3D Indoor Positioning for 5G Networks

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"ἓν μόνον ἀγαθόν εἶναι, τὴν ἐπιστήμην, καὶ ἓν μόνον κακὸν, τὴν ἀμαθίαν"
(Σωκράτης, 469 - 399 π.Χ.)

I would like to dedicate this work to my father, Mohamed Salem El Boudani, to the memory of my mother, Izzana El Boudani, and my step-mother, Khadija Zein. ...

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[Brahim El Boudani]
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Abstract

Over the past two decades, the challenge of accurately positioning objects or users indoors, especially in areas where Global Navigation Satellite Systems (GNSS) are not available, has been a significant focus for the research community. With the rise of 5G IoT networks, the quest for precise 3D positioning in various industries has driven researchers to explore various machine learning-based positioning techniques.

Within this context, researchers are leveraging a mix of existing and emerging wireless communication technologies such as cellular, Wi-Fi, Bluetooth, Zigbee, Visible Light Communication (VLC), etc., as well as integrating any available useful data to enhance the speed and accuracy of indoor positioning. Methods for indoor positioning involve combining various parameters such as received signal strength (RSS), time of flight (TOF), time of arrival (TOA), time difference of arrival (TDOA), direction of arrival (DOA) and more. Among these, fingerprint-based positioning stands out as a popular technique in Real Time Localisation Systems (RTLS) due to its simplicity and cost-effectiveness.

Positioning systems based on fingerprint maps or other relevant methods find applications in diverse scenarios, including malls for indoor navigation and geo-marketing, hospitals for monitoring patients, doctors, and critical equipment, logistics for asset tracking and optimising storage spaces, and homes for providing Ambient Assisted Living (AAL) services.

A significant challenge facing all indoor positioning systems is the objective evaluation of their performance. This challenge is compounded by the coexistence of heterogeneous technologies and the rapid advancement of computation. There is a vast potential for information fusion to be explored. These observations have led to the motivation behind our work. As a result, two novel algorithms and a framework are introduced in this thesis.

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Abbreviations

The following abbreviations are used in this thesis:

Abbreviation	Description
3/2D	3/2 Dimensions
5G	5th Generation
ADAM	ADAptive Momentum
AGV	Automated Guided Vehicle
ANN	Artificial Neural Network
AP	Access Points
AoA	Angle of Arrival
AoD	Angle of Departure
BLE	Bluetooth Low Energy
BSN	Body Sensor Networks
C-RAN	Cloud-Radio Access Network
CAE	Convolutional AutoEnconde
CD-1	Contrastive Divergence with one-step iteration
CDF	Cumulative Distribution Function
CID	Cell Identity
CNN	Convolutional Neural Networks
D2D	device-to-device
DBN	Deep Belief Network
DCM	Database Correlation Method
DELTA	DEep Learning cooperaTive Architecture
DNN	Deep Neural Network
DoA	Direction of arrival
ETSI	European Telecommunication Standards Institute
FSPL	Free Space Path Loss

GNSS	Global Navigation Satellite System
GPS	Global Positining System
HetNet	Heterogeneous Network
i-KNN	intelligent KNN
IMU	Inertial Measuring Unit
IoT	Internet of Things
KNN	K-Nearest Neighbour
K-DNN	K-Nearest Neighbour and Deep Neural Network
LBS	Location Based Services
LOS	Line-Of-Sight
MED	Mean Euclidean Distance
MLP	Multiple Layers Perceptron
mm-Wave	Milimeter Wave
NN	Nearest Neighbour
PaaS	Positioning as a Service
PPDR	Public Protection and Disaster Recovery
PRR	Packet Reception Ratio
RFID	Radio Frequency Identification
RNN	Recurrent Neural Networks
RP	Reference Point
RSS	Received Signal Strength
RSSD	RSS Difference
RSSI	Received Signal Strength Indicator
RTI	RSS Temporal Image
RTLS	Real Time Localization System
RTOF	Return Time of Flight
SNR	Signal-to-Noise-Ratio
SVC	Support Vector Classification
SVM	Support Vector Machine
SVR	Support Vector Regression
TDOA	Time Difference of Arrival
TOA	Time of Arrival
ToF	Time of Flight
UAV	Unmanned Aerial Vehicle
V2X	Vehicle-to-Everything
VLC	Visible Light communication

WSN	Wireless Sensors Networks
WKNN	Weighted K Nearest Neighbour

Chapter 1

Introduction

1.1 A preamble to Indoor Positioning in 5G Networks

Indoor positioning or localisation of either valuable assets or personnel is the process of tracking and locating them through a wireless device, usually carried by users themselves or attached to the assets. Research in positioning methods and techniques has been carried out for many decades in both indoor and outdoor settings. However, since the introduction of the 5G IoT[6], real-time positioning is becoming increasingly required by context-aware and location-based use cases. Typical scenarios include hospitals for locating doctors and patients, malls for navigating and advertising products to target groups, oil and gas plant monitoring, precision agricultural applications, positioning to identify victims in public protection and disaster recovery, etc. Moreover, several advanced applications can provide cellular phone fraud detection, location-sensitive billing, as well as navigation from and to almost everywhere through the use of heterogeneous wireless technologies, the fusion of sensor and IoT data ([7], [8], [9], [10]). A recent report published by IEEE has estimated 50 billion [11] mobile devices will be connected to the cloud. These devices will need constant access to data anywhere. Cisco has predicted that 26 billion [12] of these devices will be IoT or Wireless Sensor Network (WSN) devices. In this respect, technologies like Cloud Radio Access Network (C-RAN), Millimeter Wave (mm-Wave) communication, ultra dense communication [13], device-to-device (D2D) communication and Vehicle-to-everything (V2X) [14], [15] and protocols like IEEE 802.11be (Extremely high Throughput WLAN)[16], IEEE 802.11az (Next Generation Positioning)[17] are not only introduced to increase the bandwidth of communication, but also to offer the possibility of cooperative and precise localisation.

Furthermore, with 5G paving the path for seamless collaboration among heterogeneous wireless systems (cellular, WiFi, WSN, IoT, etc.), a great opportunity has arisen in the area of indoor localisation in urban areas under the framework of smart cities. Such high dense networks could be utilised to solve multi-agent positioning and offer agility and scalability for accurate positioning as a service. Finally, to standardise this technological hype, in their 3GPP technical report [18], European Telecommunication Standards Institute (ETSI) focused on several criteria and use cases to achieve high precision for indoor and outdoor positioning for 5G networks. In this respect, the aforementioned observations have motivated us to set three main research scopes for this thesis:

- To improve 3D indoor positioning in 5G IoT network through cooperative learning.
- Leverage 5G IoT heterogeneous networks signal data to improve vertical and horizontal indoor positioning using a novel technique for information fusion

- To solve the issue of a standardised localisation platform through a novel Positioning as a Service (PaaS) architecture for massively deployed assets.

In this direction, the following concepts are introduced in this thesis.

- A Deep Learning-based with Co-operative Architecture (DELTA) for enhanced 3D indoor localization using multilayered radiomap as described in **Chapter 3**.
- Information fusion for 5G IoT 3D localisation using K-Nearest Neighbour (KNN), Deep Neural Networks (DNN), and multilayered hybrid radiomap as demonstrated in **Chapter 4**.
- PaaS architecture for massively deployed assets in 5G IoT Networks, as presented in **Chapter 5**.

1.2 3D Positioning using Deep Learning

Deep learning is a subclass of machine learning algorithms based on artificial neural networks (ANN) and representation learning [19]. The Artificial Neural Network (ANN) itself was inspired by the biological network. Figure 1.1 shows the similarity between the human biological neuron and a calculation node in ANN.

These types of algorithms are more powerful than traditional machine learning algorithms as they use multiple connected layers to extract complex patterns from raw data [20]. The training technique used in deep learning can be supervised, semi-supervised, or unsupervised [19]. Nowadays, deep learning has emerged as a powerful approach to 3D indoor positioning,

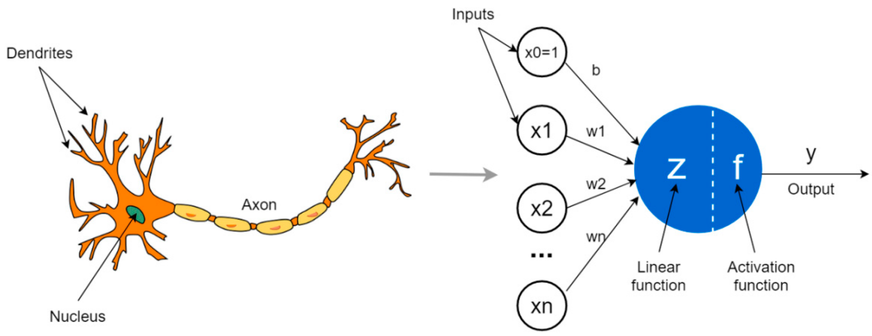


Fig. 1.1 The human neuron and its similarity to the neural network perceptron [1]

leveraging its capacity to automatically learn complex representations from large datasets. Using techniques such as Convolutional Neural Networks (CNNs) [21] for image-based positioning or Recurrent Neural Networks (RNNs)[22] for sequential data analysis, deep learning models can extract relevant features from WiFi signal strength [23], Bluetooth beacons[24], geomagnetic fields [25] and other sensor inputs commonly available in indoor environments. These models not only offer high accuracy, but also adapt well to dynamic indoor conditions, making them particularly suitable for real-time positioning applications as studied in [26] [27] and [28]. However, it is important to address challenges such as data variability, data quality, model robustness, and the need for extensive training data to fully harness the potential of deep learning in indoor positioning systems. This has made the concept of improved cooperative 3D localisation through collaboration between deep learning models as a solution to face these challenges, as we analyse in Chapter 3.

1.2.1 Contribution to the Knowledge

Chapter 3 describes a DELTA algorithm for improved 3D indoor localisation. The contributions of this part of the thesis can be summarized as follows:

- A realistic 3D indoor localization scenario for 5G IoT networks has been designed using an emulated 5G C-RAN and Zolertia IoT nodes.
- We present a novel approach to Received Signal Strength (RSS)-based fingerprint using 3D multilayered radiomap to enhance the learning of network signal behaviour.
- A deep learning cooperative algorithm is implemented on the constructed multilayered radiomap for an improved 3D localization indoor localization. The proposed method targets improving vertical and horizontal localization for use case scenarios such as indoor navigation or people tracking in multi-floor smart or large complex buildings. Based on the results of the emulated realistic radio-planning, we have shown how the DELTA outperformed KNN and Support vector Machine (SVM).

1.3 Information Fusion

Information fusion for indoor positioning is a crucial area of research and development aimed at enhancing the accuracy and reliability of location-based services within indoor environments. This approach involves the integration and combination of data from multiple sensors and sources, such as Wi-Fi signals, Bluetooth beacons, Inertial Measurement Units (IMUs), magnetometers, and visual data, to provide a more robust and precise indoor positioning solution.

The concept of information fusion for indoor positioning is well established in the research community, and various fusion algorithms have been proposed to optimise the integration of sensor data. To further improve positioning accuracy, researchers have focused on various hybrid approaches. For 5G IoT networks, the location of the user's equipment is estimated using a combination of signal propagation characteristics such as Angle of Arrival (AoA), Time of Arrival (ToA), Time Difference of Arrival (TDoA), RSS, RSS Difference (RSSD), Direction of Arrival (DoA), Frequency Difference of Arrival (FDoA)[29]. These hybrid approaches have recently been further surveyed in [30, 31] and [32]. Among all these approaches, the RSS fingerprint-based method is the most widely used for real-time tracking because It is capable of determining the location solely through the utilization of current network infrastructure[33]. Additionally, most of the existing approaches consider the use of RSS from specific radio technology. However, the offline phase of fingerprint collection requires a considerable amount of human resources and is also time consuming, especially for complex buildings. For this reason, in Chapter in 4, we propose a K-Nearest-Neighbour and Deep Neural Network (K-DNN) algorithm to improve 3D indoor positioning. The concept presented is a continuation of our previous work in [34] [35] towards cooperative localization.

1.3.1 Contribution to the knowledge

The main contribution of chapter 4 can be summarised as follows:

- A realistic information fusion scenario for 5G IoT networks has been planned and deployed utilizing a 5G IoT gateway, a Bluetooth Low Energy (BLE) network and a set of wireless IoT access points without requiring any extra information such as (magnetic-inductive sensor, acoustics, visible light or powerline)

- Our implementation uses a novel data-augmentation concept for RSS-based fingerprint technique to produce a 3D fused hybrid. This concept was supported by the Interquartile Range (IQR) method for the detection and elimination of outliers.

- To improve 3D positioning accuracy, a K-DNN cooperative algorithm has been implemented on the constructed hybrid multilayered radiomap.

1.4 Positioning as a Service

In the context of 5G, PaaS refers to the innovative capability of accurately determining the geographical position of massively deployed devices or users within a 5G IoT network's coverage area, leveraging advanced localisation techniques. This service has significant implications for various industries, such as transportation, logistics, emergency services, and augmented reality applications [36]. With the advent of 5G's higher data rates, lower latency, and enhanced connectivity, PaaS can achieve remarkable precision and responsiveness in real-time location tracking, providing crucial data for critical decision-making processes.

One of the key technologies driving PaaS in 5G is the integration of multisensor systems, including GPS, Wi-Fi, and cellular signals, along with the utilisation of advanced signal processing algorithms. This combination allows for more accurate positioning, even in challenging environments where GPS signals may be weak or obstructed. Additionally, the high bandwidth and low latency capabilities of 5G networks enable fast and reliable data exchange between devices and the central positioning infrastructure, facilitating real-

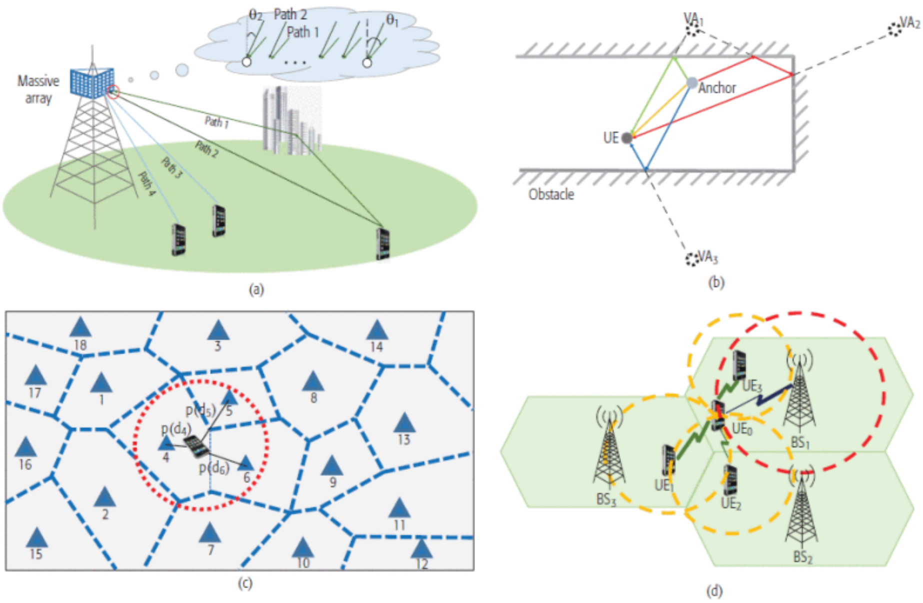


Fig. 1.2 5G large scale positioning

time updates and reducing latency in location-based services (LBS). Figure 1.2 shows how massively connected UEs can be tracked through the concept of 5G large-scale localisation.

