RSSI-based Indoor Localization with LTE-A Ultra-Dense Networks

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Abstract—**Indoor localization has received much attention recently, due to the emergence of location-based mobile applications. In addition to such applications, indoor localization can be used for other purposes, such as optimization of building operations. We present new models to study the performance of a localization method based on the Received Signal Strength Indicator (RSSI), using Long Term Evaluation-Advanced (LTE-A) Ultra Dense Networks (UDNs). Fingerprinting and Machine Learning (ML) algorithms are used to estimate the location of User Equipments (UEs) in a building from their RSSI value. The simulation results show that LTE-A UDNs can provide indoor localization service with good accuracy.**

Keywords—LTE-A, UDNs, fingerprinting, machine learning

I. INTRODUCTION

In recent years, localization has become an important topic as several mobile phone applications require location awareness to provide the intended services. In particular, indoor localization received interest from both industry and academia [1] as it can be used for indoor navigation, location-based marketing, visitor traffic analysis, and building occupancy count estimation to optimize heating and cooling services.

The Global Navigation Satellite System (GNSS) has been popular for localization, and most mobile devices nowadays are equipped with a GNSS antenna. However, this technology is not dependable in indoor environments due to signal obstruction. Consequently, other approaches have been proposed. Some of them use different transmission technologies such as Wi-Fi, Bluetooth, and Radio Frequency Identification Device (RFID). Wi-Fi and Bluetooth technologies are suitable for localization as most mobile phones today are equipped Wi-Fi and Bluetooth antennas. There has also been some interest for 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 spanning large areas and it opens the door for other services such as tracking. This makes it possible to track users over the area of interest (e.g., throughout a corridor, university campus, etc.).

Tracking of users over areas of interest can be used to provide different services such as indoor navigation, location-based marketing, analyzing visitor traffic, and building occupancy count estimation to optimize heating and cooling services. Furthermore, this information can be used to study and analyze individual as well as emergent behavioral 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 is based on existing infrastructure and does not require installation and setup of sensors and networks for localization purposes.

Cellular and mobile networks have witnessed an increasing demand for higher data rates and continuous growth of data traffic and number of subscribers. Furthermore, the number of devices to be connected through them will continue increasing exponentially due to Internet of Things (IoT) applications that can be deployed over cellular networks such as smart cities, autonomous vehicles, etc. Network densification provides an approach to increase the provided data rates over cellular networks to satisfy the increasing demands. Network densification increases the density of elements in the Radio Access Network (RAN). This includes both operator-deployed and user-deployed elements to increase the networks coverage, frequency reuse, and achieved data rates [2]. Due to the advantages of network densification, Ultra Dense Networks (UDN) are expected to be widely adopted in the future, to the point where each UE might have its own serving element.

In this research, we introduce various models and conduct varied simulation studies for an indoor Long Term Evaluation-Advanced (LTE-A) UDN network. The models are built as Discrete Event System Specification (DEVS) components [3], [4]. Based on the models we defined, we executed a variety of simulations scenarios for indoor LTE-A UDN. From the simulation results, we extracted various data sets for the UEs locations and their corresponding Received Signal Strength Indicator (RSSI) values. The collected data was used to build a fingerprinting database. Machine Learning (ML) algorithms were used with the constructed database to perform and evaluate fingerprinting-based indoor localization with LTE-A UDNs.

The rest of this paper is organized as follows. In Section II, we provide a review of the work in the literature on cellular-based localization systems. In Section III, we provide a brief review of LTE-A UDNs. In Section IV, we present the localization method and our DEVS model. In Section V, we discuss the obtained results. In Section VI, we state the conclusion and future work.

II. Background and Related Work

Indoor localization is becoming an important topic due to its importance in location-based services, such as mobile applications which require accurate location of the smart devices running these applications. Indoor localization has potentially other important use cases. For instance, it can be used for building occupancy-count estimation to optimize building operation and reduce energy consumption of buildings. Reducing this significant portion of the world's energy consumption [5] would help with energy shortage and reduce carbon footprints of buildings. In order to deliver building services to occupants in an energy-efficient manner, such services need to be provided in the correct time, location, and amount [5], [6]. This applies for a number of services such as lighting as well as heating, ventilating, and air conditioning (HVAC) [5]–[7].

