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Machine learning-based indoor localization and occupancy estimation using 5G ultra-dense networks

Ala'a Al-Habashna [a,*], Gabriel Wainer [a], Moayad Aloqaily [b]

[a] Department of Systems and Computer Engineering, Carleton University, Ottawa, ON, Canada
[b] Machine Learning Department, Mohamed Bin Zayed University of Artificial Intelligence (MBZUAI), Abu Dhabi, United Arab Emirates

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ABSTRACT

Nowadays, mobile applications need the location of the running devices to operate properly. This has increased the interest in indoor localization. Furthermore, the ability to sense mobile devices in indoor environments opens the door for building occupancy-count estimation. Studies have shown that occupant's detection and building occupancy-count estimation can be utilized to improve the efficiency of building operation and management. This research introduces new models to study the performance of such indoor localization and building occupancy-count estimation using the available technological advances in 5G Ultra-Dense Networks (UDNs). We propose an algorithm to collect the Received Signal Strength Indicator (RSSI) from User Equipments (UEs) and use it to build a fingerprinting database. We then use Machine Learning (ML) to estimate the location of the UEs in buildings from their RSSI values. Detecting users in the building is treated as a binary-classification problem. We then use various ML algorithms to build models for indoor occupancy-count estimation. Finally, the localization of users is used to estimate occupancy in specific sections of the building. The simulation results show that UDNs can provide accurate indoor localization, occupancy-count estimation in a building and in parts within the building.

1. Introduction

The interest and market for indoor localization are increasing at a rapid rate. Localization is becoming an essential part of Internet of Things (IoT) applications in many areas, such as healthcare, defense and military, logistics and warehousing as it allows adding location context to the IoT data automatically. Another reason for this increasing interest in indoor localization is the proliferation of mobile devices and the emergence of mobile applications that depend on the location of the operating devices to provide the intended services. As such, indoor localization has received much interest from both industry and academia [1].

In addition to indoor localization, there has been an increasing interest in building occupancy detection and occupancy-count estimation [2,3], which can be used to optimize the operation of different systems within a building, such as lighting and HVAC (Heating, Ventilation, and Air Conditioning). For instance, such systems can be activated only when the building is occupied, which can significantly reduce the energy consumption and carbon footprint of buildings. This is particularly important nowadays because studies have shown that buildings are responsible for approximately 40% of the main energy consumption in the U.S. and Europe, and

* Corresponding author.
E-mail addresses: Alaa.Alhabashna@carleton.ca (A. Al-Habashna), Gabriel.Wainer@sce.carleton.ca (G. Wainer), Moayad.Aloqaily@mbzuai.ac.ae (M. Aloqaily).

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27.3% of that in China. Furthermore, space and water heating account for the majority of building energy consumption, which translates to approximately 40% of the CO_2 emissions [4].

The Global Navigation Satellite System (GNSS) has been the main technology for localization, and most mobile devices nowadays are equipped with a GNSS antenna. Nevertheless, this technology is not reliable in indoor environments due to signal obstruction. As such, other transmission technologies have been utilized for indoor localization. This includes Wi-Fi [5–7], Bluetooth [8,9], and Radio Frequency Identification Device (RFID) [10]. Wi-Fi and Bluetooth technologies are suitable for localization as most mobile phones today are equipped with Wi-Fi and Bluetooth antennas.

There has also been an increasing interest in utilizing cellular communication for indoor localization. Localization using cellular-based system has advantages over Wi-Fi and Bluetooth. First, cellular networks are widely adopted and capable of covering areas where Wi-Fi access points or Bluetooth devices are not available. The geographically wide area that can be covered by cellular networks makes it possible to provide the locations of users sparsely distributed. Such localization over a wide geographical area can be used to provide different services, such as indoor navigation, location-based marketing, analyzing visitor traffic, and building occupancy-count estimation. Furthermore, this information can be used to study and analyze occupancy and traffic patterns. An example is analyzing the times and locations of pedestrian high traffic within a building for future expansion purposes. Another advantage of cellular-based localization is that it relies on existing infrastructure and does not require the installation and setup of sensors and networks for localization purposes. In addition to the above, emerging 5G technologies provide promising solutions for mass-market localization applications. Cellular and mobile networks have seen a continuous and dramatic increase in the expected requirements (e.g., coverage, availability, data rate, and latency). Moreover, the Internet of Things (IoT) applications that can be implemented over cellular networks (e.g., traffic monitoring, wearables, and health) are causing the number of devices connected through such networks to continue increasing exponentially. Network densification provides an approach to increasing the provided data rates over cellular networks to satisfy the increasing demands. Network densification increases the number of nodes in the Radio Access Network (RAN). This includes the nodes (deployed by the operator or user) that reside between the mobile device, i.e., User Equipment (UE) and the core network (CN) [11]. Due to the advantages of network densification (increasing network coverage, throughput, and frequency reuse), Ultra Dense Networks (UDNs) are widely adopted, and the degree of densification is expected to continue increasing.

In this research, we introduce various models and conduct many simulation studies for indoor UDNs based on scenarios from the 3GPP standards. The models are built as Discrete Event System Specification (DEVS) components [12,13]. Based on the models we defined, we executed a variety of simulation scenarios for indoor UDNs. From the simulation results, we extracted multiple data sets of UEs' positions and their Received Signal Strength Indicator (RSSI) values. The collected data was used to build a fingerprinting database for each scenario. Various Machine Learning (ML) algorithms were used with the constructed databases to build and evaluate models for indoor localization and building occupancy-count estimation. Furthermore, we evaluate the use of UDNs for occupancy-count estimation at parts of a building (e.g., lab areas). For this purpose, we construct a model of a UDN in a real building and evaluate the occupancy-count estimation in 3 subareas in that building. Results show that UDNs and ML can be used for localization of users, and occupancy-count estimation at the building level, and finer levels, i.e., areas of a building. In the following, we summarize the contributions of this work:

- An algorithm for RSSI reporting for localization and occupancy estimation purposes
- A model for UDNs based on the 3GPP standards
- Multiple fingerprinting datasets collected through experiments with the developed model
- Using ML algorithms with the collected datasets to build and evaluate models for indoor localization
- Proposed approach for building occupancy-count estimation using binary classification models
- Employing the proposed approach using many ML classification algorithms with the collected datasets to build and evaluate models for building occupancy-count estimation
- Studying the use of UDNs for occupancy-count estimation at parts of a building (e.g., lab areas) based on an actual building plan

The rest of this paper is organized as follows. In Section 2, we present the different background topics for this work and review the related work in the literature. In Section 3, we provide a brief review of UDNs. In Section 4, we present the proposed algorithm for RSSI reporting and collection for localization and occupancy estimation, as well as our DEVS model. In Section 5, we discuss the obtained results. In Section 6, we state the conclusion and future work.

2. Background and related work

2.1. Indoor localization and occupancy-count estimation

Indoor localization has many applications in various areas nowadays (e.g., healthcare, defense and military, logistics and warehousing, mobile applications). Localization is becoming an essential part of the Internet of Things (IoT), which is an important technology that is not only shaping the future of various industrial applications, but also becoming an integral part of our lives. IoT has important applications nowadays, in areas such as healthcare, traffic monitoring, agriculture, the smart grid, and wearables. Localization and positioning techniques allow adding location context to IoT data without human intervention. As such, there has been an increasing deal of work to integrate localization with IoT and provide location-enabled IoT [9,14,15]. Furthermore, localization is becoming important for mobile applications that depend on the location of the operating devices to provide the intended services.