PaaS has the potential to revolutionise industries that rely on precise location information. For example, in the transportation sector, PaaS enabled by 5G can improve autonomous vehicle navigation, optimise fleet management, and improve traffic flow through intelligent routing as suggested in [37]. Emergency services can benefit from faster and more accurate location information during rescue operations conducted either by drone [38] or UAV [39], leading to more efficient response times. Furthermore, augmented reality [40] applications can create immersive experiences that are tightly integrated with users' real-world locations.

The combination of 5G and PaaS represents a powerful synergy that unlocks new possibilities for various sectors. As 5G networks continue to expand and mature, the impact of PaaS is expected to grow, creating a foundation for innovative LBS that can redefine how we interact with technology and the physical world. Several recent studies have highlighted this impact, especially in [41] and [42]

1.4.1 Contribution to the Literature

Despite the existence of encouraging works in the literature like [43], [44] and [45], most of the existing literature does not highlight the role of 5G, machine learning, and big data to cater for massively tracked assets in indoor environments. This has been our main motivation for proposing our architecture. In chapter 5 , we contribute with the following:

- A solid scalable and expandable architecture for decentralised positioning in a 5G enabled environment such as warehouses, malls, and factories.
- An implementation use case of vertical and horizontal positioning model for massively deployed positioning in complex buildings

1.5 Research Motivation

The challenges in indoor positioning systems (IPS) have created a crucial need for innovation. The need for a paradigm shift in positioning technology is evident in the current landscape. The proposed approaches are driven by the following motivations:

1. Although commercial off-the-shelf solutions boast high accuracy, their prohibitive costs and independence from existing network infrastructure create hurdles for widespread adoption.

2. Collaboration between machine learning models, especially deep learning, remains largely unexplored, leaving untapped potential to take advantage of the power of these advanced algorithms for precise localisation in 5G IoT rich signal data.

3. The lack of a standardised platform to track critical assets and personnel limits the promotion of a single architecture for positioning as a service. It is imperative that we bridge these gaps, unlocking new avenues for location-based services, indoor navigation, and asset tracking, ultimately empowering organisations with a comprehensive, cost-effective, and reliable platform.

4. Although information fusion has addressed 2D and floor localisation and area segmentation, the challenge of achieving both horizontal and vertical localisation, essential for complex building navigation, remains unmet.

1.6 Research Publications

As an outcome of this research, the following academic journals and conference papers have been published:

- **Journal paper**: El Boudani, B., Kanaris, L., Kokkinis, A., Kyriacou, M., Chrysoulas, C., Stavrou, S. and Dagiuklas, T., 2020. Implementing deep learning techniques in 5G

IoT networks for 3D indoor positioning: DELTA (DeEp Learning-Based Co-operaTive Architecture). Sensors, 20(19), p.5495.

- **Conference paper**: El Boudani, B., Kanaris, L., Kokkinis, A., Chrysoulas, C., Dagiuklas, T. and Stavrou, S., 2021, February. Positioning as service for 5g iot networks. In 2021 Telecoms Conference (ConfTELE) (pp. 1-6). IEEE.

- **Conference paper**:Gosh, S., El Boudani, B., Dagiuklas, T. and Iqbal, M., 2021, March. SO-KDN: A Self-Organised Knowledge Defined Networks Architecture for Reliable Routing. In Proceedings of the 4th International Conference on Information Science and Systems (pp. 160-166).

- **Journal paper**: El Boudani, B., Dagiuklas, T., Kanaris, L., Iqbal, M. and Chrysoulas, C., 2023. Information Fusion for 5G IoT: An Improved 3D Localisation Approach Using K-DNN and Multi-Layered Hybrid Radiomap. Electronics, 12(19), p.4150.

1.7 Structure of thesis

The rest of this thesis is structured as follows: **Chapter 2** introduces localisation techniques for 5G networks and highlights the predominant methods for indoor location applications. A literature review focuses on the main objectives of this work, starting with advances in fingerprint methodologies discussing their advantages and limitations. The chapter also examines the commonly used performance evaluation processes in indoor Positioning Systems (IPS) and provides an overview of hybrid indoor positioning platforms proposed by the research community.

Chapter 3 showcases our contribution to improving 3D positioning using multilayered radiomaps for 5G IoT networks. In **Chapter 4**, we introduce a novel algorithm which involves combining different technologies and fusing data to enhance indoor localisation accuracy. These contributions are supported by experimental performance evaluations, result analysis, and scientific publications. **Chapter 5** introduces a new architecture for the localisation of massively deployed assets and personnel in a 5G IoT network environment. Lastly, **Chapter 6** concludes the work and outlines potential directions for future research.

1.8 Chapter Summary

Chapter 1 provides an introduction to the topic of indoor positioning in 5G networks. It begins by defining indoor positioning and highlighting its increasing importance in various contexts, such as transportation, first responders, and augmented reality. The chapter emphasises the role of 5G IoT in driving the need for real-time positioning and discusses the potential applications and challenges in this domain. It also touches on the concept of information fusion, deep learning, and the idea of PaaS in the context of 5G networks.

The chapter outlines the main research scope of the thesis, which includes improving 3D indoor positioning through cooperative learning, leveraging 5G IoT signal data for better indoor positioning, and creating a standardised positioning platform for mass deployment. It introduces the concepts of DELTA for enhanced 3D indoor localisation, information fusion techniques using K-DNN, and the PaaS architecture for 5G IoT networks.

Furthermore, the chapter discusses the significance of deep learning in indoor positioning, highlighting its advantages over traditional machine learning approaches. It mentions the contributions of the research, such as the development of the DELTA algorithm and the information fusion techniques, as well as their implications for indoor positioning accuracy.

The chapter concludes by emphasising the motivation behind the research, including the need for cost-effective positioning solutions, collaboration between machine learning models, the standardisation of positioning platforms, and achieving horizontal and vertical localisation in complex indoor environments.

The structure of the thesis is briefly outlined with references to subsequent chapters that delve into specific research contributions and experimental evaluations.

Chapter 2

Related Work

As previously highlighted, this thesis focuses on three main aspects: cooperative localisation of 3D multilayered radiomap, information fusion based on hybrid radiomaps and PaaS for 5G. This chapter provides an extensive overview of positioning techniques in 5G networks, specifically focusing on their applications in IoT heterogeneous networks. It also introduces the positioning techniques and their limitations as it sets the stage for the development of a novel indoor positioning system that addresses the challenges and limitations identified in the literature. The rest of this chapter is structured as follows: **Section 2.1** explores various positioning methods, categorizing them into four primary groups: cell-identity-based, angle-based, range-based, and fingerprinting-based techniques. RSS-based fingerprinting in 2D and 3D environments is extensively covered in **Section 2.2**. **Section 2.3** introduces the use machine learning in indoor positioning is with a discussion of probabilistic and deterministic approaches, emphasizing the use of algorithms like KNN and Deep Learning methods. **Section 2.4** examines existing positioning frameworks and their limitations and challenges . **Section 2.5** delves into research made in information fusion. It studies the systems developed and locates the research gap in this area. **Section 2.6** provides a summary of this chapter.

2.1 Positioning Techniques in 5G Networks

This section presents a comprehensive overview of the most relevant positioning techniques used in 5G IoT hetrogenous networks. Positioning technologies within the cellular domain can be categorised into four primary groups: cell-identity-based, angle-based, range-based, and fingerprinting-based [13].

2.1.1 Cellular-Identity-Based Positioning

The Cell Identity (CID) or proximity-based method represents the most straightforward of the four techniques, primarily depending on determining if the target object exists within a specific radio coverage zone. This approach requires knowledge of the serving base station's location and the coverage region of the serving cell to estimate the location of the User Equipment (UE). However, it requires a significant number of base stations to achieve an accuracy comparable to alternative methods, making it unsuitable for extensive regions or areas with sparse populations as highlighted in [46]. This technique is very useful for outdoor localisation. Figure 2.1 demonstrates how CID determines the position of a user device.

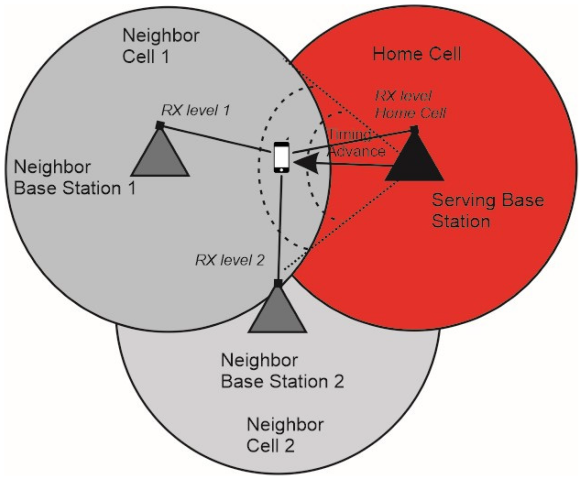


Fig. 2.1 Cell-ID based localisation [2]

2.1.2 Angle-Based Positioning

Angle-based positioning determines the position or orientation of an object or device relative to a reference point or axis using angles. This approach measures angles between known reference points or devices, which can then be used to calculate the object's position or orientation. Angle-based techniques can employ either the Angle-of-Arrival (AoA), Angle-of-Departure (AoD), or both. The AoA corresponds to the direction from which a radio signal is received, as illustrated in Figure 2.2, while the AoD signifies the direction in which the signal is transmitted. Angle-based positioning solutions are used in various fields, including navigation, robotics, and wireless communication.

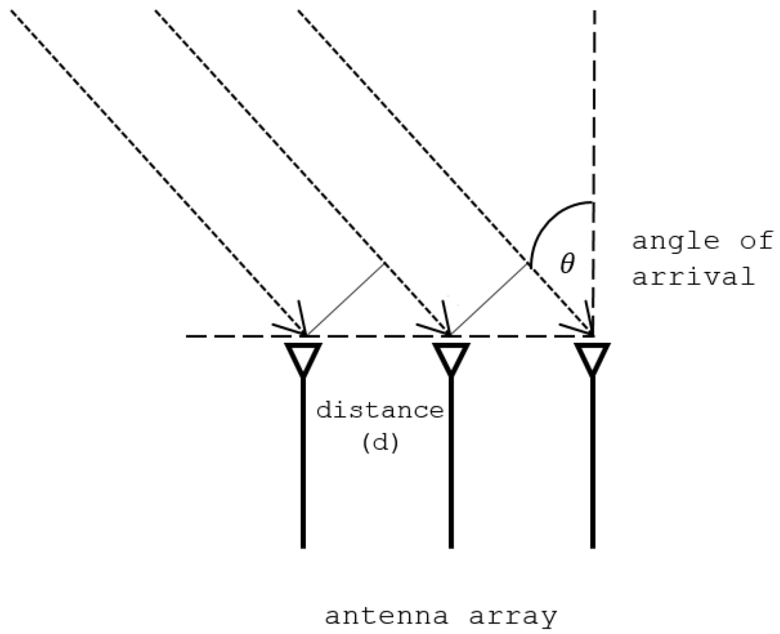


Fig. 2.2 Angle of Arrival (AoA) based localisation

In 5G networks, especially those equipped with massive Multiple-Input, Multiple-Output (MIMO) technology, base stations (BS) are fitted with multiple antennas, often in the tens or even hundreds. This vast antenna array creates a substantial aperture and supports beam operations [47]. In angle-based positioning systems, precise measurements of angles are essential, and errors in angle measurements can lead to inaccuracies in position or orientation calculations. Therefore, these systems often incorporate advanced sensors and algorithms to minimise errors and improve accuracy. In terms of positioning for 5G IoT networks, a major limitation of this technique stems from the fact that the accuracy of the AoA obtained depends on the number of antennas involved and the size of the array. In other words, better position estimation can only be achieved if an increased number of antennas and large arrays are deployed as studied in [48–50].

2.1.3 Range-Based Positioning

Range-based positioning technique determines the position of the User Equipment (UE) by calculating distance measurements between transmitters and a receiver (or vice versa). These measurements are derived from the data within the received signal, such as RSS, Time of Arrival (ToA), or Time Difference of Arrival (TDoA) [51].

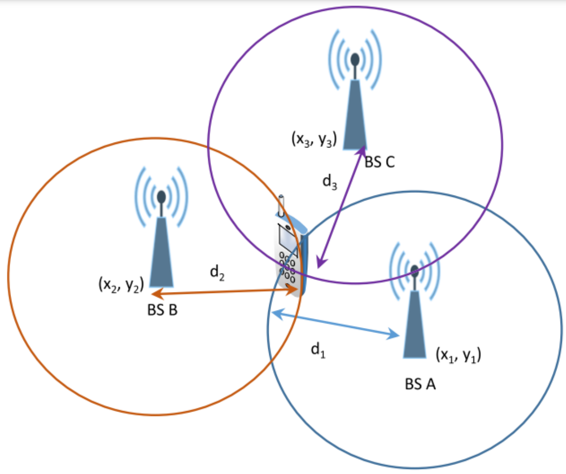


Fig. 2.3 Localisation by range [3]

2.1.4 Fingerprint-Based Positioning

Fingerprint-based positioning is based on unique radio frequency signal characteristics and patterns present in indoor space to create a robust fingerprint database. This database contains signal strength measurements, signal propagation models, and other relevant features collected from multiple reference points in the environment. When a target device, such as a smartphone or wearable, measures the signals it receives, the fingerprinting algorithm compares these measurements to the stored reference database, allowing it to determine the location of the device with relatively high precision [52]. The effectiveness of fingerprint-based methods lies in their ability to capture the intricate details of the indoor signal environment. This includes factors such as signal attenuation, multipath effects, and interference, which are characteristic of indoor spaces due to the presence of walls, obstacles, and varying materials. Using this rich information, fingerprinting-based techniques can overcome the limitations of angle-based and range-based techniques, especially in areas where line-of-sight communication is obstructed [53] . This has been a big factor for us in choosing the fingerprint-based technique. However, to be fair to each method, we have listed in Table 2.1 the limitations of all four.

Table 2.1 Limitations of Indoor Positioning techniques

Positioning Technique	**Limitations**
Cell-Identity-Based[54]	1) Limited precision in densely populated areas 2) Susceptible to signal attenuation and interference 3) Cannot differentiate between nearby cells if they have similar signal strengths 4) Prone to non-uniform cell size and coverage gaps
Angle-Based [55]	1) Requires complex hardware for accurate angle measurements. 2) Sensitive to multipath effects, especially in indoor environments 3) Challenging to implement in environments with obstacles or blockages. 4) Often requires line-of-sight (LOS) for optimal accuracy
Range-Based [51]	1) Susceptible to signal attenuation and interference, affecting accuracy 2) Performance affected by obstructions and reflections in indoor environments 3) Accuracy decreases with increasing distance from signal source 4) Requires careful calibration and updates to maintain accuracy.
Fingerprinting-Based [56]	1) Requires extensive and labour intensive site surveys for fingerprint creation. 2) Vulnerable to environmental changes, requiring frequent updates 3) Limited scalability due to the need for extensive fingerprint databases 4) Performance affected by dynamic changes in the indoor environment

2.2 RSS-based Fingerprinting

2.2.1 Received Signal Strength

RSS is a way to measure the signal power strength received by a user's equipment. This is expressed in decibels milliwatts (dBm) or milliwatts (Mw). The RSS-based method is one of the widely adopted methods by the indoor localisation research community. RSS can be used to approximate the distance between a user device and a transmitting device, as shown in Figure 2.4.