Various methods have been proposed for indoor localization based on different technologies such as Wi-Fi, Bluetooth, and Radio Frequency Identification Device (RFID) [1]. Wi-Fi and Bluetooth technologies provide a good option for indoor localization because most smart phones nowadays have Wi-Fi and Bluetooth antenna integrated in 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.

Recent work has considered employing the radio signals transmitted by the Base-Stations (BSs) of the LTE-A cellular networks for localization. The advantage of such system over approaches based on sensor data is that it eliminates the need to install and setup sensors in the building, as the infrastructure of such systems are widely available and employed for cellular communications. Furthermore, such approach is expected to provide more accurate results in terms of occupancy count estimation than sensor data-based approaches, due to the wide spread of mobile devices nowadays and ability to detect them, which could provide accurate estimation of occupants' headcount.

The advantage of a cellular-based system over a Wi-Fi and Bluetooth systems is its wide availability and ability to cover areas where Wi-Fi access points or Bluetooth devices are not available. The geographically wide area that can be covered by cellular networks can provide valuable data. With cellular-based localization, occupants can be tracked over the area of interest (e.g., at the building or university campus). This can allow analyzing occupants' movement and understand individual as well as emergent behavioral patterns. For example, the movement of students on a university campus can be analyzed to find the locations and times with high student density for design improvement to eliminate traffic jams. In the following, we provide an overview of LTE-A networks and the recent work in the literature on cellular-based localization systems.

A cellular network is defined as a communication network with the last link to the end user takes place over a wireless radio link. The coverage area of the network is divided into smaller areas referred to as cells. Each cell is covered by a transceiver (usually stationary) that is called the Base-Station (BS) or the evolved Node B (eNB) [1]. Voice and data communications between the network and the mobile devices (known as User Equipment (UE)) take place over radio frequency links between the covering eNB and the UEs. The part of the network that includes the eNB, UEs, and connecting frequency links is called the RAN. eNBs are usually connected via a high-speed wired network called the backhaul.

The LTE-A standard for the 4th generation (4G) mobile networks was introduced by the 3rd generation partnership project (3GPP) to satisfy the increasing demands for mobile broadband services with higher data rates and Quality of Service (QoS). In its Release 8, the cellular network architecture is referred to as the Evolved Packet System [8]. The LTE and System Architecture Evolution projects were two subprojects of the 3GPP. The two projects have resulted in three specifications, namely the Evolved Packet Core (EPC), Evolved Universal Terrestrial Radio Access Network (E-UTRAN), and Evolved Universal Terrestrial Radio Access (E-UTRA). The EPC contains the specifications for the core network, while the E-UTRAN and E-UTRA contain the specifications for the RAN and the system's air interface, respectively [8].

Cellular and mobile networks have witnessed an increasing demand for higher data rates and continuous growth of data traffic and number of subscribers. Furthermore, the number of devices to be connected through cellular and mobile networks will continue increasing exponentially due to new applications that can be deployed over cellular networks such as smart cities, autonomous vehicles, etc. Network densification is one key technology to satisfy these increasing demands; it is achieved by increasing the density of elements in the RAN. This includes both operator-deployed and user-deployed elements to increase the network coverage, frequency reuse, and achieved data rates [2]. Due to the advantages of network densification, UDN are expected to be widely adopted in the Fifth Generation (5G) wireless network.

Several localization systems based on measurements from LTE signals have been proposed. In [9], a localization system that employs Channel State Information (CSI) extracted from LTE signals was proposed. The system uses CSI measurements for signal fingerprinting localization. Experiments in indoor and outdoor environments show that localization based on CSI from LTE signals can be used for both indoor and outdoor localization.

The authors in [10] proposed a fingerprinting approach for localization of UE in LTE-A networks mapping multiple radio channel parameters formulated as a fingerprint vector and a geographical location. Furthermore, the authors employ a feature-extraction algorithm to identify unique channel parameters and use a neural network to build a fingerprinting database of channel parameters and UE locations. Results show that by using only one LTE eNB, the proposed technique provides a median error distance of 6 and 75 meters in indoor and outdoor environments, respectively.

The authors in [11] also considered employing the CSI from LTE signals for fingerprinting-based indoor localization. The authors propose a technique where the fingerprint contains a vector that serves as the shape of the channel frequency response instead of the CSI. The approach uses BS signaling messages and does not need designated communication between the BS and the UEs. The approach reduces computation complexity and memory requirements.

