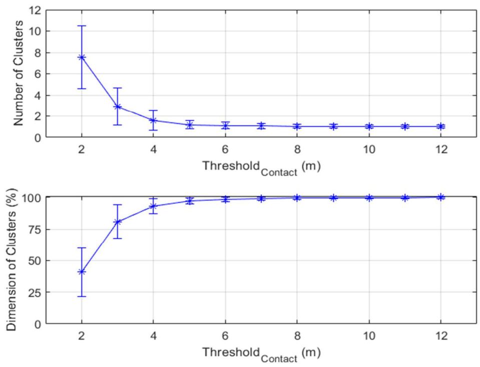

Fig. 9. Connected people shown as number of cluster (upper) and dimension of cluster (lower) vs contact distance threshold for Brownian mobility model.

VII. CONCLUSIONS AND FUTURE WORK

In this work, our experimental results on BLE channel model are presented to provide some insights regarding the development of smartphone Covid contact tracing applications. Evaluations confirmed that RSSI values can vary by different factors. This analysis suggested that the development of accurate methods for proximity detection based on Bluetooth LE Received Signal Strength is yet an open issue to be further investigated in a realistic environment to correctly estimate a suitable indication of the epidemic trend. Next step is to leverage new APIs given by Google and Apple to activate advanced BLE PHY layer functionalities. It is important to investigate the possibility of sending advertising packets on a fixed frequency while varying the TX power transmission. It is also important to include a more realistic population mobility model, to reduce uncertainty in contact estimation. Future works will consider other wireless ranging techniques such as 5G Time Sensitive Networks (TSN) to better approximate the distance estimation between mobile devices.

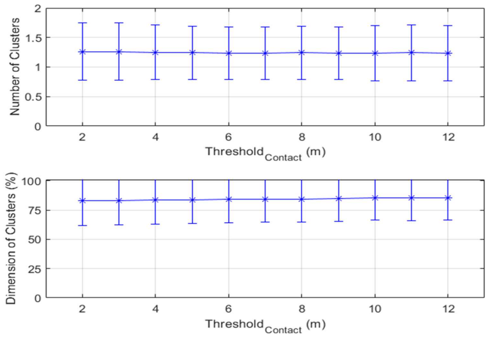

Fig. 10. Connected people shown as number of clusters (upper) and dimension of cluster (lower) vs contact distance threshold for Manhattan mobility model for people density of 10/km^2.

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