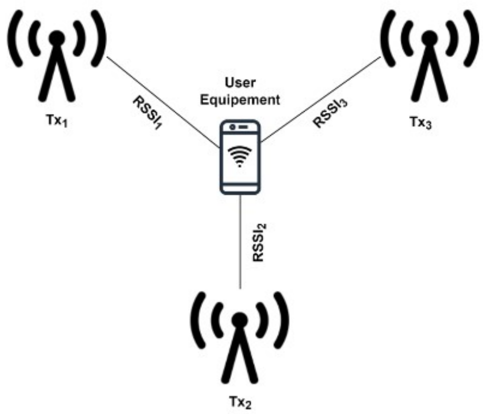


Fig. 2.4 RSS based positioning

Using Received Signal Strength Indicator (RSSI), a relative measurement of RSS, and a Free-Space Path-Loss (FSPL) propagation model [57], the distance δ between a UE and Tx can be estimated using the formula below:

$$FSPL(dB) = 20log_{10}(d) + 20log_{10}(f) + \Phi \tag{2.1}$$

Where d is the distance expressed in metres; f is the frequency measured in kilohertz, megahertz, or gigahertz. ϕ is a constant depending on the frequency unit. During location determination, this formula assumes that the antennas are lossless and their polarisation is the same. However, this is not often the case in complex and unpredictable environments with continuous noise.

2.2.2 RSS-based Fingerprinting for 2D and 3D Indoor Positioning

In RSS-based fingerprint-based method, unlike the FSPL model, the location is estimated by matching the received signal from user equipment with a database of a preconstructed location's radiomap. The most significant advantage of this method is its ability to maintain high accuracy in a cluttered multipath environment based on studies conducted in [58] and [59]. As shown in Figure 2.5, this technique has two phases: offline and online. In the offline phase, a site survey or measurement campaign is conducted by which a set of RSS signals is collected and linked to its corresponding location XY in 2D and XYZ in 3D case. The constructed radiomap is then used to train a localisation algorithm with a distance error loss function such as least squares [60], weighted least means [61], maximum likelihood estimation [62] or convex optimisation [63]. To construct a radiomap, the most commonly used method for collecting signal fingerprints is called war-diving [64]. After identifying the indoor area of interest, the user equipment stays in each position for a specific time interval to obtain enough fingerprint information. As the monitoring device moves along the grid, the collected RSS single is stored in the database along with a reference point. Regarding the positioning of the 5G IoT indoors, the use of this technique has been

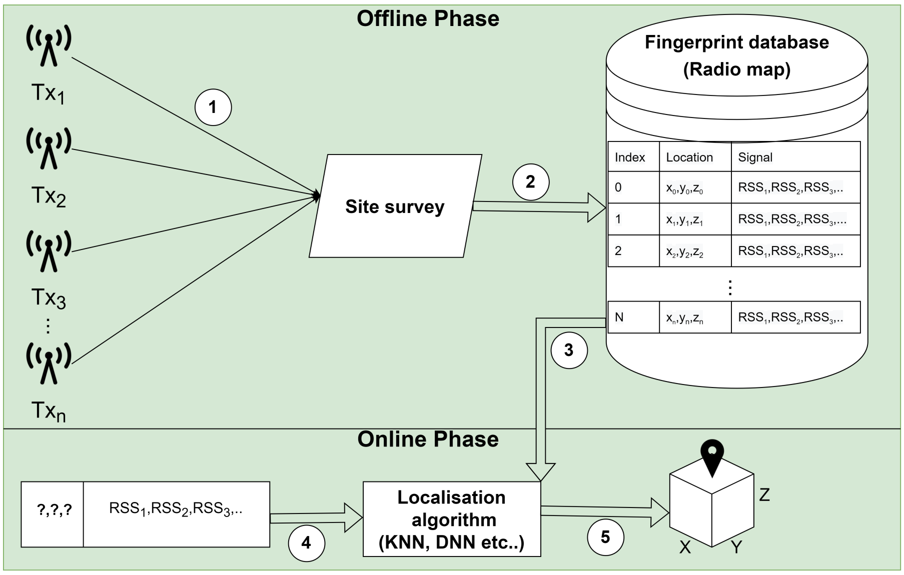


Fig. 2.5 Fingerprints-based positioning phases

investigated by Huan et al. in [65]. The authors used the Kalman filter to remove the noisy RSS values. Next, a Universal Kriging (UK) algorithm was used for spatial interpolation for data augmentation to reduce dependency on the fingerprinting database. Finally, the authors have trained a KNN model to calculate the user equipment's location achieving a 1.44 m positioning error. Although this approach is interesting, it has not been established whether the system could perform equally in a 3D environment. Additionally, the use of a single base station might seem power saving, but it does not guarantee the same accuracy given the changes in the environment and the LOS issues in cluttered space. Similarly, Gong et al. [66] have suggested a two-step KNN (2-KNN) that uses reference signals from the state information of the channel (CSI). During the offline phase, a Smooth Rank Sequence (SRS) estimates the number of received signal paths. During the online phase, a trained 2-KNN is used to determine the 2-D location of the user equipment. Most studies have overlooked 3D localisation, which is essential for scenarios like robots navigation, immersive shopping, and virtual reality. This is the main motivation for us to investigate this area. Further studies for 5G and beyond (6G) can be found in the following survey papers [67, 68].

2.3 Machine Learning

In fingerprint-based localisation method, the application of machine learning involves training a model on a radiomap dataset that has been collected during the offline phase. Given a radiomap database, the localisation model aims to infer the state or location of the user device from the received measurement vector σ, which includes RSS values σ_i from several access points. According to the literature, widely used algorithms can be classified into deterministic and probabilistic algorithms. The principle behind these methodologies is based on searching a database of fingerprints and finding one or more locations whose RSS values have the highest similarity to the one currently observed.

2.3.1 Probabilistic Approach

In the probabilistic approach, the position is determined based on the likelihood that the user is in the location 'x' given vector or RSS values received during the online phase. Assuming that a set of location candidate L is L = $\{L_1,L_2,L_3,...,L_m\}$ for any obtained RSS vector values 's' Select L_i if:

$$P(L_i|\sigma) > P(L_j|\sigma) \;\; \text{for} \;\; j,k = 1,2,3,....n, \;\; i \neq j \tag{2.2}$$

Where $P(L_i|\sigma)$ is the probability that a user device is at location L_i, given the RSS vector σ if its likelihood is higher than that of $P(L_j|\sigma)$.

Finally, using equation 2.2, 3D location $(\hat{x}, \hat{y}, \hat{z})$ can be estimated using the weighted average probability as follows:

$$(\hat{x}, \hat{y}, \hat{z}) = \Sigma_{i=1}^{n}(P(L_i|s)(x_{L_i}, y_{L_i}, z_{L_i})) \tag{2.3}$$

2.3.2 Deterministic Approach

In the deterministic positioning approach, location λ is considered a non-random vector[69]. The main objective is to estimate $\hat{\lambda}$ at every step. Usually, the location estimate is treated as a linear combination of calibrated points p_i. The principle behind this approach can be summarised in the following equation:

$$\hat{\lambda} = \Sigma_{i=1}^{k} \frac{w_i}{\Sigma_{j=1}^{M} w_j} \lambda_i \tag{2.4}$$

Here, the set $\{\lambda_1 \dots \lambda_k\}$ denotes the sequence of reference points associated with Δ_i, which is the distance between the respective radiomap fingerprint $\bar{r}_i$ and the measurement x taken during live positioning, i.e., $\Delta_i = ||x_i - \bar{r}||$. The norm $||.||$ in this equation can be any arbitrary formula. This can be the Mahalanobis norm [70], the Manhattan norm (1 norm)

[71], or the Euclidean norm (2 norm) [69]. As this thesis focusses on the latter, w_i can be written as follows:

$$\Delta_i = \sqrt{\sum_{j=1}^{N} x_{ij} - s_j)^2} \tag{2.5}$$

In equation 2.4, w_i is a set of non-random weight coefficients assigned to each reference point based on its importance in distinguishing it from other fingerprints. Consequently, the value of w_i assigned to each fingerprint impacts the location estimation. In this case, the weight allocation expressed in equation 2.4 refers to the Weighted K-Nearest-Neighbour (WKNN) algorithm [71]. A possible value for w_i can be the inverse of the RSS information [71], which can be expressed as follows:

$$w_i = \frac{1}{||x - \bar{r}||} [72][72] \tag{2.6}$$

If equation 2.4 is simplified, it can be assumed that all fingerprints are assigned equal weights. As a result of this assumption, w_i is eliminated and the formula becomes the KNN method. Thus, setting K = 1, the equation yields the simple Nearest-Neighbour (NN) method[69] [73]. In terms of performance, it has been demonstrated in [69] and [71] that the KNN and WKNN methods offer a higher degree of accuracy than the NN method in the cases of K = 3 and K = 4, respectively. However, the NN method appears to perform satisfactorily and offers the same results in the presence of high-density RSS radiomaps [74]. In terms of performance, It has been demonstrated in [69] and [71] that the KNN and WKNN methods offer a higher degree of accuracy than the NN method in the cases of K = 3 and K = 4, respectively. On the other hand, the NN method appears to perform satisfactorily and offers the same results in the presence of high-density RSS radiomaps [74].

Several researchers have addressed the question of indoor localisation in 5G networks using KNN in [66, 65, 75–79]. Despite this, the KNN method alone fails to deal with a highly dense 3D radiomap, as studied in [80], [81], and [82]. This has motivated us to propose a combination of deep learning and KNN methods to improve localisation in complex 3D environments. Since the main focus of this thesis is on the deterministic positioning approach based on deep learning and KNN approaches, more complex methods such as the database correlation method (DCM) and linear discriminant analysis (LDA) can be found in [83] and [84] respectively. The following subsection deals with existing research contributions related to deep learning.

2.3.3 Indoor Positioning Using Deep Learning

In the fingerprint-based approach, deep learning techniques have been widely used to extract common patterns from a sparse radiomap database and to improve localisation[85, 86]. In recent years, it has gained great popularity among researchers in indoor localisation, in particular due to its robustness and high accuracy [87]. Supervised and unsupervised deep learning algorithms have recently been implemented in 2D localisation [88] and multi-floor localisation [89]. Wafaa et al. [90] have studied the use of CNN to reduce the localisation error and improve accuracy. Their approach converts a 2D fingerprint radiomap and its kurtosis values to a 3D RSS radio image. This 3D tensor is then used as an input for their proposed model. This localisation framework was tested in a 20 m x 20 area. The reported results suggest that this concept can achieve a precision of up to 94.13% in a grid size of 2 m x 2 m and 10 anchors. Although it sounds promising, this concept has not been tested in a 3D environment. Additionally, a similar system was also implemented in [91] and usually requires a large number of access points deployed in a small space to achieve this result. Similarly, Yang et al. [92] have proposed an indoor 3D localisation scheme based on 1D CNN and BLE signal fingerprinting. This approach was tested in a 3D space of 4.0 m x 2.0 m x 3.0 m. The authors have deployed eight BLE beacons and divided the 3D space into 16 grids of 1 m x 1 m x 1 m in size. Following these steps, the system was able to achieve a 0.25 m error and a precision of almost 100%. A serious limitation of this work is that the framework was tested in a small, uncluttered environment. Furthermore, to achieve the same result, according to the adopted setup, a BLE must be deployed for each 1 m^2. This is usually not cost-effective, especially for large complex buildings. To overcome these two limitations, we suggest the use of hybrid radiomap and a combination of KNN and DNN to realise a cost-effective scalable solution. In [93], authors have implemented Deep Belief Network (DBN) on active RFID tag system for accurate location estimation. Their solutions consisted of set of stacked Restricted Boltzmann Machine (RBM) layers called autoenconders trained using Contrastive Divergence with one-step iteration (CD-1). This algorithm has improved the 2D positioning. To achieve this, the authors have deployed a large number of radio-frequency identification (RFID) tags in 12m x 12m indoor environment which does not take into account the power consumption of the devices. Finally, Wang et al. [94] have suggested a hybrid deep learning solution combining a regression DNN with a Convolutional AutoEncode (CAE) using Visible Light Communication (VLC). To overcome the issue of fluctuated signal reading in RSS-based fingerprint method, the authors have proposed an algorithm taking into account a set of consecutive signal readings and converts them into an RSS Temporal Image (RTI), instead of implementing traditional RSS measurements processing technique. However, despite having been used in several works [95, 96], VLC suffers from issues such as interference with other ambient lights, signal shadowing, and generally requires the receiver to be in LoS, which can affect the accuracy of location estimation. A detailed comparison of deep learning and other machine learning algorithms used in the localisation for theIoT environments is covered in [97, 98].

2.3.4 Challenges and Limitations

There are major challenges facing 3D indoor localisation field. Despite their high precision, commercial off-the-shelf solutions are costly and do not rely on existing network infrastructure. Until now, most of the existing IoT-based indoor localisation solutions have focused mainly on 2D localisation or floor detection. However, in some special use cases, scenarios such as indoor navigation for Unmanned Aerial Vehicle (UAV) or Automated Guided Vehicle (AGV) in smart factory or large supermarket, precise 3D positioning is indispensable for daily operations. Furthermore, there is limited research work on collaboration between machine learning models and specifically deep learning. To address these challenges and limitations in Chapter 3, we propose the DELTA to maximise the localisation accuracy and minimise distance error in a 3D indoor environment.

2.4 Positioning as a Service for 5G Networks

Indoor positioning in 5G IoT networks is still a very new research area. It involves making use of new emerging radio technologies to improve the location accuracy. In [99], authors have proposed an indoor positioning architecture for 5G. Their concept depends on MEC (Multi-Access Edge Computing) to determine the current location. The idea is a very promising start but does not support concepts such as big data and edge device scalability. However, offering positioning services on the MECs might expose sensitive users' data. The bottleneck here is related to the location-based service scaling to support thousands of user equipment.

In the context of indoor positioning for multiple tracked assets and people, Michal et al.[100] have proposed an architecture for real-time location tracking using information fusion from both Wi-Fi and dead reckoning sources. However, since the current position of the tracked item is calculated using the previous location, the distance error becomes cumulative and increases over time. Moreover, this system does not offer 3D positioning, which is critical nowadays for indoor settings. Additionally, it suffers from attenuation, and additional hardware is always required to support the accuracy. Therefore, it is not effective for tracking multiple agents in complex environments. The concept of data fusion can be found on [101]. Similarly, to recognise the location of an item inside a warehouse, authors in [102] a passive radio-frequency localisation system which utilises passive RFID . The systems attach reference tags to each item and recognise the position through scanning. Since it relies purely on installation and configuration RFID localisation system. This solution is costly to setup and maintain especially for mega-warehouses and massively stored assets. Another interesting system for positioning called SnapLoc has been presented in [103]. The authors have implemented a UWB (Ultra Wide-Band) system, which they claim to be scalable to unlimited tags. However, UWB is known for slower adoption, high implementation cost, and signal penetration, especially inside complex buildings [104]. A survey of similar applications and systems can be found in [105].