In [12], the authors evaluate the accuracy of localization based on radio fingerprinting of LTE signals on 800 MHz, 1800 MHz and 2600 MHz frequency bands. Field measurements are conducted to collect training data that consist of UE locations and the corresponding received signal strength radio measurements from several base stations. Collected data is used to provide a fingerprint of the radio conditions at a specific geographical location. The performance of two systems composed of LTE and LTE+WLAN grid-based RF fingerprint measurements utilizing partial fingerprint matching were studied and compared. Obtained results show that partial fingerprints that consist of LTE and WLAN radio measurements improves localization accuracy by at least a factor of 3.5x while keeping the percentage of discarded samples low.

The work in [13] used Cell-Specific Reference signal measurements from LTE signals for indoor localization to complement outdoors localization systems such as Global Navigation Satellite System. Two algorithms were used for localization. The first one is a Time-Of-Arrival approach called the Threshold-to-Noise Ratio algorithm. The second one is an estimator that is more complex but also robust against multipath fading, and it is called “ESPRIT and Kalman filter for time of Arrival Tracking” (EKAT). The EKAT ranging algorithm provides more accurate, robust and smooth results indoors, at the cost of increased complexity.

All the research above considers LTE-A networks with macro cells, where a macro eNBs with high power provides the coverage for a wide geographical area and high number of users. In our work, we will be studying the performance of localization over LTE-A UDNs. The availability of high number of elements such as femtocells and picocells are supposed to increase the accuracy of localization over mobile networks for indoors environments.

In this study, we used the Discrete Event System Specification (DEVS) formalism [4] to build a model for an indoor LTE-A UDN network. Based on the developed model, we run simulations for indoor LTE-A UDN scenarios. From these simulations, we extract various data sets for the UEs locations and the corresponding RSSI values. From the collected data, we build a fingerprinting database. ML algorithms were used with the constructed database to perform and evaluate fingerprinting-based indoor localization with LTE-A UDNs.

and evaluate the performance of indoor fingerprinting localization with LTE-A UDNs. There are some simulation-based studies on wireless localization, but they are mostly on localization for wireless sensor networks [14], or other transmission technologies [15], but they do not consider LTE-A UDNs.

DEVS provides a sound formal framework for modeling generic dynamic systems. DEVS includes hierarchical, modular, and component-oriented structure. It provides formal specifications for defining structure and behavior of a discrete event model. A DEVS model is composed of structural (Coupled) and behavioral (Atomic) components, in which the coupled component maintains the hierarchical structure of the system, while each atomic component represents a behavior of a part of the system. This modular nature is a particularly useful property for modeling and simulating LTE-A networks. The network model can be built using different submodels; each one implements a different component of the wireless network such as the BS or the UE. Each one of these submodels can be tested and verified, independently, and integrated into the whole model. These submodels can also be reused in other LTE-A network models. Furthermore, each submodel, such as the BS, can also be implemented using multiple submodels in a hierarchical manner. Each one of these submodels implements a certain subcomponent or functionality. This makes it easy to design, implement, and evaluate LTE-A network models.

III. LTE-A UDN FOR INDOOR LOCALIZATION

A. LTE-A UDN Scenarios

As discussed in the previous section, new network architectures such as UDNs and Ultra-Dense Heterogeneous Networks (UDHetNets) are enabling technologies to meeting the increasing demands and achieve the required performance of 5G cellular networks [2]. With UDNs, the density of the operator-deployed and user-deployed elements is increased, improving the coverage, frequency reuse, and achieving higher data rates. In UDHetNets, several types of wireless access nodes with different capabilities are employed, and hence, macrocells are overlaid with low-power nodes such as Remote Radio Head, Pico eNB (PeNB) and Home eNB. These smaller cells can be used to offload traffic, which improves the network coverage at the cell edge and increase the data rates.

The LTE-A Pro standard [16] proposes different scenarios for implementation of UDNs and UDHetNets. These include scenarios for UDNs where similar elements are employed in the network, such as PeNBs, as well as heterogeneous scenarios where distinct types of cells coexist such as eNBs and PeNBs.