Different approaches have been proposed to use transmission technologies, such as Ultra-WideBand (UWB), Wi-Fi, Bluetooth and RFID, for localization [1,5,6,8,10,16–18]. UWB is a radio technology that utilizes low energy transmission over a wide portion of the radio spectrum for high-bandwidth and short-range communications [19]. It has been employed in applications such as localization [17,18], tracking, and sensor data collection [19]. Although UWB can be used to provide accurate indoor localization, it can be a costly solution. The location tags and infrastructure of UWB systems are very expensive and could be an order-of-magnitude more expensive than the tags of Bluetooth. For indoor localization, Wi-Fi and Bluetooth technologies provide good options because most smart phones nowadays have Wi-Fi and Bluetooth antennas integrated into them. However, such methods would require a Wi-Fi or Bluetooth network to be setup in the building for localization to be performed. Unfortunately, this is not always the case, and even if such networks are available, there are always gaps in the coverage within a building. As such, there has been interest in utilizing cellular communication for indoor localization. Due to the wide adoption of cellular networks and their capability of covering areas where Wi-Fi access points or Bluetooth devices are not available, they can provide advantages for indoor localization.

Many localization methods, such as the Received Signal Strength Indicator (RSSI), Time of Arrival (TOA), Time Difference of Arrival (TDOA), and Angle of Arrival (AOA)-based methods, have been implemented with the aforementioned transmission technologies [1,20]. The TOA, TDOA, and AOA-based localization methods either require sophisticated hardware (antenna arrays) or accurate time synchronization to estimate the location of the intended device. The requirements above increase the cost and complexity of the localization system and might not always be available. RSSI-based systems employ the variation of the signal strength over space, and hence, do not necessarily require sophisticated hardware, which makes them implementable with available hardware and reduces the cost. Furthermore, RSSI-based systems do not need time synchronization and angle measurement, which makes them much simpler to implement. The majority of RSSI-based localization systems use fingerprinting, trilateration, or triangulation as the localization approach based on measured RSSI values. Among these approaches, fingerprinting is widely adopted due to its high accuracy, and hence it is used in this research.

There has also been an increasing interest in building occupancy detection and count estimation to optimize building operation and reduce the energy consumption of buildings. Reducing buildings' energy consumption, which accounts for a significant share of energy consumption worldwide [3], would reduce the carbon footprint of buildings and alleviate the energy shortage problem. Occupancy detection can be used to efficiently operate buildings and reduce their energy consumption, by activating and controlling the amount and location of services (e.g., HVAC systems [2,3,21]) only when and where needed (e.g., when occupants' presence is detected).

Building occupancy estimation has received much interest due to its importance in optimizing buildings' operations [2,3]. Different types of sensors can be used to extract data (e.g., Passive InfraRed (PIR) sensors, CO2 sensors, humidity sensors, temperature sensors, pressure sensors, keyboard and mouse activities, and camera footage). Some of the work in the literature relies on such data for detecting and estimating the number of occupants [2,3]. However, such methods can be costly due to the need to deploy and maintain systems of sensors. There have also been methods that utilize transmission technologies (e.g., Wi-Fi and Bluetooth) for occupancy detection and estimation. Such systems sniff the signals of Wi-Fi or Bluetooth devices and use the sniffed data for occupancy detection and estimation. However, cellular networks can also be used for occupancy detection and count estimation, and they can provide advantages over Wi-Fi and Bluetooth, as discussed above.

2.2. 5G ultra-dense networks and cellular networks-based localization

Recent work has considered employing the signals transmitted by the Base-Stations (BSs) of cellular networks for localization. The advantage of such a system over approaches based on sensor data is that it does not need the setup and maintenance of dedicated sensors, as the infrastructure of cellular networks is widely available and employed for cellular communications. Furthermore, such an approach has the potential to generate more accurate occupancy-estimation results than sensor data-based approaches due to the popularity and proliferation of mobile devices.

In addition to the above, cellular-based localization systems can provide localization in areas where Wi-Fi and Bluetooth coverage is unavailable. This is due to the extensive coverage of cellular networks which, spans large geographical areas. This large coverage can also be used to track occupants' movement within a building, to analyze occupancy and traffic patterns, and identify any trends. For example, the location of occupants throughout the day can be analyzed to identify times or areas of high density.

A cellular network is a communication network in which the coverage area is partitioned into cells. Mobile devices (known as UEs) communicate with a transceiver called a BS or evolved Node B (eNB) [22]. This communication between the UEs and their BS occurs over radio links, and this part of the network that includes the eNBs and the radio links is called the RAN (Radio Access Network). BSs are usually interconnected through the backhaul; a high-speed wired network.

Cellular and mobile networks have seen a continuous increase in the expected requirements (e.g., coverage, availability, data rate, and latency). Moreover, the Internet of Things (IoT) applications that can be implemented over cellular networks (e.g., traffic monitoring, wearables, and health) are causing the number of devices connected through such networks to continue increasing exponentially. Network densification is a key technology in 5G systems that will help satisfying these increasing demands [22,23]. Network densification increases the number of nodes in the RAN. This includes the nodes (deployed by the operator or user) that reside between the mobile device, i.e., UEs and Core Network (CN) [11]. Due to the advantages of network densification (increasing network coverage, throughput, and frequency reuse), UDNs are widely adopted in 5G networks, and the degree of densification is expected to continue increasing.

There has been an increasing effort to utilize cellular wireless systems for localization. A technique for anonymous outdoor location tracking of mobile users in cellular networks was proposed in [24]. The proposed method runs on the network side to use collected information for automatic traffic monitoring, population movement estimation, and criminal activity monitoring. The topology of the cellular network is also exploited, along with open maps, modes of transportation and route filtering. While such a technique can be used to track users at a coarse level to estimate traffic and population movement, it is meant for outdoor environments and it does not provide accurate locations of individual users, as best performances were obtained in urban environments with median accuracies of up to 112m.

In [25], a method was proposed to estimate the BS location using RSSI with only one mobile receiver in conditions where the path-loss exponent is unknown. This provides a more convenient and economic alternative to methods that require multiple mobile receivers. While it is important to localize the BS, there is more interest and demand for new methods to localize UEs in the cellular network as it has many applications that were discussed in the introduction.

The use of different measurements from LTE networks for localization has been previously proposed. In [26], the use Channel State Information (CSI) of LTE signals for localization was proposed. CSI measurements were used in a fingerprinting-based localization system. The usability of LTE CSI feedback in localization has been evaluated through multiple experiments in indoor and outdoor settings.

In [27], another localization system based on LTE-A networks is proposed. In the proposed system, multiple radio channel parameters are mapped to geographical locations, creating a fingerprinting database. Moreover, a feature-extraction algorithm was employed to identify unique channel parameters and use them in the fingerprinting database of channel parameters and UE locations. Results conducted in indoor and outdoor environments show that localization errors (median) of 6 and 75 meters, can be obtained in indoor and outdoor settings, respectively.

The use of CSI from LTE signals for fingerprinting-based indoor localization was also proposed in [28]. In this approach, a vector that serves as the shape of the channel frequency response is used to build the fingerprinting database, as opposed to the CSI measurements themselves. Furthermore, BS signaling messages are used for localization (as opposed to designated communication between the BS and the UEs) which allows passive localization and reduces the computational complexity and memory requirements.

The authors of [29] evaluated the accuracy of LTE-based localization. Fingerprinting was used by collecting LTE measurements in the 800 MHz, 1800 MHz, and 2600 MHz frequency bands. The fingerprinting database consisted of UE positions and their received signal strength radio measurements from multiple BSs. Two systems were evaluated. The first system is composed of an LTE network, while the second system is composed of LTE and WLAN networks. Obtained results show that partial fingerprints that consisted of LTE and WLAN radio measurements improve localization accuracy by at least a factor of 3.5x while keeping the percentage of discarded samples low.

In [30], Cell-Specific Reference Signal (CSRS) measurements from LTE signals were used for indoor localization. Two algorithms were proposed for localization. In the first approach (Threshold-to-Noise Ratio), TOA was used for localization. The second algorithm is known as "ESPRIT," which stands for "ESPRIT and Kalman filter for time of arrival tracking" (EKAT). The second algorithm is more accurate and robust to multipath fading, at the expense of increased complexity.

In [31], a fingerprinting-based localization method was proposed for commercial LTE systems. In the proposed method, CSI feedback is collected from the LTE BS. Intrinsic features are extracted from the collected CSI feedback to be used for localization. Furthermore, a time domain fusion approach was used to assemble multiple positioning estimations.