2.4.1 Challenges and Limitations

Despite the existence of encouraging works in the literature like [43], [44] and [45], there is undoubtedly a lack of a standardised platform to track critical assets and personnel. Additionally, most of the existing literature does not highlight the role of 5G, machine learning, and big data to cater for massive indoor positioning. This is one of the motivations for proposing this architecture. The second motive is the lack of 3D positioning for complex environments. These challenges and limitations have motivated us to propose solid scalable and expandable architectures for centralised positioning in 5G-enabled environments such as warehouses, malls, and factories.

2.5 Information Fusion for 5G Networks

2.5.1 Information Fusion for 5G IoT

Information fusion for the 5G IoT has attracted considerable attention from the research community. This technique, as shown in Figure 2.6 , involves blending data from various sources or sensors using a data fusion system to gain better inference and improve accuracy/-precision. This concept produces an effective and reliable IPS (Indoor Positioning System) while saving the cost of expensive infrastructure[106]. Over the last decade, researchers have attempted to merge data readings from sources such as RFID [107], GPS [108], Pedometer [109], BLE [35], VLC and many other technologies as stated in [110] and [34]. Very recently, Klus et al [111] have examined combining Global Navigation Satellite Systems (GNSS) with WLAN data in a 5G network to improve positioning. The authors' have implemented a Neural Network as their main algorithm. Based on the authors' conclusion, the proposed approach has achieved an accuracy of 1 m in an open space and 3.4 m in a cluttered area. A serious limitation of this study is the inability of GNSS to penetrate walls of different materials, especially in complex environments. In a more recent work, Alvarez-Merino et al. [112] have investigated using WiFi fine-time measurement (FTM), UWB and Cellular-Based radio fusion to improve the indoor location accuracy. The authors' approach has shown promising results. However, unlike [111], this system does not rely on existing infrastructure but requires the UWB setup that can be costly and limited to user equipment with this capability. These limitations have motivated us to propose a cost-effective setup based on

BLE and WiFi. A detailed discussion of these techniques can be found in these resources [113–115].

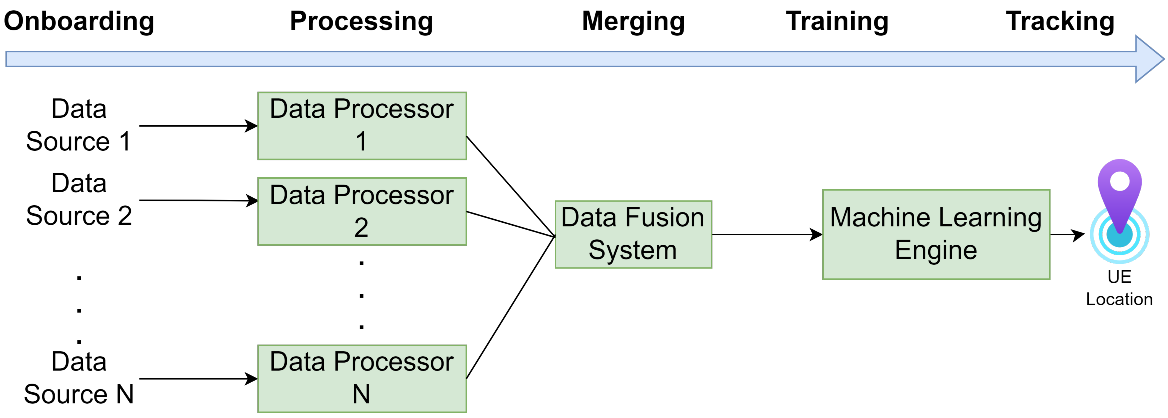


Fig. 2.6 Information fusion localisation process

BLE Technology

BLE has emerged as a low-cost wireless solution for localising people and assets, offering both traditional Bluetooth protocol capabilities over ultra-low power consumption circuits [116]. BLE enabled devices communicate over 2.4GHz and use 40 channels (PHY channels) divided by 2MHz of frequency gap. Channels 37, 38, and 39 are used for advertising, while the rest are used for data transfer during a connection. This technology uses a Neighbor Discovery Process (NDP) in which a BLE-enabled device, often referred to as a "scanner", searches for nearby BLE devices called "advertisers" [117]. Once the discovery process has finished, a list of available devices is returned based on availability and RSS value. According to the core specification, BLE 5.0 has improved drastically compared to version 4.2, offering two types of discovery processes: basic and advanced [118]. Recently, BLE has become a central source of information fusion amongst the research community. several research papers have explored the use of this technology to improve indoor localisation accuracy. Kanakareja et al [119] have investigated using the BLE protocol along with LoRa to reduce the distance error of an indoor tracker called "The Things Network" (TTN). The idea is very promising; however, it only works for environments where Low-Powered Wide Area Network(LP-WAN) is deployed like WSNs. To track elderly movements indoors, Kolakowski et al [120] have used BLE and Ultra-Wide Band technologies. While this is a very effective low-powered solution, realising it requires the deployment of UWB infrastructure. Additionally, UWB suffers from clock synchronisation issues due to the time-sensitive nature of its pulses, which is not practically real-time localisation systems [121]. Finally, to get localisation information labelled areas like parking lots and meeting rooms etc., Hu et al [122] proposed a system called Grid-Loc that combines both active RFID and BLE. Similarly, this solution needs a pre-setup to start tracking and does not make use of wildly existing infrastructure technologies such as WLAN.

2.5.2 Challenges and Limitations

The previous subsection highlights the research work conducted in the area of fusion of information for 5G IoT indoor positioning systems (IPS) using technologies such as GNSS, BLE, RFID, UWB and VLC. While this approach offers various advantages, including cost-effectiveness and improved accuracy, there are several limitations and challenges associated with it. Some of these techniques mentioned, such as combining active RFID and BLE, require pre-setup and do not leverage existing infrastructure technologies like WLAN. This can be costly and limit the applicability to user equipment with specific capabilities.

Additionally, it is important to consider environmental factors such as the materials of walls and obstacles within indoor spaces. These factors can affect the effectiveness of various fusion techniques.

In general, the limitations outlined in this section highlight the need for a cost-effective set-up based on BLE and WiFi for indoor positioning systems, addressing some of the challenges associated with other fusion techniques. These limitations also underscore the importance of considering specific technologies and infrastructure limitations when designing indoor localisation solutions. In our work, to address these limitations, we have implemented a novel fusion concept as discussed in Chapter 4.

2.6 Chapter Summary

Chapter 2 focuses on related work in the field of indoor positioning, particularly in the context of 5G networks. The chapter covers various positioning techniques and the challenges pertaining to them. It starts by providing an overview of different positioning techniques used in 5G IoT heterogeneous networks, categorizing them into four main methods:

- **Cell-identity-based positioning** relies on determining if a target object is within a specific radio coverage zone. It requires knowledge of the serving base station's location but may need a significant number of base stations for high accuracy.

- **Angle-based positioning** measures angles between known reference points or devices to calculate an object's position or orientation. These methods are used in various fields and can be complex due to the need for precise angle measurements.

- **Range-based positioning** calculates distances between transmitters and receivers based on signal measurements like RSS, Time of Arrival (ToA), or Time Difference of Arrival (TDoA).

- **Fingerprint-Based positioning** relies on unique radio signal characteristics in indoor spaces to create a robust database for localization. It can overcome the limitations of other techniques, especially in obstructed environments.

Furthermore, the chapter delves into RSS-Based Fingerprinting as a method for estimating the distance between a user device and a transmitter. It discusses the challenges and limitations of RSS-based methods. Additionally, in the machine learning subsection, we explore how machine learning techniques, such as KNN and Deep Learning, can be applied to fingerprint-based positioning for improved accuracy. Next, the PaaS for 5G Networks subsection discusses the emerging concept of offering positioning services within 5G networks and the challenges associated with it. It also mentions existing solutions and their limitations. Lastly, information fusion for 5g networks subsection explores how combining radio signal data from heterogeneous technologies can improve the accuracy in both 2D and 3D settings.

Throughout the chapter, various challenges and limitations of existing positioning techniques and information fusion methods are highlighted. These include cost, infrastructure requirements, and environmental factors. In summary, Chapter 2 provides an overview of the various positioning techniques and machine-learning approaches used in 5G IoT environments for indoor positioning, highlighting their limitations and challenges. It sets the stage for proposing the DELTA and K-DNN architecture in the subsequent chapters.

Chapter 3

Deep Learning for 3D Indoor Positioning

As highlighted in Chapter 2, indoor positioning is a key enabler of the 5G IoT context-aware localisation application. It will significantly improve various location-based scenarios, including tracking assets in smart factories, precise management of hydroponic indoor vertical farms, and wayfinding within smart hospitals. In this context, this chapter introduces an experimental 5G testbed that combines C-RAN and IoT networks. This testbed is designed to enhance both vertical and horizontal localisation (3D localisation) in a 5G IoT environment. To accomplish this, we propose the use of the DELTA machine learning model, implemented on a 3D multilayered fingerprint radiomap. The DELTA model starts by estimating the 2D location and then recursively predicts the 3D location of a mobile station. This approach is particularly beneficial for scenarios like 3D indoor navigation in multi-floor smart factories or complex large buildings. Notably, our observations demonstrate that the proposed model outperforms traditional algorithms such as the support vector machine (SVM) and KNN.

The remaining of this chapter is organised as follows: **Section 3.1** describes the problem related to indoor positioning in 3D environment. **Section 3.2** gives a detailed description of the underlying architecture of the DELTA model. **Section 3.3** consists of a discussion and analysis of the performance results produced by our proposed approach compared with other traditional models. Lastly, **Section 3.4** provides an overall summary of this chapter.

3.1 System Model & 3D Localization Problem

In this section, we introduce our proposed system model using DNN and multilayered radiomap to perform 3D indoor localisation. To the best of our knowledge, this is a novel approach to implementing deep learning on multilayered radiomaps for localisation purposes. The main benefit of the proposed method is improved localisation accuracy and computational complexity minimisation during online fingerprinting through the adoption of deep learning techniques, while at the same time utilising the widely spreading WSN and/or IoT infrastructure, making it an economical solution. To realise these steps, we consider N to be the number of transmitters in the environment, and x, y, and z, the corresponding coordinates of each fingerprint entry on the constructed radiomap. The 3D multilayered fingerprint database has been constructed by linking the RSS values received from the transmitters to a 3D location on the radiomap [123]. This can be mathematically expressed as:

$$M = \{(L_1,S_1),(L_2,S_2),\ldots,(L_{n-1},S_{n-1}),(L_n,S_n)\} \tag{3.1}$$

Where M is the ratio-map database, $S \in \mathbb{R}^{NxM}$ is a vector of RSS signal values and L is a vector of three values: $L \equiv \{x,y,z\}$ and L_n represents the total number of sample location of x_n, y_n and z_n associated with each signal vector sample S_n collected during the offline-phase.

In this respect, the estimation problem is defined by solving the 3D localisation problem using a matrix of historical location points and their corresponding signal values. However, the challenge is to model the non-arbitrary relationships between N transmitters members of S signal matrix to accurately predict the 3D location L using a deep learning algorithm. To achieve this, the 3D localisation has been segmented into two sets of problems:

Problem 1: Given a matrix of S signal sent from N transmitters, predict the x and y coordinates of a 2D mobile station location. This can be written as follows:

$$\lambda_1 = f(\bar{S}_{ij}) \tag{3.2}$$

Where λ_1 represents x_i and y_i location which we would like to estimate, and $f(S_{ij})$ represents the function that utilizes RSS values received by the transmitters to predict the location of mobile station.

Problem 2: Given a matrix of S signal sent from N transmitters to the mobile station and x_i, y_i, known from problem 1, estimate the coordinate z_i. This can be mathematically expressed as :

$$\lambda_2 = f(\bar{S}_{ij}, \lambda_1) \tag{3.3}$$

Where λ_2 is the z_i location, λ_1 is the output of problem 1 solution, and S_{ij} represents a matrix of signal values S as previously stated in problem 1.

3.2 DELTA 3D Localisation For 5G WSN Network

In this section, the DELTA system has been developed for 3D multilayered indoor environment localisation. Figure 3.1 depicts the steps undertaken to realise a cooperative system for accurate 3D prediction.

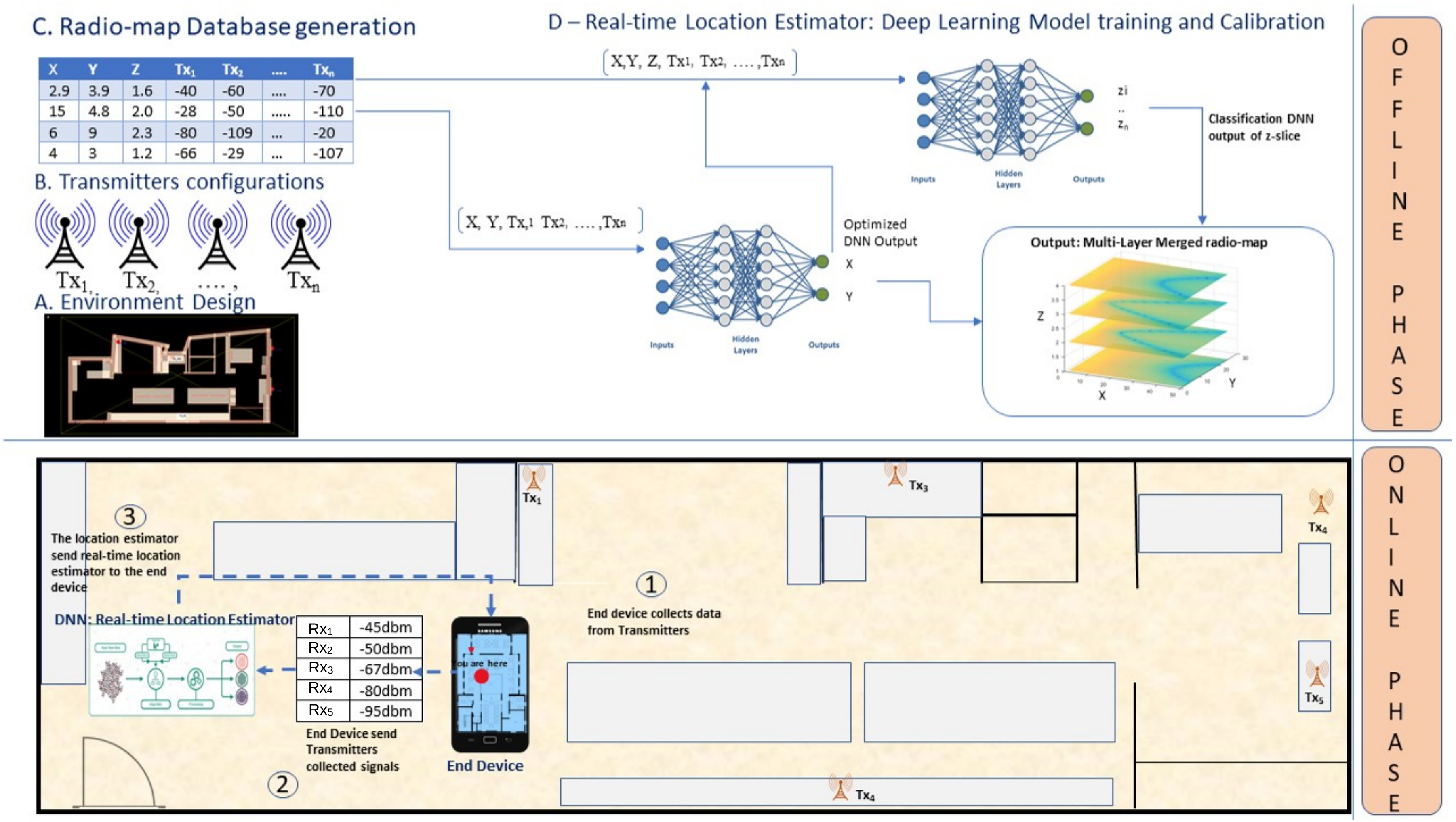


Fig. 3.1 Detailed architecture of DELTA

3.2.1 Test Environment Description

In this subsection, we describe the test environment. The area of interest is a typical laboratory, with open spaces as well as private rooms defined by the following dimensions: 8m width x 16m depth x 2.75m height.The lab environment is dynamic during this experiment. .