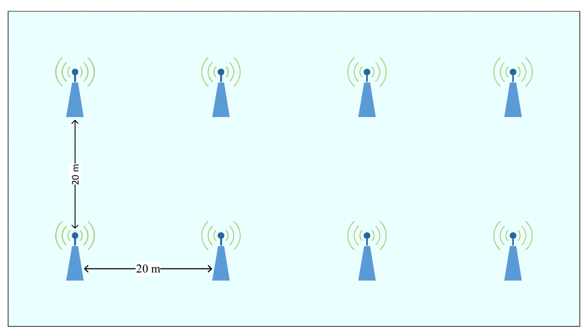

Fig. 1. LTE-A UDN scenario A.

In the following, we list the possible scenarios considered in the LTE-A Pro standard [16]:

- Scenario A-Indoor small cell deployment: this scenario consists of a single layer of small cells in an indoor environment. This scenario is shown in Fig. 1.
- Scenario B-macro cell deployment: this scenario consists of a single layer of macro cells.

- Scenarios C and D-Heterogeneous network of urban macro and outdoor small cell deployment: these scenarios contain macro cells coexisting with small cells. The two scenarios differ in the method of channel allocation for the two different layers.

TABLE I. TRANSMISSION PARAMETERS FOR SCENARIO A

Parameters	**Scenario A**
Type	Indoor Hotspot (Fig. 1)
Layout	Single layer Indoor TP: Number of TPs: N=8, N=12 (optional) per 120m×50m
ISD (inter-site distance)	20m, 30m
Carrier frequency	3.5 GHz
Coordination cluster size for ideal backhaul	All sites
System Bandwidth	10MHz (50RBs)
Channel model	Channel model available in document TR 36.814

We are interested in scenario A (the scenario for indoor environments) because our work is focused on indoor localization and building occupancy count estimation (future work). The transmission parameters for such scenario is provide by the LTE-A standard and presented in Table I. These parameters will be adopted in our study.

B. Methodology and Localization Approach

In this section, we propose employing the RSSI values sent from the UEs to the PeNBs for localization. A fingerprinting-based method will be used for localization. Fingerprinting is composed of two main phases, the training phase and the localization phase. In the training phase, a database of pairs of locations inside the building and corresponding RSSI values will be first built. During 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.

In this study, we run simulations for indoor LTE-A UDN scenarios. From these simulations, we will extract various data sets for the UEs locations and corresponding RSSI values as per the approach presented in the previous section. From the collected data, we will build a fingerprinting database, and evaluate the performance of indoor fingerprinting localization in LTE-A UDNs. The localization accuracy will be considered as the performance metric.

In the following sections, we discuss in detail the approach used for localization as well as the developed model for LTE-A UDN.

IV. LOCALIZATION METHOD AND MODEL

A. Localization method

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. The PeNBs send a RS periodically. The RS is a special signal that exists only at 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 in order 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.

As previously discussed, we employ the RSSI values estimated by the UEs in LTE-A UDNs for indoor localization, and study the localization accuracy under such system. The steps for the localization process are as follows. First, the PeNBs send the RS periodically. The RS is received by UEs within the transmission range. The UEs send to their serving PeNBs reports of the RSSI values from the surrounding PeNBs. These reports are forwarded to the Mobility Management Entity (MME) for central processing and localization. The MME is a part of LTE-A core network. We discuss the MME in more detail in the next section. Locations of UEs can be provided as a service (security is beyond the scope of this work).

B. Localization Method: the Model

As previously mentioned, we defined a DEVS model for an indoor LTE-A UDN network (scenario A) [16].

Fig. 2 shows the structure of this model, which consists of an *Area* coupled model, which contains a *Transmission Medium* atomic model. The model also includes many *PeNB* atomic models and *UE* coupled models. Furthermore, the model contains the *MME* and *Manager* atomic models.