In [32], a NN-based indoor localization approach was proposed for LTE signals. The approach estimates, from the channel impulse response (CIR), the range between the LTE BS and the UE. A software-defined radio extracts the CIR. A Long Short-Term Memory (LSTM) model recurrent neural network (RNN) is used to estimate the range from the extracted CIR. When compared to the results obtained using an RNN without LSTM, the obtained results show a reduction in the ranging error was reduced from 13.11m to 9.02m.

In [33], the uplink sounding reference signal (SRS) in LTE networks, which includes timing and RSSI information, is used for indoor localization. In this approach, an LTE-based localization system using TDOA and the fingerprint of RSSI that operates in two steps is proposed for indoor positioning. In the first step of the proposed method, SRSs are collected from spatially separated sensors and peak value detection is applied to the collected SRSs to estimate the TDOAs, from which a coarse target location is estimated. Thereafter, fingerprinting in a subarea containing the coarse solution is applied to extract a final estimate of the location.

Many of the methods above are based on TOA or utilize CSI estimates, which require either accurate time synchronization or sophisticated hardware (antenna arrays), to estimate the location of the intended device. Furthermore, all the proposed methods above are based on the macro-cell architecture, with relatively high transmission power and large coverage area eNBs that serve a high number of users. There are also some simulation-based studies on wireless technology-based localization, but they are mostly on localization for wireless sensor networks [34], or other transmission technologies [35], and they do not consider 5G UDNs. Here, we focus on localization over UDNs. The accuracy of localization with such architectures should be higher due to the high number of deployed elements (e.g., Pico eNB (PeNB)) in the RAN.

In [36], we presented the idea of using UDNs for localization and occupancy-count estimation. Furthermore, in [37], we used the DEVS formalism [13] to build a model for indoor UDN networks. The considered scenarios and parameters used in the models are obtained from the 3GPP standards. Based on the developed models, we ran simulations for indoor UDN scenarios and collected data sets for the UEs positions and their RSSI measurements. From the collected data, we compiled a fingerprinting database and used the kNN algorithm to build a localization model and evaluate the accuracy of fingerprinting-based indoor localization with UDNs. Here, we extend our work in [37]. First, we use DNNs to build localization models and achieve an improvement over the results obtained with kNN. Furthermore, we show that more accurate results can be achieved by decreasing the inter-distance between the stations in the building. In addition to indoor localization, we propose ML approaches for building occupancy-count estimation using RSSI of 5G UDNs. We treat the detection of occupants inside the building as a binary classification problem. Many ML algorithms (e.g., kNN, SVM, decision tree, etc.) are used to build occupant detection models, and the results of the classification algorithms can be used for building occupancy-count estimation. Furthermore, we evaluate the use of UDNs for occupancy-count estimation in different parts of a building (e.g., lab areas). For this purpose, we build a model of a UDN in a real building and evaluate the occupancy-count estimation in 3 subareas (labs) in that building. Results show that UDNs and ML can be used to achieve localization of users, and accurate occupancy-count estimation at the building level, and at a finer level, i.e., areas of a building.

DEVS provides a sound formal framework for modeling generic dynamic systems [12,13,38,39]. The hierarchical and modular nature of DEVS makes it very suitable for modeling such systems. Furthermore, the framework also includes formal specifications, which help defining the behavior of the components of the system, and its structure. There are two types of components in a DEVS model: structural (coupled) and behavioral (atomic) components. The coupled components are used to build the structure of the system, while the atomic components are used to define the behavior of the components of the system. All the facts above make DEVS very suitable for modeling and simulating mobile networks. With DEVS, different submodels can be defined; each one implements a different component of the wireless network, such as the BS or the UE. These submodels can be tested and verified, independently, and integrated into the whole model. These submodels can also be reused in other relevant models. These features make it easy to design, implement, and evaluate network models with DEVS.

2.3. Machine learning for regression and classification

An ML model is a mathematical representation of the patterns or structures hidden in data. When the ML model is trained on training data, it finds patterns or structures in that data. Such patterns or structures are formalized into a mathematical model, which can be used on unseen data to predict values or to discover some relationship within it. ML models are categorized as either supervised or unsupervised [40,41]. In this work, we focus on supervised learning, as all the used algorithms fall under this category. With supervised learning, a model is trained by example using a labeled dataset, i.e., a dataset where the input-output pairs are provided. Supervised learning models can be used either for regression or classification. In regression models, the output is continuous (e.g., predicting house prices based on their sizes), while in classification models the output is discrete (e.g., classifying people as diabatic/non-diabatic based on their weight, height, etc.).

In this work, we use regression algorithms to build models to estimate the locations of the UEs from the RSSI values (of received signals from all the PeNBs in the building). We also use classification algorithms to build models to classify UEs as inside or outside the building and use those for building occupancy-count estimation. In the following, we present the regression and classification algorithms used in this work.

The k Nearest Neighbors (kNN) algorithm is used in this work for localization (predicting the coordinates of devices). The kNN algorithm is an ML algorithm that consists of the following steps:

1 Calculate the distance between test data and each row of the training data (Euclidean distance)
2 Sort the calculated distances in ascending order based on distance values
3 Get the top k rows from the sorted array
4 Predict the distance from the nearest neighbors

In addition to solving regression problems, the kNN algorithm can be used as a classification algorithm as well. The difference is in the last step. When used for regression, the algorithm uses the values of the nearest neighbors to predict the value (e.g., by taking the average value). On the other hand, when used for classification, it will use the most popular value among the values of the nearest neighbors as the chosen class.

An Artificial Neural Network (ANN), or simply a Neural Network (NN), is a computing system that is designed to build ML models by loosely modeling the human brain. An ANN contains a group of nodes that are connected to each other. These nodes are referred to as artificial neurons [42]. Each artificial neuron receives an input or a set of inputs, applies a non-linear function, and produces one or more output values (that might be used as the input to other neurons). An ANN is typically structured into layers, where these layers may perform different transformations on their inputs. An ANN is composed of an input layer, one or more hidden layers, and an output layer. Features (values used for prediction or classification) are used as the input of the ANN and fed to an input layer. These values traverse the hidden layer(s), into the output layer. A Deep Neural Network (DNN) is an ANN with multiple hidden layers. DNNs are considered a powerful category of ML algorithms that demonstrated exceptional learning capabilities over a wide range of applications.

Decision trees are popular algorithms that can be used to build classification models [40,41]. A tree is built by dividing the root node (which comprises the whole dataset) into subsets, i.e., successor children. This splitting of the node into children is done based on rules that group entries with similar features into the same subgroup (child node). The splitting process is usually repeated multiple times to create a multi-level tree in a recursive fashion. The recursive partitioning stops when the subset at a node has all the same values as the target variable, or when splitting no longer adds value to the predictions.

Support Vector Machine (SVM) is another popular supervised learning algorithm that is used for classification [40,41]. A SVM finds the best hyperplanes in a multi-dimensional space that separate the data points into multiple classes. SVM tries to find the hyperplanes that are the furthest from the nearest training-data point of any class. This distance to the nearest data point is called the functional margin, and it represents the lowest relative confidence of all classified points. SVM is effective in high-dimensional spaces and gives reliable results when there is a clear margin of separation between classes.

Logistic regression (LR) is a popular algorithm that is usually used for binary classification [40,41]. LR is an extension of the linear regression model for classification problems. Instead of fitting a straight line or hyperplane, LR uses the logistic function to transform the output of a linear equation into another value between 0 and 1. LR also gives the probability that a data point belongs to each of the considered classes.