Step I: The Physical Network Setup

For the physical setup, an indoor test environment has been deployed where a 5G network is emulated by typical IoT network with Zolertia RE-Mote Revision B nodes connected to a LoWPAN Border Router as illustrated in Figure 3.2. We have randomly placed 5 Zolertia nodes, with their antennas at vertical polarization as shown on the Figure 3.2. The nodes and the ray tracing propagation mechanisms have been configured as per Tables 3.1 and 3.2

Step II: Connecting the IoT to 5G C-RAN

To simulate the 5G WSN environment, each Zolertia node has been connected to an experimental 5G C-RAN. The setup has been built using the GNS3 network simulator[124] and the OpenDaylight Software Defined Controller[125]. These two can control the network setup behaviour at the network layer level. Figure 5 shows a set-up built using GNS3, a network simulator and a software-defined controller OpenDaylight dashboard for the network topology. These two elements can control the network setup behaviour at the network layer level.

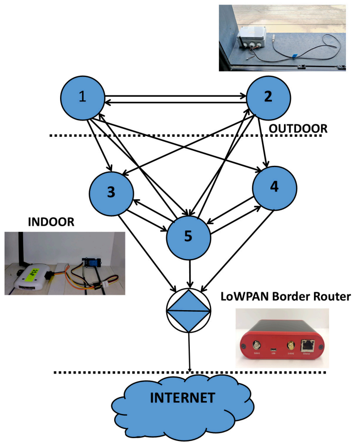


Fig. 3.2 Network setup topology

Table 3.1 WSN and radio propagation parameters

Parameter	Value
Operating Frequency	2.4GHz
Rx sensitivity (dBm)	-97
Tx power (dBm)	7
antenna Type	omni
Max refractions	12
Max reflections	12
Max diffractions	1

(a) 5G emulated C-RAN testbed on GNS3

(b) WSN and GNS3 emulated 5G C-RAN connected on OpenDaylight

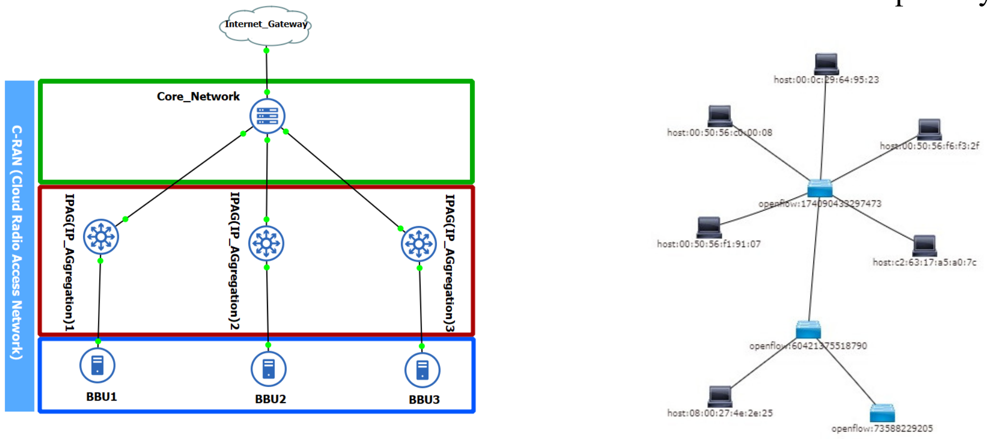


Fig. 3.3 5G C-RAN setup on GNS3 and WSN network connected to OpenDaylight SDN controller

Table 3.2 Material constitutive parameters of the test environment

Material	El. Relative. (F/m)	Loss
Concrete	3.9	0.23
Wood	2	0.025
Brick	5.5	0.03
Metal	1	1,000,000
Plasterboard	3	0.067
Glass	4.5	0.007

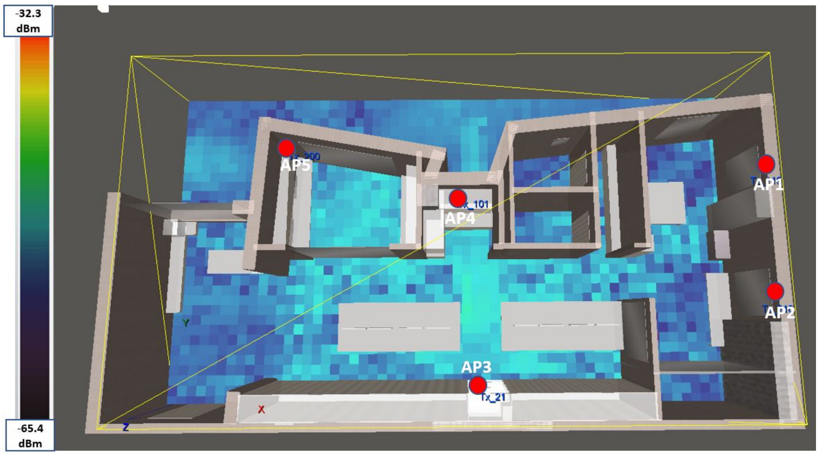


Fig. 3.4 TruNET wireless simulator radiomap for access point 3

Step III: Simulating the Test Environment

Using a 3D deterministic simulator called TruNET Wireless [126], we have constructed a multilayered fingerprint radiomap dataset, in order to conduct the offline training phase as illustrated in Figure 3.1. During this procedure, in addition to the network setup configuration, the constitutive parameters of all environment object materials have been also configured as per Table 3.2, in order to retrieve realistic results [127]. The benefits of utilizing a deterministic simulation are to construct radiomaps instead of launching measurement campaigns as analysed in [128]. The summary correlation results of this study is covered in Section 3.3. The simulation environment for this study is shown on Figure 3.4.

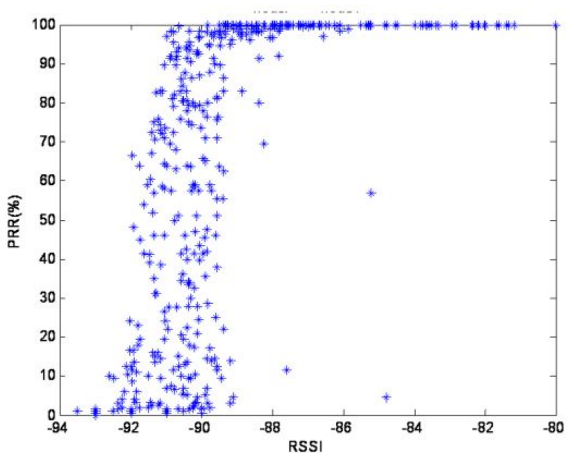


Fig. 3.5 PRR vs RSSI signal CC2420 chip Baccour et al[4]

Physical Network Behaviour

The signal propagation can be affected by various factors leading to the degradation of the signal quality especially in low power radio networks such as WSNs. For a successful simulation, it is always crucial to observe the physical network behaviour during the offline measurement campaign. The effects of physical layer and the various factors contributing to changes in the environment have been extensively in [4]. Using Link Quality Estimation(LQE) metrics such as Packet Reception Ratio (PRR) and Signal-to-Noise-Ratio (SNR), Baccour et al [4] have studied the factors affecting similar transmitter chip used in this experiment. It is very crucial to note, that the simulated environment can be affected by various changes happening at the physical network. For the nodes used in this simulation, Figure 3.5 shows how the change in RSSI can affect the PRR.

Sometimes, measurement campaigns can be affected by various environmental noises which may lead to unrealistic readings, either due to signal spikes or fluctuations. This noise can be either thermal noise or interference from other people's equipment operating at the

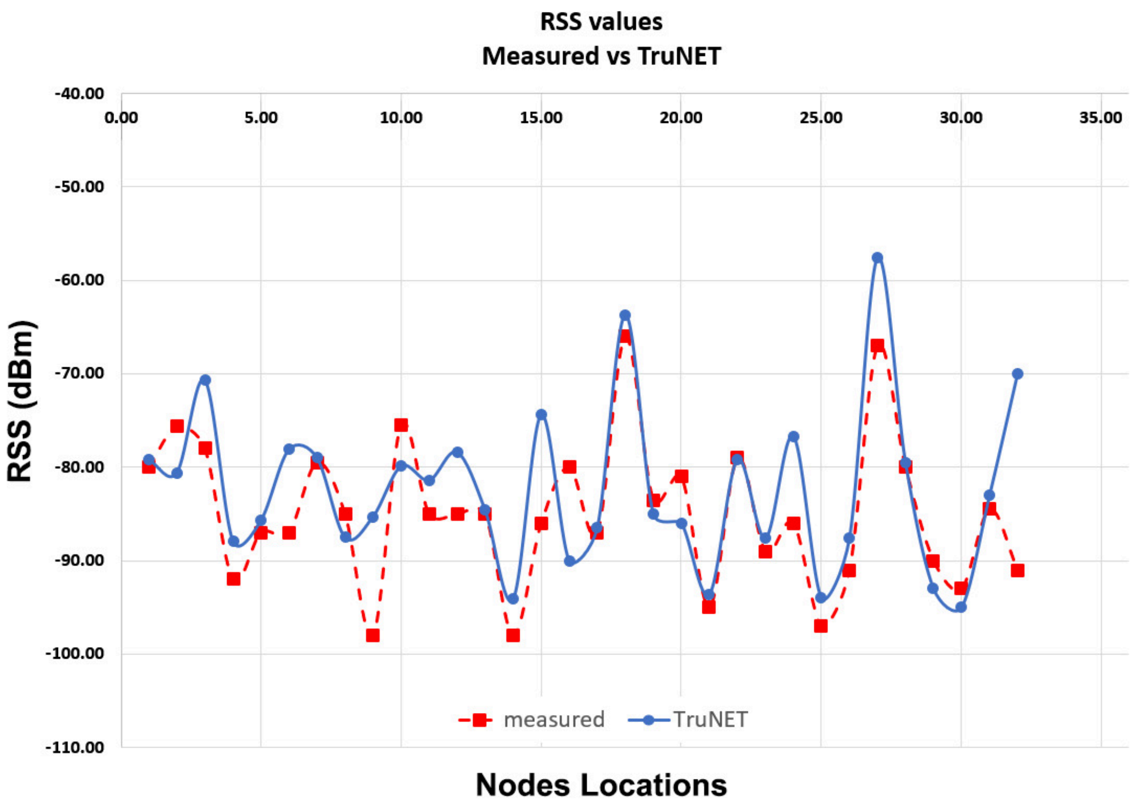
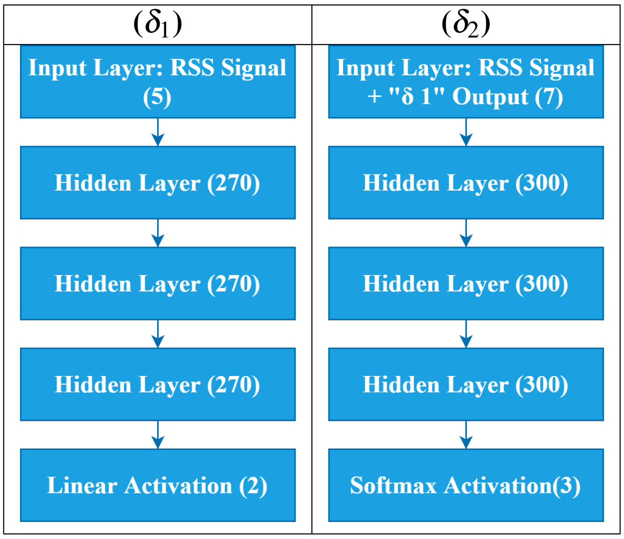


Fig. 3.6 RSS values measured vs TruNET Kanaris et al [5]

same frequency. To ensure signal samples obtained from TruNET Wireless are realistic, Figure 3.6 depicts the RSS coverage correlation analysis experiment conducted in [5]. The samples have been collected from Zolertia nodes over a week period at different instants with an interval of 15 minutes for each sample. The produced measurements for each RP have been averaged using the mean value. During this experiment, the IoT nodes have been always fixed and the environment was dynamic with people moving around.

Finally, it is clearly indicated that the simulated RSS values from TruNET wireless simulator highly approximate the measured ones reaching a correlation level of more than 73%.

Fig. 3.7 Layers of DELTA architecture network



3.2.2 DELTA Architecture

Deep learning is a fundamental building block of the proposed architecture. It allows computational models consisting of multiple processing layers to learn the representation of data within multiple abstract levels [19]. One of the most important elements of deep learning is DNN. Bengio et al [129] refer to this as either deep feed forward networks or Multiple Layers Perceptron (MLP) since they have more than two hidden layers.

Our proposed architecture, as illustrated in Figure 3.7, consists of two DNNs. The first is a regression model δ_1 used to predict the 2D location of a mobile device. The second is a classification model referred to as δ_2. Figure 3.7 illustrates the number of layers, neuron, input and output parameters used for both models. Based on numerous trials and hyper-parameters tuning, we observed that three hidden layers were the best fit model for both networks.

3.2.3 DELTA Layers

Input Layers

For δ_1, the input is a transposed vector of RSS signals that can be expressed as follows:

$S = [s_1, s_2, \dots, s_n]^T$.