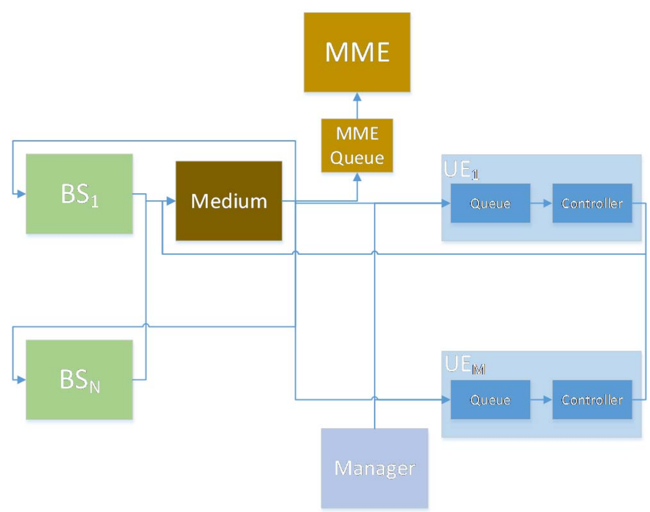

Fig. 2. LTE-A UDN DEVS model.

Instances of the *PeNB* model represent PeNBs in the studied area. The PeNBs send Reference Signal (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 contains two atomic models: UE *Queue*, and UE *Controller*. Received messages are buffered at the UE *Queue*. The *Queue* checks the destination address of a received message. If it matches that of the UE (or if it is a broadcast address), the message will be buffered, otherwise it will be discarded. The UE *Controller* is where the processing performed by the UE is implemented. The *Medium* model represents the transmission medium. It receives a message sent from the PeNB or any UE and broadcasts it to the other nodes in the area (UE/PeNB).

The *MME* is a key component in LTE-A networks. In fact, it is a critical component in the System Architecture Evolution (SAE) architecture of the EPC, as it is the main signaling entity of the EPC. The *MME* roles include initiating paging and authentication of the mobile device, as well as selection of the appropriate gateway during the initial registration process. In our proposed approach, we employ the *MME* as the central entity where RSSI data is used to build the fingerprinting data base, and where the localization is performed.

The *Manager* atomic model initializes and updates the parameters of the cellular downlinks (DLs) and uplinks (ULs) between the PeNBs and the UEs. In the following, we discuss the transmission model adopted in this study.

C. Transmission model

We consider pathloss, shadowing, as well as small-scale fading in this study. The pathloss model for indoor hotspot [17] was employed here. This model is composed of two pathloss equations. One for the Line Of Sight (LOS) case, and the other is for the None Line Of Sight (NLOS) case. These are shown in Table II.

TABLE II. INDOOR HOTSPOT PATHLOSS MODEL [16].

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 m < d < 100 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 m < d < 150 m h_{BS} = 3-6 m h_{UT} = 1-2.5 m

PL in Table II is the pathloss in dB, d is the distance between the transmitter and receiver in meters, f_c is the carrier frequency in GHz, 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 [17]. The formula of the LOS probability is given as follows,

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

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

$$P_{NLOS} = 1 - P_{LOS} \quad (2)$$

As can be seen from the equation, the LOS probability depends on the distances between the transmitter and receiver. In addition to pathloss and shadowing, we considered small-scale fading.

V. SIMULATION SCENARIO AND RESULTS

In this section, we first discus the simulation scenarios considered here, and then we present and discus the obtained results. 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. 3 shows the employed scenario.

The figure depicts a scenario with 8 PeNBs distributed in an area of 40m×80m. Furthermore, a grid of UEs are distributed in the area with separation of 2m×2m. These UEs will be used to build the fingerprinting database.

The k Nearest Neighbors (kNN) algorithm was used for the localization phase. The kNN algorithm is 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 near neighbors

In our study, we use different values for k. We divided the data set into a training set, which comprises 70% of the data set, and a test set which includes 30% 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.

Fig. 3. Simulation scenario.

Table III 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 where collected. The longer the period T the bigger the data set collected and used in the fingerprinting database.

Table III shows that an estimation accuracy of 5.7m can be achieved with data captured in as low as 500ms. The results also show that a k value of 12 seems to give the lowest estimation error. Increasing the k value will cause more close neighbors to be involved in estimating the location, and hence achieve 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, and hence, increase the estimation error.

Fig. 4 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 500ms. After 500 ms, doubling the dataset/interval only achieved 0.14m improvement in the localization error.

TABLE III. MEAN LOCALIZATION ERROR FOR DIFFERENT VALUES OF K AND T.