There are many evaluation metrics for classification algorithms. Before defining some of the popular metrics that are used in this research, we will define 4 important concepts: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These are defined as follows:

- TP: A data point predicted to belong to certain class, and it does belong to that class
- TN: A data point predicted to not belong to certain class, and it does not belong to that class
- FP: A data point predicted to belong to certain class, but it does not belong to that class
- FN: A data point predicted to not belong to certain class, but it belongs to that class

Accuracy is a metric that measures the fraction of correct predictions produced by the model. It is defined as the number of correct predictions over the total number of predictions. The accuracy value ranges from 0 to 1, with a higher value representing a better and more accurate model. The recall (also known as the true positive rate) gives the ratio of the correctly identified TPs out of all positives, i.e., TP/(TP+FN). Precision is the ratio of correctly identified as positive out of all predicted as positives, i.e., TP/(TP+FP). The F1 score is a metric that tries to measure the precision and recall simultaneously, as it is important to have good values for both measures. The F1 score is defined as (precision * recall) / (precision + recall). The F1 value ranges from 0 to 1, with the higher value representing a better model. The Jaccard index is a statistical metric that is used to measure the similarity of two different sets. In the context of classification, the Jaccard index is used to measure the similarity between the sets of actual classes and predicted classes. The Jaccard index value ranges from 0 to 1, with the higher value representing a higher similarity between the two sets (better model). Finally, the log loss is a metric used with models that predict the probabilities of a data point belonging to each one of the considered classes, such as LR. In such cases, it would be useful to have a metric that measures how far each predicted probability is from the actual class, and that is what is measured by the log loss. The log loss value ranges from 0 to 1. However, unlike the other metrics, the lower the log loss value the better the prediction, as it is related to the complement of the classification probability of the correct class.

3. UDNs for Indoor Localization

3.1. 3GPP UDN scenarios

As discussed in the previous section, new network architectures such as UDNs and Ultra-Dense Heterogeneous Networks (UDHetNets) provide many performance gains, which helps meeting the increasing performance requirements of 5G cellular networks [11].

With UDNs, the number and density of radio elements is increased, which improves the throughput, delay, and network coverage. UDHetNets are different from UDNs in that several types of radio elements (with different capabilities) coexist in the network. This is achieved by overlaying macrocells with low-power nodes, which can offload traffic, such as Remote Radio Head (RRH), PeNB and Home eNB.

Different scenarios for UDNs and UDHetNets were proposed in the 3GPP standards [43]. Some of these scenarios are for homogenous networks where similar elements, such as PeNBs, are deployed in the network. Other scenarios are for UDHetNets where different types of cells coexist in the network (e.g., eNBs and PeNBs).

The following four scenarios were proposed in the 3GPP standards [43]:

- Scenario A-Indoor small cell deployment: In this scenario (Fig. 1), the network is built from a single layer of small cells in an indoor environment.
- Scenario B-macro cell deployment: In this scenario, the network comprises of a single layer of macro cells.
- Scenarios C and D-Heterogeneous network of urban macro and outdoor small cell deployment: In these scenarios, the network consists of macro cells that coexist with small cells. The two scenarios differ in the method of channel allocation for the two different layers.

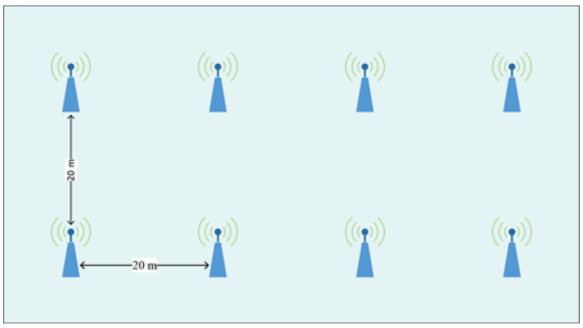

Fig. 1. Indoor small cell deployment (scenario A).

In this work, we focus on scenario A (indoor small cell deployment) because our goal is utilizing UDNs for indoor localization and building occupancy-count estimation. Table 1 lists the transmission parameters provided by the 3GPP standard for this scenario. These parameters will be adopted in our work. Most importantly, the table states that the scenario is constructed from a single layer (homogenous network) of Transmission Points (TPs), and the recommended distances between these points are 20 m or 30 m.

3.2. Methodology and localization approach

In this work, the RSSI values sent from the UEs to the PeNBs are used for localization. Fingerprinting-based localization is employed here. Fingerprinting is composed of two main phases: the training phase and the localization phase. In the training phase, a database of pairs of positions in the building and the corresponding RSSI values (for that position) is first built. In the localization phase, the fingerprinting database is used to estimate the location of the UEs from the RSSI values received from the devices to be localized.

We ran simulations for indoor UDN scenarios. Multiple datasets (of UEs' locations and corresponding RSSI values) were collected from the outputs of the simulation experiments. From the collected data, a fingerprinting database is built. Various ML models for indoor localization and building occupancy-count estimation in UDNs were developed and evaluated. Localization accuracy is considered as the performance metric for indoor localization. Various metrics (accuracy, precision, etc.) are used to evaluate occupancy detection inside the building.

In the following sections, we discuss in detail the approach used for localization and occupancy-count estimation, as well as the developed model for UDNs.

4. Data collection method and the model

4.1. Data collection

In the proposed method, we employ the RSSI values that are calculated by the UEs, based on the strength of the received Reference Signal (RS) that is transmitted by the PeNBs. Here, we discuss the proposed method for data collection, which is illustrated in Fig. 2.

PeNBs send a RS periodically to the UEs. RS is a special signal that exists only at the PHY layer, and it is not used to deliver data, but rather to convey to the UEs the reference point for the downlink power. The RS is also used by the UEs for channel estimation. As the RS data is known by both the sending PeNB and the UE, the UE can compare the received RS to the original RS to estimate how the channel impacts the transmitted signal. The UEs also calculate the RSSI, which measures the average total received power observed only in OFDM reference symbols in the measurement bandwidth over N resource blocks.

The steps for the collection of the fingerprinting data are as follows:

- PeNBs send the RS periodically.
- The RS is received by UEs within the transmission range.
- The UEs estimate the RSSI values.
- UEs send to their serving PeNBs reports of the RSSI values from the surrounding PeNBs.
- These reports are forwarded to a central processing unit/server to process the data and perform localization.
- ML-based models are used to estimate locations of UEs. Location of UEs can be provided as a service (security is beyond the scope of this work).

4.2. DEVS model

As previously mentioned, we defined a DEVS model for an indoor UDN network (scenario A) [43]. Fig. 3 illustrates our model, which contains an *Area* coupled model, which comprises of a *Transmission Medium* atomic model, many *PeNB* atomic models, and many *UE* coupled models. Furthermore, the model contains the *Processing Unit/Server* and *Manager* atomic models.

Instances of the *PeNB* model represent PeNBs in the studied area. The PeNBs send RS that is received by the UEs in the area. RS is generated by the PeNBs regularly (e.g., every 5 ms).

A *UE* coupled model consists of two atomic models: UE *Queue* and UE *Controller*. Incoming messages are cached in the UE *Queue*. The *Queue* atomic model includes a functionality to check the destination address of a received message and drop messages with a destination address that is not a broadcast address or does not match that of the UE. The UE *Controller* is where the processing

Table 1
Transmission parameters for scenario A.

Parameters	Scenario A
Type	Indoor Hotspot (Fig. 1)
Layout	Single layer (indoor TP)
Inter-Site Distance (ISD)	20m, 30m
Carrier frequency	3.5 GHz
System Bandwidth	10MHz (50RBs)
Channel model	Channel model available in document TR 36.814

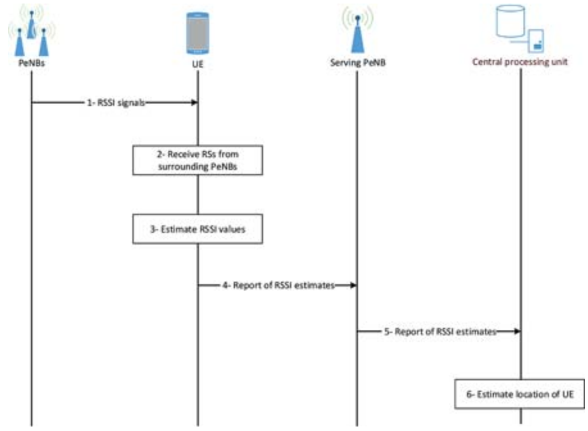

Fig. 2. Data collection method.