For δ_2, the input is slightly different to δ_1. It consists of RSS signal input S and the output of δ_1. Each observation has a set of signals and predicted locations. This can be written as:

$$\delta_{2\_input} = S \cup (L_x, L_y) \tag{3.4}$$

Where S is the signal and L_x, L_y are the corresponding x and y locations. These two value are approximated using δ_1 as shown on Figure 3.7

Hidden Layers

Each element of this input gets multiplied by a its specific weight vector $\vec{w}$ and the product is added to a bias b. For the first hidden layer, this is expressed as follows:

$$h1 = \sum_{i=1}^{n} w_i^1 I_i + b_i^1 \tag{3.5}$$

Where I_i is an element from the input vector. Each I_i represents an input from a transmitter in the constructed fingerprint database. A summation of all these inputs is then fed to an activation unit A. In this case, the type of activation function used is called Rectified Linear Unit (ReLu).

$$A_1 = max(0, h1) \tag{3.6}$$

Where A_1 is an activation unit for the first hidden layer. The output of this hidden layer is the number of hidden neurons specified in the first hidden layer. Similarly, equation 3.7 for hidden layer 2 is expressed as follow:

$$h2 = \sum_{i=1}^{n} w_i^2 a_i^1 + b_i^2 \tag{3.7}$$

This result is then fed into a further activation unit A_2:

$$A_2 = max(0, h2) \tag{3.8}$$

The hidden layer three receives the output of equation 3.8 and makes similar calculations to $h2$:

$$h3 = \sum_{i=1}^{n} w_i^3 a_i^2 + b_i^3 \tag{3.9}$$

Finally, the results returned in equation 3.9 is fed into the activation unit A_3.

$$A_3 = max(0, h3) \tag{3.10}$$

Output Layers

For δ_1 model, since the desired output is a real-valued number, a linear function has been applied using the following equation :

$$g(y = j|a_i) = \sum_{i=1}^{n} w_i^4 a_i^3 + \varepsilon_i \tag{3.11}$$

For δ_2 model, the output is multiple class labels, therefore the Softmax function equation below has been used:

$$\theta(a_i) = \frac{\exp(a_i^3)}{\sum_j \exp(a_j^3)}[19] \tag{3.12}$$

To obtain the best final approximation, δ_1 supports δ_2. Algorithm 1 explains how both networks cooperate to make a final localisation.

Algorithm 1: DELTA algorithm for 3D localization

Input :RSS ▷ `Get Signal Vector`
Output :3D Location
Require: Signal UpperThreshold η;
Require: Signal LowerThreshold μ;
for *RSS_i in RSS* **do**
  $r \leftarrow \frac{RSS_i - \mu}{\mu - \eta}$ ▷ `Normalize signal`
  $2D \leftarrow \delta_1(r)$ ▷ `Apply first model prediction`
  $1D \leftarrow \delta_2(r, \delta_1)$ ▷ `Apply second model prediction`
  $3D \leftarrow 2D \cup 1D$ ▷ `merge` δ_1 `and` δ_2 `results`
end
return 3D Location

3.2.4 Prepossessing

Fingerprints Radiomap Database

As previously mentioned, we begun by constructing the radiomap database using eight features. Table 3.3 gives a detailed explanation of each variable. The constructed radiomap consists of 2880 3D References Points (RPs) associated with RSS values from five different WSN Access Points(APs). Each AP is placed at least three meters away. The position of these APs is shown on the lab floor-plan illustrated in Figure 3.8. To ensure that there is no redundancy in the information collected, a Pearson correlation test has been conducted

Table 3.3 The features used to construct the fingerprints database

Variable	**Min. Value**	**Max. Value**	**Type**
X	0	8	coordinates
Y	0	16	coordinates
Z	0.25	1.75	coordinates
AP1	-120 dBm	-28 dBm	RSS value
AP2	-100 dBm	-30 dBm	RSS value
AP3	-100 dBm	-40 dBm	RSS value
AP4	-90 dBm	-50 dBm	RSS value
AP5	-100 dBm	-60 dBm	RSS value

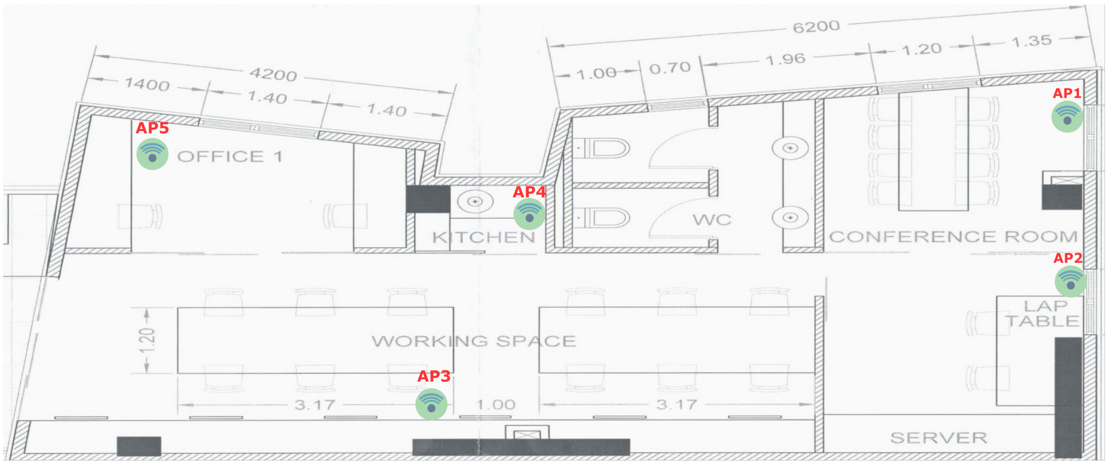


Fig. 3.8 Access Points position on the setup environment floor-plan

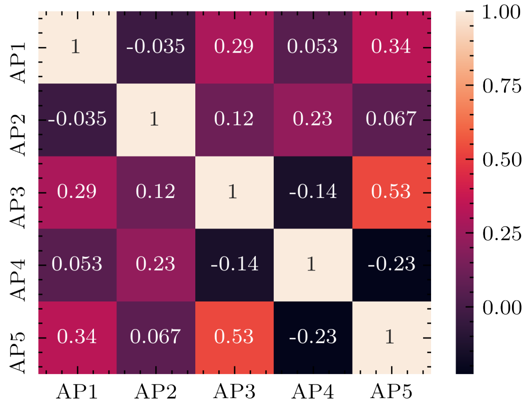


Fig. 3.9 WSN access points correlation matrix

between each AP and the result is shown in Figure 3.9. There is clearly no high negative or positive correlation between the APs used in this experiment. In addition to this, Figure 3.10 shows each layer on the radiomap database constructed is significantly different from the other layer. The Figure shows the signal at 0.25 meter, 0.75 meter and 1.75 meters for Access Point 1.

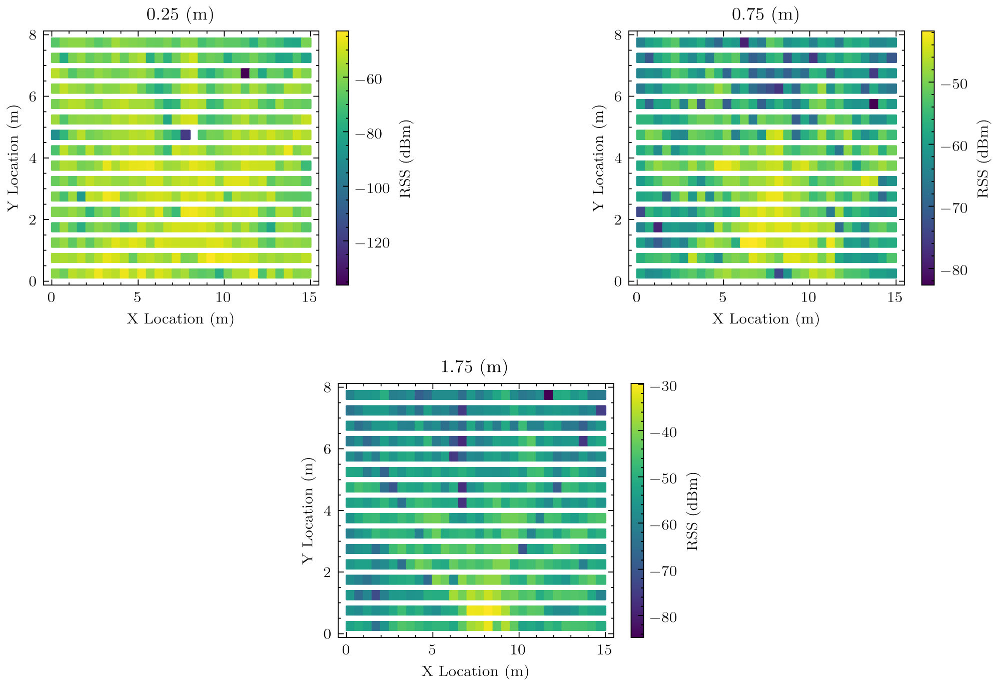


Fig. 3.10 Signal strength map for WSN access point 1 for each Z layer

One-hot Encoding

One-hot encoding is one of the most common techniques for converting a token into a vector [130]. The conversion is achieved by associating each unique integer with every unique value from the column z. This turns every unique value into a binary vector having the size of the unique values. As a result, every column will have zero except for where the unique value is occurred. In our case, we have used the steps followed in Algorithm 2 to one-hot encode our target variable:

Min-Max Normalization

Min-Max normalization has been implemented to make sure the learning of signal representation data is faster for DELTA architecture models to converge quickly. This concept works by

Algorithm 2: One hot encoding

Input : Column Z ▷ `get Z columns`
Output : Result Matrix of N binary vectors unique values from Z
Dictionary D=[];
Results R={[],[],[],[]};
for *i in Z.length* **do**
    if i $\notin$ D:▷ `If value not in dictionary add it`
    key=D[i]
    D[i]=Z[i]
end
return D
Map D into results R columns as binary vector $\{[Z_1], [Z_2], \ldots, [Z_n]\}$

fitting the original data into a new scale between 0 and 1. After this numeric transformation, the highest value becomes close to 1 and the lowest value is close to 0 as stated in [131]. The formula used to achieve this, is the following:

$$\frac{RSS_i - min(RSS)}{min(RSS) - max(RSS)} \tag{3.13}$$

Where $min(RSS)$ represents the values minimum threshold signal specified during the training signal i.e $-120dBm$ and $max(RSS)$ represents the maximum value measured i.e $-30dBm$. Each signal measurement we want to convert is denoted by RSS_i where i is the i^{th} row in N Transmitter. For other scenarios, it is important to use the receiver sensitivity level as the minimum value and the strongest measured signal during the offline-phase as the maximum value.

3.2.5 Hyper-Parameters Fine-Tuning

Loss Functions

- Using Euclidean Distance as loss function for δ_1 model, the purpose is to train the model to minimize the Mean Euclidean Distance (MED) error between the actual and the predicted location.

$$D(\mathbf{L}^{act}, \mathbf{L}^{pred}) = \frac{1}{M} \sum_{n=1}^{m} \sqrt{(x_j^{act} - x_j^{pred})^2 + (y_j^{act} - y_j^{pred})^2} \tag{3.14}$$

L^{act} here denotes the actual location and L^{pred} denotes the predicted location.

- for the δ_2 model, Categorical Cross-entropy is implemented as a loss function . This can be written as:

$$H(\mathbf{L}^{act}, \mathbf{L}^{pred}) = -\sum_{j=0}^{M} \sum_{i=0}^{N} (z_{ij}^{Act} \cdot log(z_{ij}^{pred}) \tag{3.15}$$

Where L^{act} denotes the actual location and L^{pred} denotes the predicted location. While z_{ij} denotes the i^{th} observation in the j^{th} z output class or level.

Hidden Layers and Neurons Size Determination

The number of hidden layers and neurons count used in the DELTA has been determined using the loss function specified the previous subsection. Figure 3.11 shows the performance of each network for each neuron count and layers number selected. As demonstrated in this

Fig. 3.11 The Number of hidden layers and neurons vs each loss functions

figure, the categorical cross entropy loss is minimized after a 3rd hidden layer has been added and the neurons count has been set to 300. Similarly, the average error was decreased in delta one after the parameters has been changed to 300 neurons and 3 hidden layers.

Batch Normalization

A batch is the number of samples propagated through the neural network model before the parameters are updated. To train each neural network faster, we have supported each layer with batch normalization. This sort of normalization is applied to input samples of the same batch size. This fine-tuning technique has been proven to speed up the training and learning process by 12 times faster than the normal architecture as described by authors in [132]. The formula for the batch normalization implemented on each DNN of DELTA system is:

$$T_i = \frac{(T_i - \mu(T)}{\sqrt{\sigma^2(T) + \varepsilon}} \tag{3.16}$$

where T is training batch, $\mu(T)$ is its mean, $\sigma^2(T)$ is its variance and ε is a small constant number added to support the variance. For this to work in Keras deep learning library[130], a layer of batch normalization with explicit parameters has to be added at the beginning of each hidden layer.

Regularization

To avoid over fitting, a regularization technique has been implemented to switch off certain neurons for some layers. This technique is called dropout. Details for this technique are provided by Nitish et al in [133]. The dropout rate used in DELTA is 0.20 as suggested by [133]. After experimentation, we have concluded that for better results are achieved when implementing batch normalization before dropout.

3.2.6 Optimization

Optimization is the process of training a network using mini-batches and iterations to get the optimum configuration for its parameter. One of the widely used stochastic optimization algorithm in deep learning ADAptive Momentum (ADAM). The algorithm can be viewed as a combination of RMSprop and Momentum [134]. It works by correcting the bias b and the weight w after each iteration. To get the best results from ADAM's parameters, we specified a learning rate $\alpha = 0.001$, β_1=0.9 for the momentum control, β_2=0.99 for squared weight in RMSprop section and $\varepsilon = 10^{-8}$ as specified by the authors in [134]. To implement this in Keras, ADAM parameters has to be specified before the model is compiled.

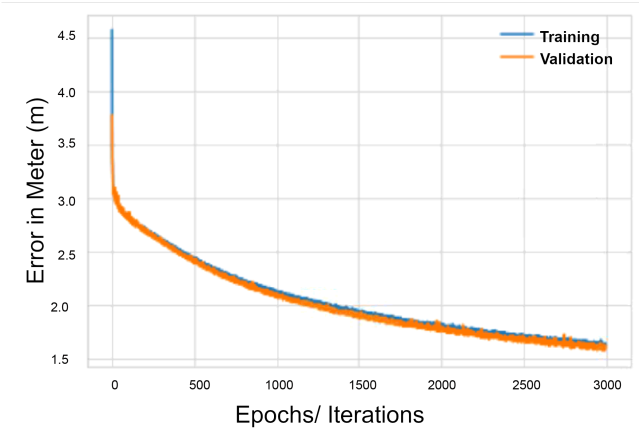


Fig. 3.12 δ_1 Model mean euclidean distance error in meter (m) vs the number of epochs

3.2.7 Scoring

Using 900 hidden neurons and three hidden layers, we have constructed model δ_1 to predict x and y locations. This has yelled 279,302 number of parameters to be to trained. Our cost function is the euclidean distance difference between each predicted observation and the original location. To minimize it, hyper-parameters have been fine-tuned such as the batch sizes and the number of time an algorithm will iterate through entire training dataset. One iteration is referred to as epochs. The aforementioned methodology resulted to an average positioning error of $1.6m$ average (less than $2m$ error over all) in both training and validation phases. Figure 3.12 shows how δ_1 model mean Euclidean distance error in meters decreases over the number of epochs chosen, in this case 3000 epochs. However, by the end of epoch 3000, the model has converged and stopped improving it's accuracy.