T (ms) \ ***k***	**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

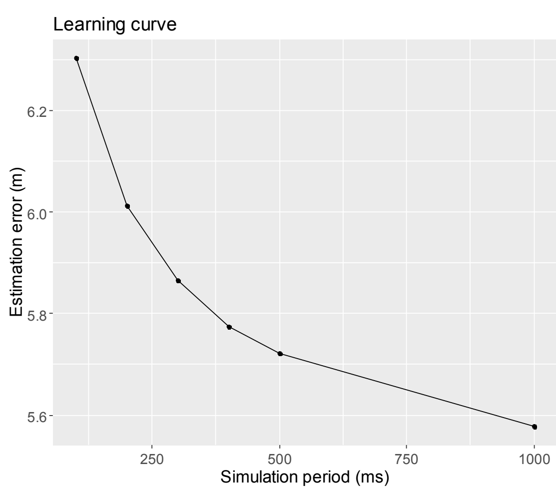

Fig. 4. A Learning curve for the kNN algorithm.

Table IV 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, represents with high confidence, the actual mean of the estimation errors.

TABLE IV. MEAN AND 95% CI OF THE LOCALIZATION ERROR FOR DIFFERENT VALUES OF K AND T=500.

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

Fig. 5 shows the boxplot of the estimation error for estimations obtained with 2 different models. The first model is trained with data collected over 0.5s, while the other was obtained with data collected over 1s. As mentioned before, the difference in the mean of the estimation error achieved by both models was only 0.14ms, which means that doubling the simulation period (dataset) did not achieve much improvement in the estimation results. Fig. 5 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.

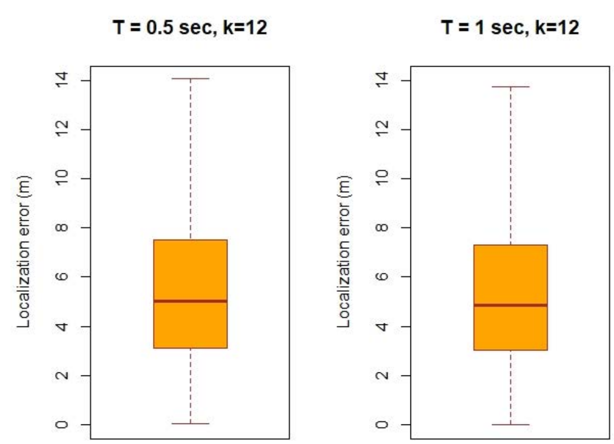

Fig. 5. Boxplot of the estimation errors with different simulation setup.

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=200ms, the mean values (for the estimation error) achieved by 2m×2m grid and 1m×1m grid are 5.72m and 5.50m, respectively. As such, reducing the spacing between the test points, which results in increasing the number of test points by roughly 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. 6 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 max estimation error achieved by the 1m×1m is not a significant improvement from the one achieved by 2m×2m. This can be explained by the fact that moving a UE closer or further way from the PeNB by 1m does not cause considerable different 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 2m×2m would be enough for training the model.

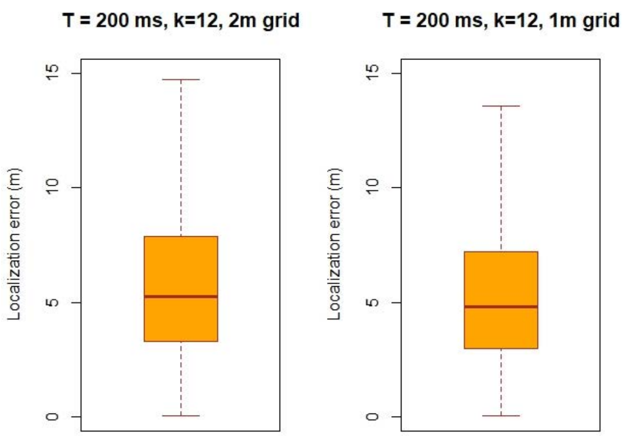

Fig. 6. Boxplot of the estimation errors with different simulation periods.

VI. Conclusion

In this paper, we study the performance of Received Signal Strength Indicator (RSSI) -based localization using Long Term Evaluation-Advanced (LTE-A) Ultra Dense Networks (UDNs). Utilizing LTE-A UDN can provide accurate localization of User Equipment (UEs) using an existing infrastructure. We used the Discrete Event System Specification (DEVS) formalism to build a model for an indoor LTE-A UDN network. Based on the developed model, we run simulations for an indoor LTE-A UDN scenario. From these simulations, we extract various data sets for the UEs locations and corresponding RSSI values. From the collected data, we build a fingerprinting database. Machine Learning (ML) algorithms were used with the constructed database to perform and evaluate fingerprinting-based indoor localization with LTE-A UDNs. Our simulations were based on the Indoor Hotspot scenario from the LTE Advanced Pro standard. Results have shown that a localization accuracy of 5.7 m can be achieved with studied scenario. In future work, we will study the results achieved in various scenarios and study the utilization of this approach for building occupancy-count estimation.