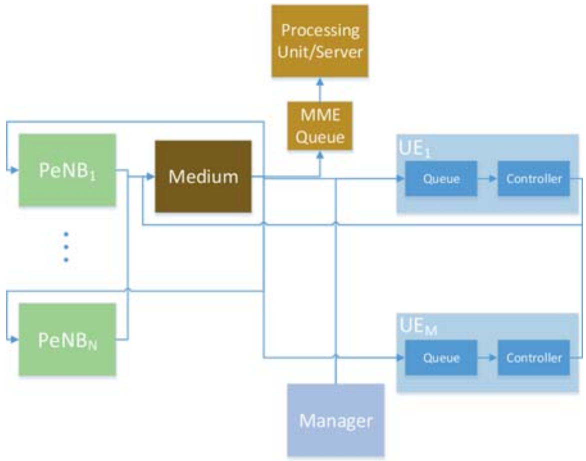

Fig. 3. UDN DEVS model.

performed by the UE is implemented. The transmission medium is modeled with the *Medium* atomic model. The *Processing Unit/Server* is any component in the access or core network that can be selected to process the data. It is the central location where RSSI data is forwarded, and where the models are used for inference to perform localization or occupancy detection.

The *Manager* atomic model is used to initialize and update the different parameters throughout the simulation, such as the wireless environment and the links between the eNBs and UEs. In the following, we discuss the transmission model adopted in this study.

4.3. Transmission model

In this study, we consider pathloss, shadowing, as well as small-scale fading. The pathloss model for indoor hotspot [44] was employed here. This model is composed of two pathloss equations. One is for the Line Of Sight (LOS) case, and the other is for the None Line Of Sight (NLOS) case. These are shown in Table 2.

PL in Table 2 is the pathloss in dB, d is the distance between the transmitter and receiver in meters, f_c is the carrier frequency in GHz,

Table 2
Indoor hotspot pathloss model [43].

Scenario	Path loss [dB] Note: f_c [GHz], Distance [m]	Shadow fading std [dB]	Applicability range, antenna height default values
LOS	$PL = 16.9\log_{10}(d) + 32.8 + 20\log_{10}(f_c)$	$\sigma = 3$	$3\text{ m} < d < 100\text{ m}$ h_{BS} =3-6 m h_{UT} =1-2.5 m
NLOS	$PL = 43.3\log_{10}(d) + 11.5 + 20\log_{10}(f_c)$	$\sigma = 4$	$10\text{ m} < d < 150\text{ m}$ h_{BS} = 3-6 m h_{UT} = 1-2.5 m

and σ is the shadow fading standard deviation in dB.

The LOS probability is used to determine whether a certain link is a LOS or NLOS. The LOS probability for Indoor Hotspot model was adopted [44]. The formula for the LOS probability is given as follows,

$$P_{LOS} = \begin{cases} 1, & d \leq 18 \\ e^{\frac{-(d-18)}{27}}, & 18 < d < 37 \\ 0.5, & d \geq 37 \end{cases} \tag{1}$$

where d is the distance between the transmitter and receiver in meters. The NLOS probability is given by:

$$P_{NLOS} = 1 - P_{LOS} \tag{2}$$

As can be seen from the equation, the LOS probability depends on the distance between the transmitter and receiver. In addition to pathloss and shadowing, we considered small-scale fading. It is worth mentioning that we use the scenario and channel model above for indoor environment because they are adopted by the 3GPP standard. However, there are other channel models proposed by researchers (e.g., [45,46]) that could be considered in future work.

5. Simulation scenarios and results

In this section, we present the results we obtained for indoor localization and building occupancy-count estimation. First, we present the results for indoor localization. Afterwards, we present the obtained results for occupancy estimation at the building level. Finally, we present the obtained results for occupancy estimation for parts of a building.

5.1. Indoor localization with kNN

As previously discussed, a fingerprinting approach is considered for localization in this study. As such, we consider a scenario with a grid of UEs distributed in the studied area to build the fingerprinting database. Fig. 4 shows the employed scenario. The figure depicts a scenario with 8 PeNBs distributed evenly in an area of 40 m × 80 m. We use the recommended ISD, i.e., 20. The same ISD can be used to distribute the PeNBs in an area with different dimensions and fewer PeNBs can be used to cover a smaller area. Furthermore, a grid of UEs is distributed in the area with a separation of 2 m × 2 m. These UEs will be used to build the fingerprinting database.

Two ML algorithms are used to build the localization models: kNN and DNN. In this section, we present the localization results obtained with kNN, and in Section 5.2, we present the results obtained with DNN.

With the kNN algorithm, we use different values for k (the number of neighbors). We divided the data set into a training set, which comprises 80% of the data set, and a test set which includes 20% of the data set. We use the test set to generate predictions with kNN with different k values. We use predictions generated with the test set to evaluate the results and choose the best k value. We use the localization/estimation error as the evaluation metric to assess the accuracy of the localization approach.

Table 3 shows the mean estimation error values for different k values, and different values for the simulation period, T, i.e., the simulation period over which the UEs locations and corresponding RSSI values were collected. The longer the period T the bigger the data set collected and used in the fingerprinting database. Table 3 shows that an estimation accuracy of 5.7 m can be achieved with data captured in as little as 500 ms. This is already an improvement over proposed systems based on cellular networks. A comparison with results achieved by other proposed cellular network-based systems is provided in Section 5.2. Furthermore, we will see in Section 5.4 that reducing the inter-distance between the stations will further improve the localization accuracy. The results also show that a k value of 12 seems to give the lowest estimation error. Generally speaking, increasing the k value will cause more nearby neighbors to be involved in estimating the location, and hence achieve a more accurate estimation. However, after a certain point, increasing the k value will cause neighbors who have values that are far from the real location to be involved, increasing the estimation error.

Fig. 5 shows the learning curve for the localization approach (with k=12), i.e., the achieved estimation error with the simulation interval, T, which indicates the length of the data set used with the kNN algorithm. The longer the simulation period, the bigger the dataset collected and used to train our model. As one can see, the approach starts to plateau after 500 ms. After 500 ms, doubling the

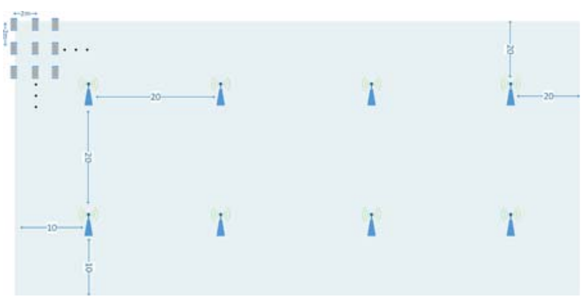

Fig. 4. Simulation scenario for the indoor localizatino experiment.

Table 3
Mean localization error (in meter) for different values of k and T..

	k			
T (ms)	4	8	12	16
100	6.4999	6.3075	6.3035	6.3839
200	6.2313	6.0313	6.0120	6.0391
300	6.1804	5.9125	5.8646	5.8773
400	6.1397	5.8292	5.7739	5.7786
500	6.0942	5.8036	5.7213	5.7245

dataset/interval only achieved a 0.14 m improvement in the localization error.

Table 4 shows the mean and the 95% Confidence Interval (CI) of the estimation errors. A 95% confidence interval is the range of values that you can be 95% certain it contains the true mean of the population. As one can see, the CI values are exceptionally low, which indicates that the shown mean values represent with high confidence, the actual mean of the estimation errors.

Fig. 6 shows the boxplot of the estimation error for estimations obtained with 2 different models. The first model was trained with data collected over 0.5 s, while the second was obtained with data collected over 1 s. As mentioned before, the difference in the mean of the estimation error achieved by both models was only 0.14 ms, which means that doubling the simulation period (dataset) did not achieve a significant improvement in the estimation results. Fig. 6 shows the minimum, first quartile (Q1), median, third quartile (Q3), and maximum values for the estimation errors achieved with both models. As one can see, the statistics obtained from both models are similar, which further confirms that increasing the size of the dataset beyond 500 ms did not achieve significant improvement.