Similarly, after an iterative tweaking of the architecture parameters, using 810 number of neurons and 3 hidden of layers, we have constructed model delta 2 where z layer is the

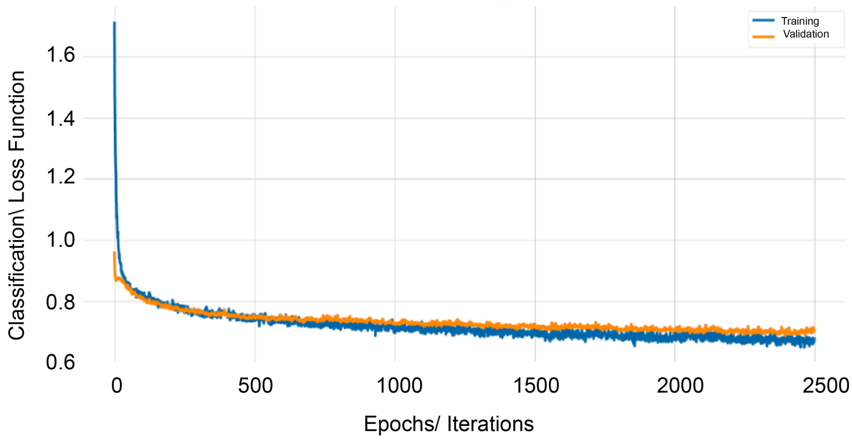


Fig. 3.13 δ_2 Categorical cross-entropy vs the number of epochs

target variable. The total number of 235,592 parameters were trained in this model. The cost function is the multi-categorical cross entropy which is used widely for classification scoring. Figure 3.13 shows how the categorical cross-entropy has been minimized after 2500 epochs.

3.3 Performance Evaluation Results

In this section, we explore, evaluate and critically analyse the simulation results against commonly used industry methods such as SVM and KNN. However, before going through the results analysis, it is worth mentioning that KNN and SVM modeling tasks have been carried out using Scikit-learn [135], a widely used Python library toolset for machine learning and statistics. More specifically, SVM models have developed using an SVM class from the Scikit-learn library and KNN models have been built using a classifier class called KNeighborsClassifier [136]. The DELTA models have been constructed using Keras API

[137], a deep learning library also available in Python. During the evaluation phase, the three algorithms were implemented using python software on the same machine with Intel i7-4790@3.60GHz CPU and 16 GB of RAM. In terms of time complexity, KNN has finished after 230ms while SVM has taken 450ms. The proposed DNN has used 160ms to execute making it more efficient than KNN and SVM.

3.3.1 Results Analysis

δ_1 vs KNN and SVM

Using 180 random samples [127], we have benchmarked and assessed DNN model δ_1 against KNN and Support Vector Regression (SVR) models. The samples have obtained for each z layer making a total of 540 RPs. The SVR has been trained using a linear kernel, a degree of 1 and an epsilon value of 1 using 80% training and 20% validation data sets. Similarly, KNN model has been trained with a K value set to 3. The results in Figure 3.14 show the error distribution in meters for all three models. SVR has scored a rather worse error distribution where the peak of its distribution ranges between 4 and 6 meters error. KNN has done slightly better compared to SVR. However, a large proportion of the distribution error falls between 3 and 5 meters, which makes it the second worse performing after SVR. DNN δ_1 has performed better. The peak of its distribution error samples falls between zero and two meters with a mean error of 1.6m. A detailed result is provided on Table 3.4.

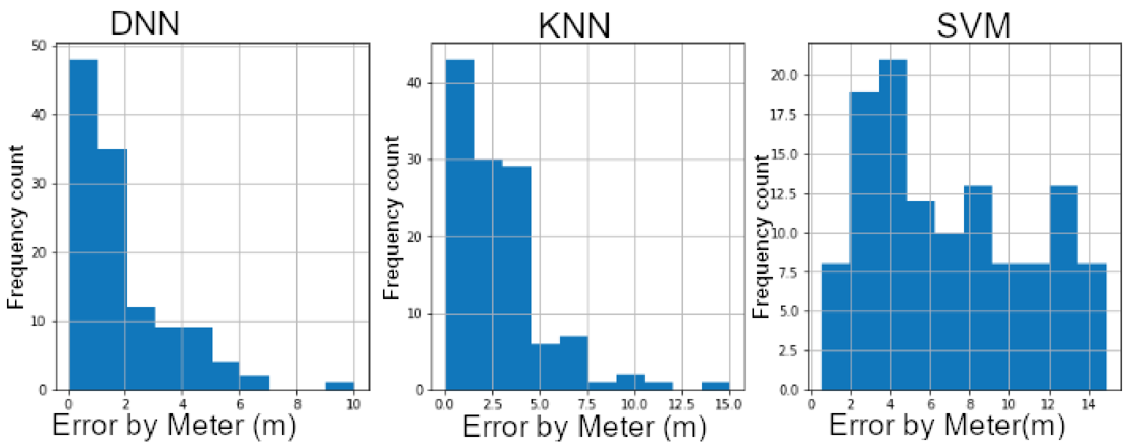


Fig. 3.14 δ_1 vs KNN vs SVR

Table 3.4 Frequency count of distance error (m) for each model

	DNN	**KNN**	**SVR**
Less Than 2m	79	51	9
Between 2m and 7m	39	64	60
More than 7m	2	5	51

δ_2 vs KNN and SVM

Using the aforementioned samples, the z layer (z coordinate) has been estimated. The results are depicted in Figure 3.15 illustrating a visual comparison of each classifier in a bar-chart using misclassification count as measure. Each model has been given an equal number of three classes 0.25m, 1.25m and 1.75m. At first glance, Figure 3.15 shows that Support Vector Classifier (SVC) has performed very badly in terms of classification of observations.The model has failed to accurately classify during the online phase. More than 66% - circa 120 samples- have been wrongly classified. With a total of 40 misclassified samples, KNN has performed better than SVC but still does not differentiate between certain classes properly. Our proposed δ_2 model of DNN, has made excellent classification compared to both later models. As an effect, 100% of 0.25m layer has been accurately classified while more than

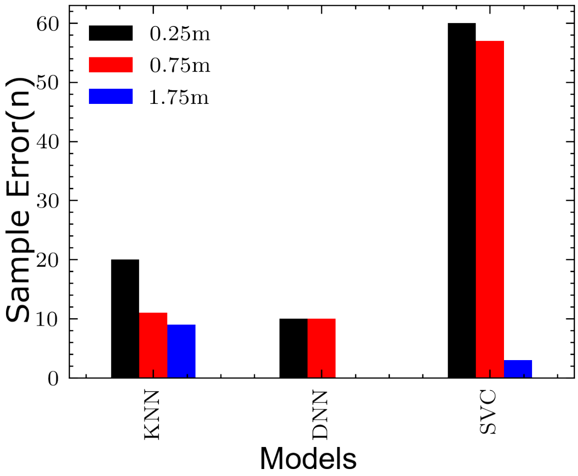


Fig. 3.15 Model comparison: δ_2 vs KNN vs SVC

Table 3.5 Misclassification count for each model

Model	0.25m	0.75m	1.75m
DNN	10	10	0
KNN	20	11	9
SVC	60	57	3

95% of the other two classes, 1.25m and 1.75m, have been also properly predicted. The total number of misclassified samples is 20 bringing the classification accuracy rate to 89%. This shows how the proposed 3-D multilayered model has outperformed the traditional models.

Table 3.5 gives a detailed count of each model and its misclassification count. The worse performing model is highlighted in red and the best performing model is highlighted in blue.

3.4 Chapter Summary

Chapter 3 of this thesis focused on the use of Deep Learning for 3D Indoor Positioning. The chapter introduced an experimental 5G testbed designed to enhance both vertical and horizontal localisation. The proposed approach employs the DELTA machine learning model implemented on a 3D multilayered fingerprint radiomap. The DELTA model predicts 3D indoor positions, starting with 2D location estimation and recursively estimating the 3D location of a mobile station. This approach is particularly useful for scenarios like 3D indoor navigation in multi-floor smart factories or complex large buildings. The chapter demonstrates that the DELTA model outperforms traditional algorithms like SVM and KNN.

Section 1 Highlights the importance of indoor positioning in the context of 5G IoT applications. Section 2 Introduces the proposed system model using DNN and multilayered radiomap for 3D indoor localisation. It defines the problem of 3D localisation and breaks it down into two sub-problems: 2D location prediction and 3D location prediction. Section 3 Describes the DELTA system developed for 3D multilayered indoor environment localisation, including details of the network setup, material parameters, and simulation environment. Section 4 presents the results of performance evaluations that compare DELTA with traditional models such as KNN and SVM. DELTA outperforms these models in terms of accuracy and efficiency. Finally, Section 5 summarises the key findings of the chapter and suggests potential future research directions, such as extending the model to incorporate information from other types of networks as covered in Chapter 3 or exploring more vertical layers.

The chapter demonstrates the effectiveness of the proposed DELTA model for 3D indoor positioning in 5G IoT environments and provides valuable insights into the potential applications and improvements for indoor localisation systems.

Chapter 4

Information Fusion for 3D Positioning

As demonstrated in Chapter 3, improved 3D positioning is possible through a Deep Learning cooperative learning and RSS fingerprints-based technique implemented on a multilayered radiomap. To further develop this concept, in this chapter, we propose a K-DNN algorithm to improve 3D indoor positioning. Our implementation uses a novel data-augmentation concept for the RSS-based fingerprint technique to produce a 3D fused hybrid. In the offline phase, a machine learning approach is used to train a model on a radiomap dataset that has been collected during the offline phase. The proposed algorithm is implemented on the constructed multilayer hybrid radiomap to improve the 3D localisation accuracy. In our implementation, the proposed approach is based on the fusion of BLE and ubiquitous WLAN. The concept presented is a continuation of our previous work in [34] [35] towards cooperative localisation. This chapter has been divided into the following parts: The proposed system model and the underlying algorithms are presented in **Section 4.1**. The 5G IoT physical network environment is explained in **Section 4.2**. The experimental setup is covered in **Section 4.3**. Section 4.4 shows the performance evaluation and **Section 4.5** analyses the results obtained. Finally, a chapter summary is drawn in **Section 4.6**.

4.1 The proposed Approach

Our proposed approach aims to improve indoor positioning using several 5G IoT wireless signal data sources. This can be achieved by merging BLE and WiFi's actual 3D location data with BLE and WiFi's simulated location data into a multilayered hybrid radiomap to save the tedious time spent constructing the fingerprints database. To support this data augmentation approach, K-DNN, a new cooperative positioning algorithm that combines KNN and DNN, was developed to reduce the localisation error. Figure 4.1 provides an overview of the algorithmic flow of the proposed K-DNN system. The following subsections describe in detail the K-DNN algorithm.

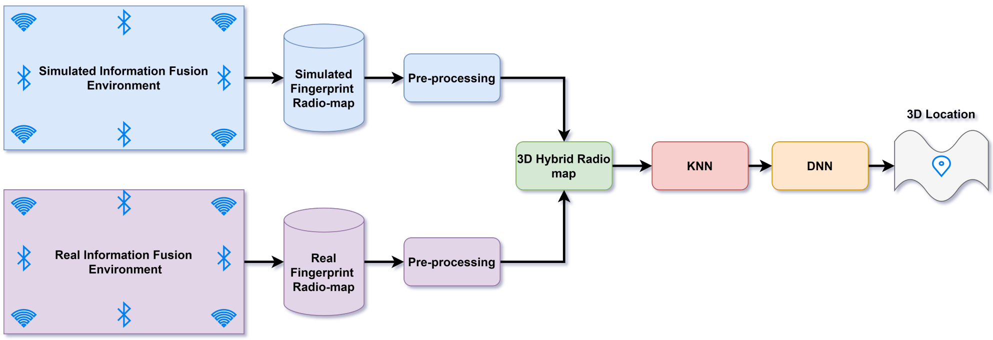


Fig. 4.1 The flow of K-DNN proposed system model

4.1.1 K-DNN Architecture and Hybrid 3D Localisation to 5G IoT

K-DNN is a novel cooperative positioning algorithm. Given a set of WLAN transmitters N and a set of BLE transmitters M connected to a set of 3D locations (XYZ), two machine learning models are trained to support each other to achieve minimal distance error. During the offline phase, the algorithm receives two matrices of hybrid radiomaps. This can be mathematically expressed as:

$$BLE\_RSS : \{(x_1, y_1, z_1, ble_1...ble_m), ..., (x_i, y_i, z_i, ble_1...ble_m)\}$$

$$WLAN\_RSS : \{(x_i, y_i, z_i, wlan_1.....wlan_n), ..., (x_i, y_i, z_i, wlan_1.....wlan_n)\}$$

K-DNN begins by eliminating outliers from the given radiomaps using the IQR (Interquartile) method [138]. The cleaned fingerprint datasets are then merged into a single radiomap. Next, a Min-Max normalisation technique is implemented to convert RSSI values of BLEs and WLAN into the same scale. As a final step in this phase, KNN is trained first to predict the 2D location (X, Y) and the DNN is trained to predict the 1D location (Z).

During the online phase, the K-DNN receives the following input:

$$BLE\_RSS_{online} : \{ble_1, ..., ble_m\}$$

$$WLAN\_RSS_{online} : \{wlan_1, ..., wlan_n\}.$$

Given this, KNN attempts to approximate the 2D (XY) locations as an output. This outcome is then fed along with the original input received by KNN into DNN, which in turn predicts the 1D (Z) location. As a result, the 3D (XYZ) location is realised through this cooperative prediction approach. The main reason for having these two models is due to the nature of the output of 1D (classes) and 2D (continuous values).

4.1.2 K-DNN Models Architecture

KNN

The KNN algorithm is a non-parametric supervised machine learning algorithm used for pattern classification and regression. This means it does not make any assumptions about the data currently analysed. Since learning in KNN is supervised, the trainer has to choose the parameters to achieve the best results. This algorithm was first proposed in 1951 by Evelyn Fix, Joseph Hodges [139], and Thomas Cover [140], who later expanded on it. In the K-DNN algorithm, KNN is used to predict the 2D (XY) location. As previously highlighted Algorithm 3, this algorithm receives a set of RSS signal values as input R. This can be written as: $R = [RSS_1, RSS_2, ..., RSS_n]$

The input given to KNN consists of a vector of 7 normalised RSS values. This part of K-DNN attempts to reduce the localisation error of the X and Y location using the Euclidean distance. The output of this model is then combined with the original input R and fed the DNN model.

DNN

Deep learning is a crucial building block in the proposed K-DNN system. It allows learning complex patterns and data representations through multiple processing layers [19]. One of the most important architectures in deep learning is DNN, a.k.a. Multiple Layer Perceptron (MLP) or deep feed forward networks[129]. The DNN considered in K-DNN is a classification model. Figure 4.2 shows the number of layers, neurons, input and output parameters used in this model.

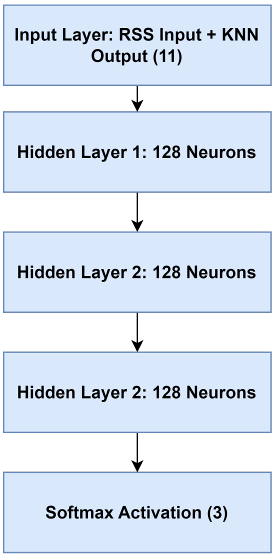


Fig. 4.2 Layers of DNN network

The input layer of this network receives a transposed vectors of signal values and 2D locations. This can be expressed as:

$$DNN_{input} = [X, Y, RSS_1, RSS_2, \ldots, RSS_n]^T \tag{4.1}$$

Where X and Y are the 2D points predicted by KNN and RSS_i represent the signal value of the i^{th} transmitter (BLE or WLAN).