References

[1] F. Zafari, A. Gkelias, and K. Leung, "A Survey of Indoor Localization Systems and Technologies," *IEEE Commun. Surv. Tutorials*, vol. 21, no. 3, Sep. 2017.

[2] A. Gotsis, S. Stefanatos, and A. Alexiou, "UltraDense Networks: The New Wireless Frontier for Enabling 5G Access," *IEEE Veh. Technol. Mag.*, vol. 11, no. 2, pp. 71–78, Jun. 2016.

[3] B. P. Zeigler, H. Praehofer, and T. G. Kim, *Theory of modeling and simulation: Integrating discrete event and continuous complex dynamic systems*. San Diego: Academic Press, 2000.

[4] G. A. Wainer, *Discrete-event modeling and simulation : A practitioner's approach*. Boca Raton: CRC Press, 2009.

[5] W. Shen, G. Newsham, and B. Gunay, "Leveraging existing occupancy-related data for optimal control of commercial office buildings: A review," *Adv. Eng. Informatics*, vol. 33, pp. 230–242, Aug. 2017.

[6] O. Tianzhen Hong, J. Langevin, and T. Hong, "The Human Dimensions of Energy Use in Buildings: A Review," *Renew. Sustain. Energy Rev.*, vol. 81, no. 1, 2017.

[7] Z. Chen, C. Jiang, and L. Xie, "Building occupancy estimation and detection: A review," *Energy Build.*, vol. 169, pp. 260–270, Jun. 2018.

[8] I. F. Akyildiz, D. M. Gutierrez-Estevez, and E. C. Reyes, "The evolution to 4G cellular systems: LTE-Advanced," *Phys. Commun.*, vol. 3, no. 4, pp. 217–244, Dec. 2010.

[9] G. Pecoraro, S. Di Domenico, E. Cianca, and M. De Sanctis, "LTE signal fingerprinting localization based on CSI," in *2017 IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, 2017, pp. 1–8.

[10] X. Ye, X. Yin, X. Cai, A. Perez Yuste, and H. Xu, "Neural-Network-Assisted UE Localization Using Radio-Channel Fingerprints in LTE Networks," *IEEE Access*, vol. 5, pp. 12071–12087, 2017.

[11] G. Pecoraro, S. Di Domenico, E. Cianca, and M. De Sanctis, "CSI-based fingerprinting for indoor localization using LTE Signals," *EURASIP J. Adv. Signal Process.*, vol. 2018, no. 1, p. 49, Dec. 2018.

[12] T. Hiltunen, J. Turkka, R. Mondal, and T. Ristaniemi, "Performance evaluation of LTE radio fingerprint positioning with timing advancing," in *2015 10th International Conference on Information, Communications and Signal Processing (ICICS)*, 2015, pp. 1–5.

[13] M. Driusso, C. Marshall, M. Sabathy, F. Knutti, H. Mathis, and F. Babich, "Indoor positioning using LTE signals," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, 2016, pp. 1–8.

[14] C. Liu *et al.*, "RSS Distribution-Based Passive Localization and Its Application in Sensor Networks," *IEEE Trans. Wirel. Commun.*, vol. 15, no. 4, pp. 2883–2895, Apr. 2016.

[15] R. Aversa, B. Di Martino, M. Ficco, and S. Venticinque, "A simulation model for localization of pervasive objects using heterogeneous wireless networks," *Simul. Model. Pract. Theory*, vol. 19, no. 8, pp. 1758–1772, Sep. 2011.

[16] 3GPP, "Technical Specification Group Radio Access Network; Study on further enhancements to Coordinated Multi-Point (CoMP) Operation for LTE," TR 36.741, Mar. 2017.

[17] 3GPP, "Evolved Universal Terrestrial Radio Access (E-UTRA); Further advancements for E-UTRA physical layer aspects," TR 36.814, 2017.