In the following, we evaluate the improvement achieved by decreasing the spacing of the test points, i.e., decrease the spacing between the UEs in the UE grid used to collect the data set. At simulation interval T=200 ms, the mean values (for the estimation error) achieved by 2 m × 2 m grid and 1 m × 1 m grid are 5.72 m and 5.50 m, respectively. As such, reducing the spacing between the test points, which results in increasing the number of test points by a factor of 4, did not cause a significant improvement in the achieved mean estimation error (only 0.22 m). It is worth mentioning that increasing the number of test points by a factor of 4 results in increasing the number of computations and the model's training time significantly. Fig. 7 shows the boxplot of the estimation error for the 2 models with different spacing between UEs in the grid. The figure shows that the statistics of the estimation errors achieved with both models are close. For instance, one can see that the maximum estimation error achieved by the 1 m × 1 m grid is not a significant improvement from the one achieved by the 2 m × 2 m grid. This can be explained by the fact that moving a UE closer or further away from the PeNB by 1m does not cause a considerable difference in the values of the received signal strength. Considering the major increase in the computations and model training time, we can conclude that a grid of 2 m × 2 m would be enough for training the model.

5.2. Indoor localization with deep neural netwrok

Here we build a localization model from the fingerprinting database used in the previous section. However, we use a DNN instead of the kNN algorithm. The DNN has an input layer, two hidden layers, and an output layer. Each hidden layer has 30 nodes. The features for the DNN are the RSSI received from the different PeNB, while the predicted values (dependent variables) are the coordinates of the device in the building. The architecture of the DNN is shown in Fig. 8. The dataset was divided into training and test sets, where the training set comprises of 80% of the complete set. The stochastic gradient descent algorithm was used to train the DNN with learning rate of 10^{-4}. The architecture of the DNN was selected empirically. Multiple NN architectures were trained as well, but we show results for the DNN above as it gives the most accurate predictions (localization results).

The localization accuracy achieved with the DNN is 5.4 m (with a simulation period of 500 ms), which is a small improvement over that achieved with kNN with k=12 and with the same simulation period (5.72 m). This improvement is expected, because a DNN is a

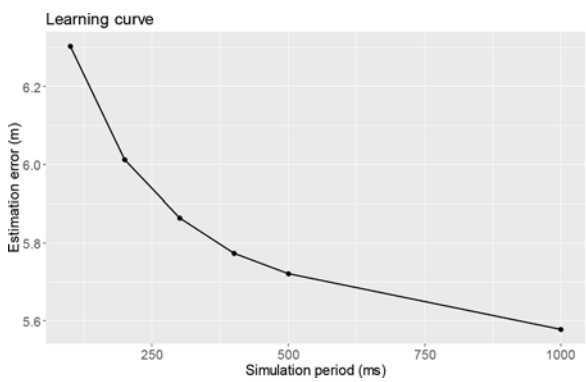

Fig. 5. Learning curve for the kNN algorithm.

Table 4
Mean and 95% CI of the localization error for different values of k and T=500.

k	Mean (m)	95% CI (m)
4	6.0942	± 0.0480
8	5.8035	± 0.0453
12	5.7213	± 0.0446
16	5.7145	± 0.0447

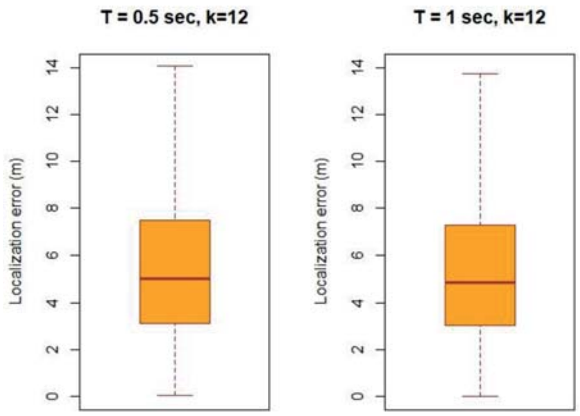

Fig. 6. Boxplot of the estimation errors with different simulation setup.

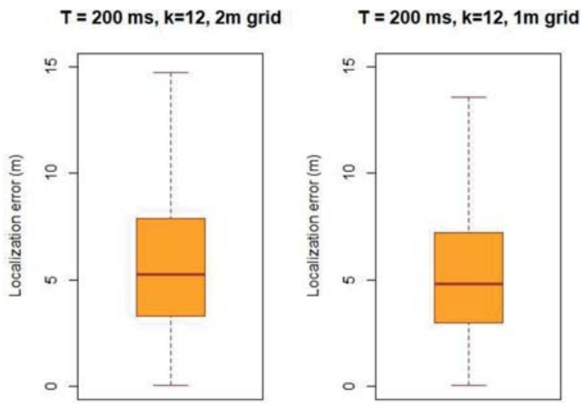

Fig. 7. Boxplot of the estimation errors with different simulation periods.

more sophisticated algorithm for supervised learning, and as previously discussed, an optimization algorithm is used to optimize the weights of the neurons to minimize the estimation error. As such, DNN is more robust to noise in the training data than other ML algorithms such as kNN.

Fig. 9 shows the learning curve for the localization model developed with the DNN, i.e., the achieved estimation error with the simulation interval, *T*, which indicates the length of the data set used to train the DNN. The longer the simulation period, the bigger the dataset collected and used to train our model. As one can see, the approach starts to plateau after 300 ms, where increasing the simulation period, and consequently the training data, did not cause a significant improvement on the localization accuracy. For instance, increasing the simulation period from 500 ms to 1 sec (double) only caused a 0.1 m increase in the localization accuracy.

Fig. 10 shows the boxplot of the estimation errors achieved with the DNN and *k*NN (k = 12). As one can see, small improvements are achieved with the DNN over the kNN in terms of localization errors. In addition to the slight reduction in the average localization error (as discussed above) and the median value (Fig. 10), one can see from Fig. 10 that the maximum localization error is also reduced by about 1 m. Again, this is since DNN is a more sophisticated algorithm for supervised learning, where an optimization algorithm is used to optimize the weights of the neurons to minimize the estimation error.

Table 5 provides a comparison of our results above (using kNN and DNN) with the results achieved by other proposed cellular network-based systems. As can be seen from Table 5, our results provide a significant improvement over those achieved by other proposed systems. Furthermore, we will see in Section 5.4 that reducing the inter-distance between the stations will further improve

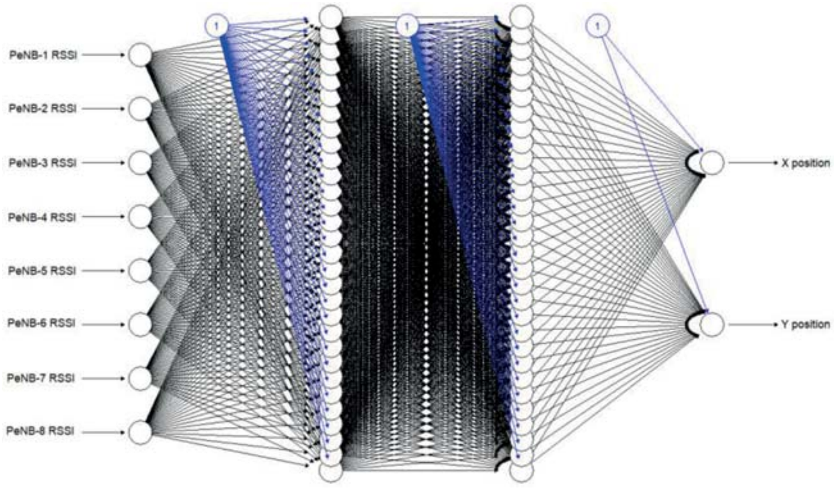

Fig. 8. The architecture of the trained DNN.

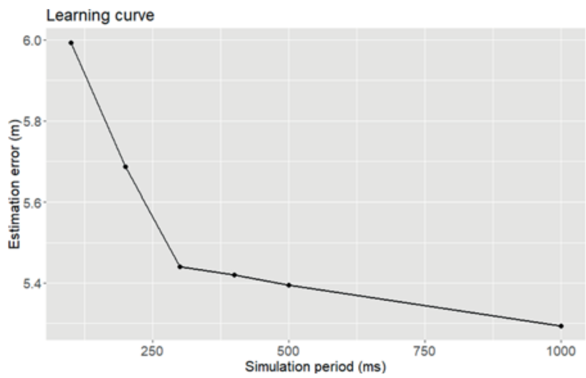

Fig. 9. Learning curve for the DNN.

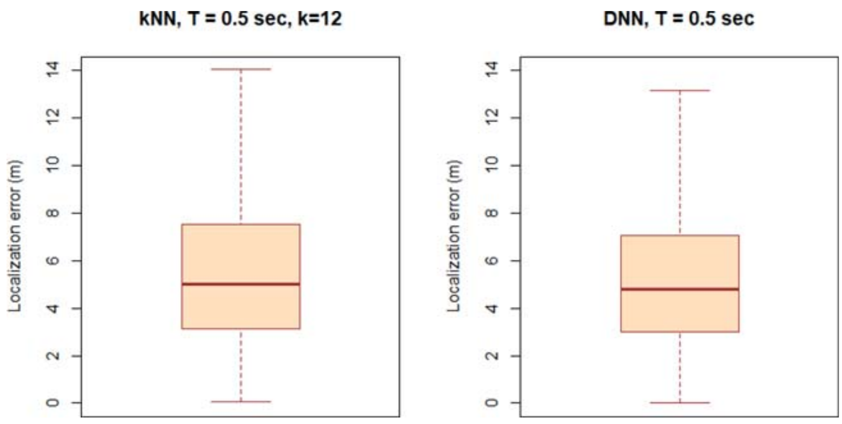

Fig. 10. Boxplot of the estimation errors with kNN and DNN.

the localization accuracy.

5.3. Building occupancy count estimation

In this section, we consider the problem of building occupancy-count estimation, i.e., estimating the number of people in the

Table 5
Comparison with results achieved with other proposed cellular network-based systems.

	Mean localization error (m)	RMSE (m)	Median (m)	68^{th} percentile (m)
Our work (kNN)	5.72	6.68	5.02	6.78
Our work (DNN)	5.39	6.36	4.79	6.29
EKAT [30]	-	9.61		-
TNR [30]	-	11.50		-
CellSense (rural) [47]	-	-	42.43	-
CellSense (urban) [47]	-	-	27.86	-
RNN-LSTM [32]	-	9.02		-
TA-based [29]	-	-	-	62.0

building using their 5G mobile devices. The problem of occupant detection inside the building is formulated as a binary-classification problem. The two classes considered are users inside the building (the “inside” class) and users outside the building (the “outside” class). The *Processing Unit* can easily use the total number of UEs that are detected inside the building (classified as inside) as the building occupancy-count estimation.

As with localization, a fingerprinting-based approach is considered here, where a grid of UEs is used to collect RSSI values and build a fingerprinting database. However, instead of estimating the location of the UEs here, the developed models classify the users into one of the two aforementioned classes, based on their RSSI values from the different stations.

The considered scenario is shown in Fig. 11. As shown in the figure, the scenario has a 100 m × 60 m area. The area contains an 80 m × 40 m building. This means that out of the total 6000 m^2 area, 3200 m^2 is an indoor sub-area, and the rest is an outdoor sub-area. A grid of UEs with 2 m × 2 m separation is used to build the fingerprinting database. UEs inside the red border are considered inside the building, and the remaining UEs are considered outside the building. The total number of UEs is 1581. The number of UEs inside and outside the building is 741 and 840, respectively. The simulation duration was set to 500 ms. Four algorithms were used to build classification models that can be used to classify whether users are inside or outside the building. The used algorithms are: kNN, decision tree, SVM, and LR.

The kNN algorithm can be used for solving regression as well as classification problems. The difference is in the last step. When used for regression, the algorithm uses the values of the nearest neighbors to predict the value (e.g., by taking the average value). On the other hand, when used for classification, it will use the most popular value among the values of the nearest neighbors as the chosen class. We train kNN models with different values of k. The obtained results are shown in Fig. 12. As can be seen in the figure, the best accuracy is achieved at $k = 3$, which is 0.999272. Furthermore, as one can tell, this is a high accuracy for classification, which means that the algorithm can be used to accurately estimate the count of devices in the building.

The second algorithm used to build a classification model is decision tree. The maximum depth parameter used is 6. This value was chosen empirically by testing with different values. The classification accuracy achieved with decision tree is 0.993548, which is also remarkably high, although it is slightly lower than that achieved with kNN. A third model was trained with the SVM algorithm. The classification accuracy achieved with SVM is 0.999557. The last classification model was trained with LR. In addition to classification, LR can be used to estimate the probability of each predicted class. The classification accuracy achieved with LR was 0.991429. High classification accuracy was achieved with the 4 classification algorithms. This verifies that the proposed approach can be used to accurately predict the number of occupants in a building. In addition to the classification accuracy, we also measured other metrics to evaluate the classification. These are the Jaccard index, F1 score, and the log loss for LR. All the obtained values are summarized in Table 6. As one can see, high values were achieved for the Jaccard and F1 scores with all the algorithms.

Comparing the results obtained here for binary classification of UEs (as “inside” or “outside”) with the results achieved for localization, we can see that the proposed approach on using ML algorithms with UDNs can achieve higher success with occupancy count estimation than with localization. This is due to the fact that occupancy estimation is a simpler problem to solve, i.e., classifying whether UEs are inside or outside the building, as opposed to localization where a model is used to accurately identify the location of a UEs within the building.

In addition to the above, further investigation was conducted into the small percentage of records that were misclassified. Analysis has shown that with all the used algorithms, the small percentage of misclassifications resulted by UEs that are very close to the edge of the building. The distortion (due to noise, shadowing, etc.) on the received signals of UE that is very close to the edge could sometimes be enough to cause such misclassification.

5.4. Occupancy-count estimation in parts of a building

In this section, we built a localization model like the one in the previous sections and use it to estimate the occupant count in parts of a building as opposed to the whole building. For the experiment in this section, we built a model for one of the floors in a building at Carleton University, Canada. The floor plan is shown in Fig. 13. The dimension of the floor is 18.56 m × 46.84 m. In this experiment, we are interested in estimating the occupant count in areas labeled as lab-1, lab-2, and lab-3. For this purpose, we build a fingerprinting database for the building, with 8 PeNBs distributed in the building. To fit them into the building, we reduced the inter-distance between them to 10 m. A grid of UEs with separation of 2 m × 2 m is also used to build the fingerprinting database.

As with the previous experiments, we divided the collected data into training (80%) and test (20%) sets. We train a localization model with a DNN, with 2 hidden layers of 30 nodes each. Results show that with this setup (reduced inter-distance), the *average*

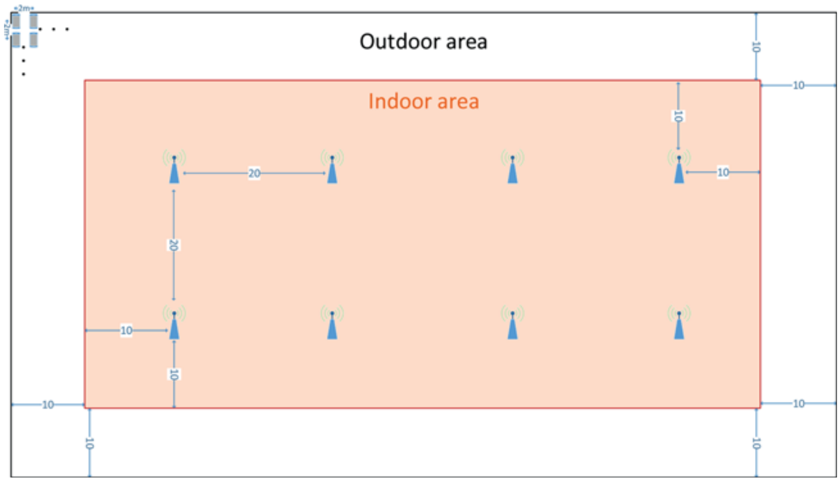

Fig. 11. Scenario considered for building occupancy-count estimation.

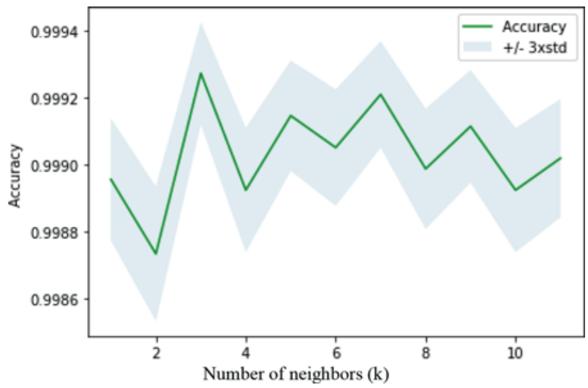

Fig. 12. Classification accuracy for kNN vs. the selected number of neighbors, k.

Table 6
Jaccard score, F1 score, and the log loss for all the classification algorithms.

Algorithm	Jaccard	F1-score	Log loss
kNN	0.998193	0.999019	-
Decision tree	0.988172	0.993548	-
SVM	0.999184	0.999557	-
LR	0.984222	0.991434	0.039799

localization error was reduced to 3.29 m. Fig. 14 shows the boxplot of the localization error with the different values of inter-distance, i.e., 20 m and 10 m. As one can see, significant improvement is achieved by decreasing the inter-distance between the stations. In addition to reducing the average localization error, the *maximum* localization error was reduced to 8 m.

After building the fingerprinting database, we use it for localization and occupancy-count estimation on a new test set of UEs located in the areas of interest, i.e., lab-1, lab-2, and lab-3. We distributed 100 UEs randomly throughout the building. Then, we use the localization model, to estimate the location of the UEs. It is worth mentioning that the *average* localization error obtained in the experiment was 2.90 m. Afterwards, we take 3 sets of measurements. The first set of measurements is the number of UEs that were originally located in each of the 3 labs. The second set of measurements comprises the number of UEs that are in each of the 3 labs based on the estimated locations. The last set of measurements includes the number of UEs that were localized correctly in each one of the labs. All the measurements are summarized in Table 7.

As shown in Table 7, lab-1 contained 10 UEs, and all of them were estimated to be in lab-1, i.e., the count estimation for UEs in lab-1 was exact. For lab-2 and lab-3, the estimated count is missing only 1 UE. From these results, one can say that the model can be used to accurately estimate the UE count in parts of the buildings (e.g., lab area).

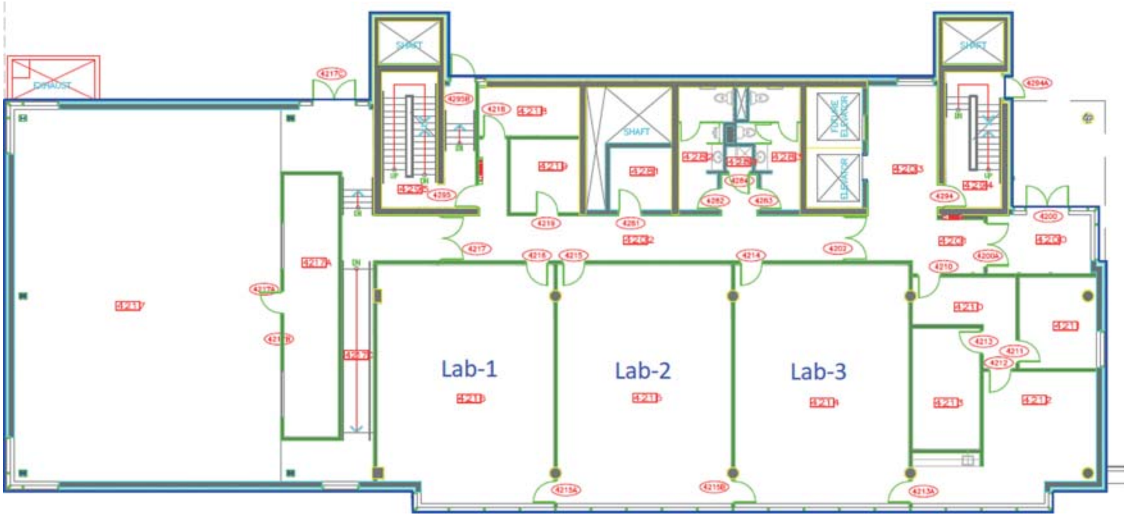

Fig. 13. Floor plan used in our experiment.

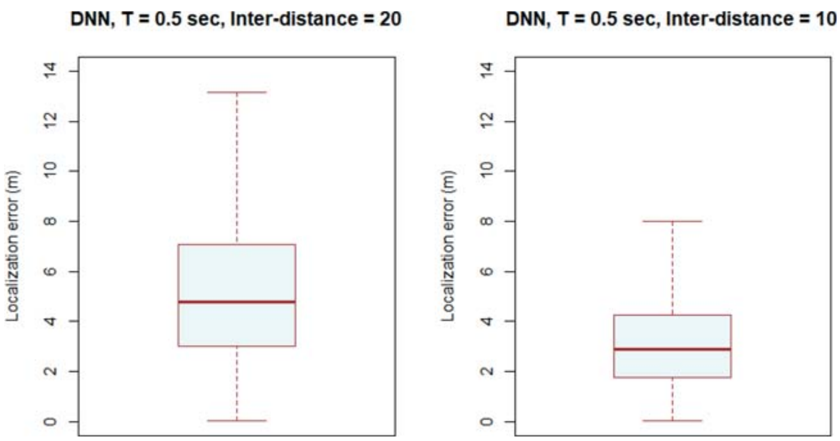

Fig. 14. Box plot of the ocalization with different values for the PeNB interdistance.

6. Conclusion

The interest and market for indoor localization are increasing at a rapid rate, due to its importance in many areas such as healthcare, defense and military, logistics and warehousing, and mobile applications. Moreover, the ability to sense mobile devices in indoor environments can be used for building occupancy-count estimation, which is crucial in optimizing building operations and management. In this paper, we present models for indoor localization and building occupancy-count estimation, with 5G Ultra-Dense Networks. An algorithm is proposed to collect Received Signal Strength Indicator (RSSI) from User Equipment (UEs) and build a fingerprinting database. Various Machine Learning (ML) algorithms were used to estimate the location of UEs in buildings from their RSSI values. Obtained results based on Indoor Hotspot scenarios from the 3GPP standards show that a localization accuracy close to 5 m can be achieved with an inter-distance of 20 m between stations, and a localization accuracy of 3.29 m with an inter-distance spacing of 10 m. This is an improvement over proposed systems based on cellular networks.

Additionally, detection of users in the building is treated as a binary-classification problem. Various ML algorithms were used to build models for the detection of users inside the building for occupancy-count estimation. Our results show that the proposed

Table 7
Results for the occupancy count for all the considered labs.

	Lab-1	Lab-2	Lab-3
Actual number of UEs	10	10	7
Estimated number of UEs	10	10	7
Number of UEs estimated correctly	10	9	6

solutions can be used to detect devices and obtain occupancy-count estimations in the building with high accuracy. Finally, the localization of users is used to estimate the occupancy count in parts of the building (e.g., lab area). Simulation results based on a model for an actual building show that UDNs can provide accurate count estimations at a finer level (e.g., parts of a building). In future work, 5G UDN scenarios with higher levels of network densification can be considered.

Acknowledgements

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