The calculated result for this layer is then fed into the first hidden layer. each input element from Equation 4.1 is multiplied by a specific weight vector $\vec{w}$. The product of this operation is then added to a bias b. The formula for this can be expressed as follows:

$$h1 = \sum_{i=1}^{n} w_i^1 I_i + b_i^1 \tag{4.2}$$

Where I_i is the element i^{th} of the input vector. The summation of all these inputs is then passed onto an activation function unit A. In our proposed network, this is the Rectified Linear Unit (ReLu).

$$A_1 = max(0, h1) \tag{4.3}$$

Here, A_1 is the activation function of the first hidden layers. The output of this layer is 128 neurones. In the same way,

$$h2 = \sum_{i=1}^{n} w_i^2 a_i^1 + b_i^2 \tag{4.4}$$

The result of this hidden layer is passed onto a further activation unit A_2:

$$A_2 = max(0, h2) \tag{4.5}$$

Finally, the output of Equation 4.5 is received by hidden layer 3 to make a similar calculation to h1 and h2:

$$h3 = \sum_{i=1}^{n} w_i^3 a_i^2 + b_i^3 \tag{4.6}$$

The calculated values of Equation 4.6 are then fed into the activation function below:

$$A_3 = max(0, h3) \tag{4.7}$$

To predict the correct height of the mobile device, the softmax function equation below has been used:

$$\theta(a_i) = \frac{\exp(a_i^3)}{\sum_j \exp(a_j^3)} \tag{4.8}$$

Here Θ is a partition function, and $\exp(a_i^3)$ is a single probability output over the some of all the probability output $\sum_j \exp(a_j^3)$.

4.1.3 K-DNN Psuedocode

For clarity purposes, the pseudocode below explains how K-DNN works.

Algorithm 3: K-DNN algorithm for 3D localisation

Input : $BLE\_RSS : \{(x_1, y_1, z_1, ble_1...ble_m)\}$; ▷ Get Hybrid BLE RSS
Input : $WLAN\_RSS : \{(x_1, y_1, z_1, wlan_1.....wlan_n)\}$; ▷ Get Hybrid WiFi RSS
Output : Λ ; ▷ Output 3D location
Require: Signal UpperThreshold μ;
Require: Signal LowerThreshold η;
Require: First quartile Q_1;
Require: Third quartile Q_3;
$IQR \leftarrow Q_3 - Q_1$; ▷ Calculate Interquartile
for *ble_i in BLE_RSS and $wlan_i$ in WLAN_RSS* **do**
    if *ble_i<Q_3+(1.5*IQR)* ***and*** *ble_i>Q_1-(1.5*IQR)* **then**
        ble_r←ble_i ; ▷ Apply IQR method to BLE
    if *$wlan_i$<Q_3+(1.5*IQR)* ***and*** *$wlan_i$>Q_1-(1.5*IQR)* **then**
        wlan_r←$wlan_i$; ▷ Apply IQR method to WLAN
    RSS←wlan_r $\cup$ *ble_r* ; ▷ Fuse BLE and WLAN Radiomaps
end
for *RSS_i in RSS* **do**
    $R \leftarrow \frac{RSS_i - \mu}{\mu - \eta}$; ▷ Normalize signal
    $X\_Y \leftarrow KNN(R)$; ▷ Apply first model prediction
    $Z \leftarrow DNN(R, X\_Y)$; ▷ Apply second model prediction
    $\Lambda \leftarrow X\_Y \cup Z$; ▷ merge results output
end
return Λ

4.2 5G IoT Physical Network Environment

In this part of the section, we explain the main components of the 5G IoT Network that is used in this experiment. For clarity purposes, Figure 4.3 shows the logical network architecture:

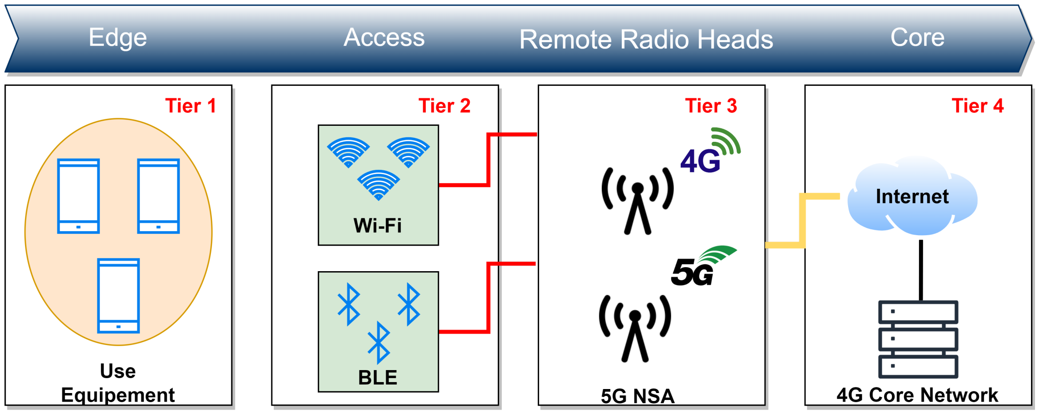


Fig. 4.3 5G IoT network logical architecture

4.2.1 5G Core Network

In this experimental testbed, we adopt 5G NSA(Non-Stand-Alone) access as suggested by the 3GPP release 15[18]. This concept uses dual connectivity (eNodeB/gNodeB) to provide radio access to 5G enabled UE (user equipment) via 4G EPC infrastructure as demonstrated in Figure 4.4a.The 5G core network complies with the 3GPP release 16[141] and uses an open-source called Open5gs[142]. This platform implements both 5G Core (5GC) and Evolved Packet Core (EPC) using C-langauge. The Open5G has evolved from 4G NextEPC and comes with a WebUI to manage network subscribers. The 5G core network developed has been used to configure NR/LTE networks for a private cellular network infrastructure. The core network has been virtualised and deployed on a 64-bit Linux machine on VMWARE workstation. At the time of writing this thesis, there are other projects such as OpenAirInterface [143] and free5GC [144]. However, these solutions are not stable yet. A detailed description of these three projects can be found in [145].

4.2.2 eNodeB (4G)/ gNodeB(5G):

Evolved/ E-UTRAN Node B is a component in the E-UTRA of 4G LTE11. This component connects subscribers to service providers through the S1-AP protocol linked to S1-MME from the Mobility Management Entity side. The eNodeB has its own radio control functionality that manages a USRP B210 SDR (Software Defined Radio) as shown in Figure 4.4a. This component offers radio service via the air interface. The operating frequency of this radio unit for 4G is going to be between 800MHz and 2600MHz as per the OfCom Regulations. A duplexer has also been used to reduce the number of antennas used to keep the transmitter (Tx) and receiver (Rx) synchronised for both radio units. The software side of this solution has been implemented on a custom-built PC powered by an i9 CPU and a total memory of 32 GB. This unit is an implementation of 3GPP release 15 [18] as previously highlighted. This means that it uses dual connectivity to offer the service to the user equipment. The 5G capable device has to first connect to the MME through eNodeB to attach to a gNodeB. This is why it is called the NSA mode. This unit uses the X2AP protocol to communicate with eNodeB nearby. The dedicated hardware for this base station is similar to the eNodeB. In order to reduce the clock drifting, the 5G radio is offered through a USRP B210 attached to a 5G band 7 cavity duplexer.

4.2.3 5G IoT Modem:

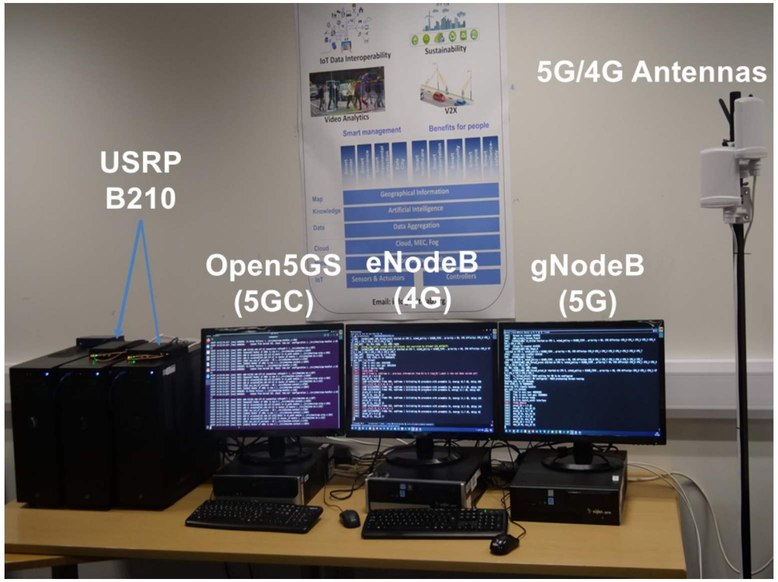
The 5G gateway implemented in this testbed consists of a Raspberry Pi 4 model B and a Quectel 5G Quectel RM500Q-GL Modem [146] as shown in Figure 4.4b. This gateway links the 5G cellular network to the WLAN and BLE networks used to extract fingerprints.

4.2.4 Wireless Local Area Networks

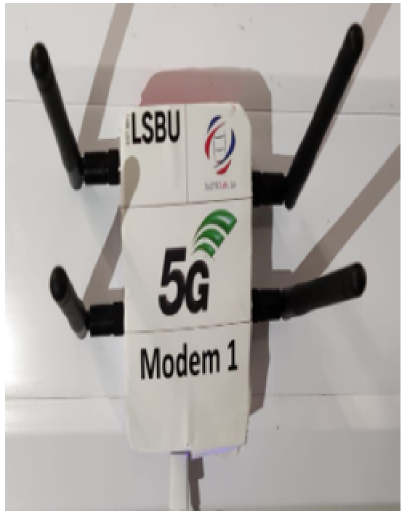
During the experimental design, 5 IEEE 802.11ac [147] wireless access points were considered for deployment at the assigned site. Figure 4.4d depicts one of the access points used in this setup. In this configuration, each transmitter operates at 2.4 Ghz and a coverage range of 45 m, although dual band is possible, as this technology also supports 5 Ghz.

4.2.5 Bluetooth Low Energy

As a secondary source for information fusion, we have considered using the IEEE 802.15.1 standard, which is BLE version 5.0 [148]. The devices used in this experiment operate at 2.4 Ghz and 350 m. Figure 4.4c illustrates one of the BLE units used in this setup. The following section covers the testing environment of this architecture.



(a) 5G testbed setup



(b) 5G modem gateway

(c) Bluetooth Low Energy 2

(d) 5G wireless access point 4

Fig. 4.4 5G IoT test environment

4.3 Test Environment

The K-DNN algorithm was tested by combining actual and simulated measurements. the experiment that took place in two teaching laboratories at London South Bank University of approximately 126 m^2 as shown in Figure 4.5. To achieve this task, a 5G IoT network has

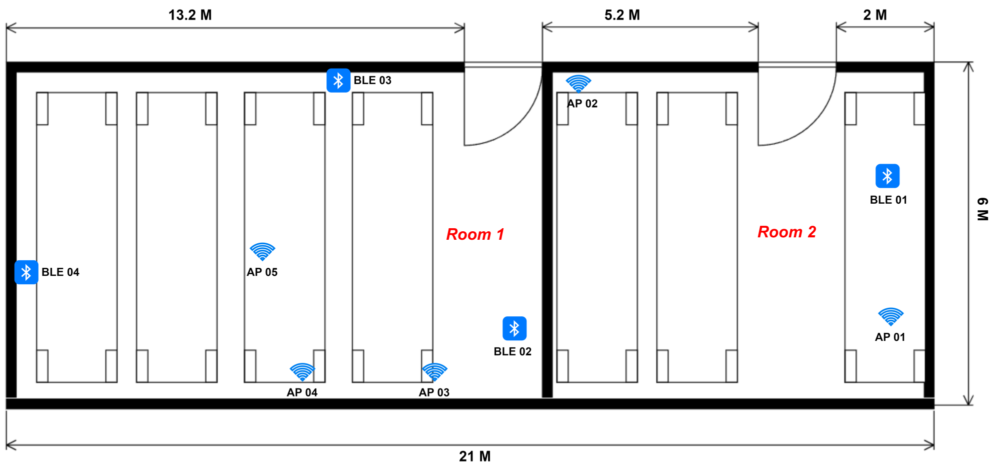


Fig. 4.5 Floor plan with access points and BLE position

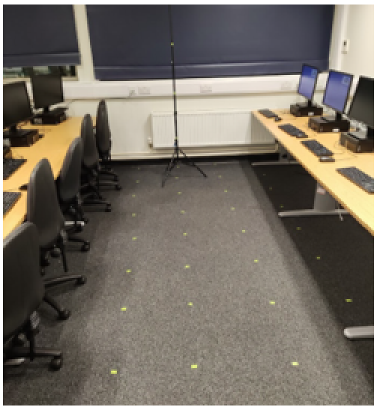
been deployed in the two laboratories. The network consisted of 5 IEEE 802.11 access points and 4 IEEE 802.15 BLE that were randomly placed based on Table 4.1. Two radiomaps were constructed: the first was generated using actual measurement campaign; and the second using TruNet wireless, a 3D ray tracing deterministic simulator [126]. It is worth mentioning that each antenna polarisation choice is based on access point within the room. This is to provide the optimum coverage for the network users. Additionally, this will ensure less correlation between access points close to each other. Thus, a better multi-layered radiomap is constructed.

Table 4.1 The 5G IoT setup location and antennas orientation

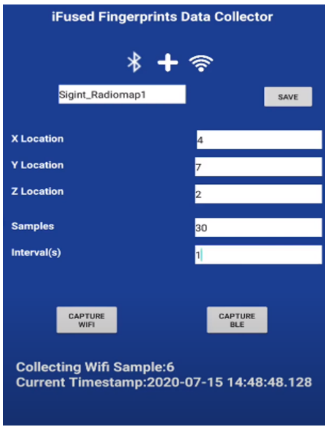
Device	X	Y	Z	Antenna Orientation
AP1	0	0	2	Vertical
AP2	6	6.5	1.5	Horizontal
AP3	0	11	1.5	vertical
AP4	0	13	1	Horizontal
AP5	3	15	0.5	Horizontal
BLE01	4	0	1	N/A
BLE02	1	9	1.5	N/A
BLE03	6	13	2	N/A
BLE04	3	21	0.5	N/A

4.3.1 Radiomap from 5G IoT actual measurements

During data collection, fingerprints were collected in 2236 equally spaced locations (0.5 m spacing) at 0.5 m, 1 m, 1.5 m and 2.5 m height, as shown in Figure 4.6a. At each measurement location, 30 distinct measurements were recorded at an interval of 1 second using the iFused Fingerprints Data Collector developed for Android-based devices as shown in Figure 4.6b. The RSS values stored in the radiomap ranged from -103 dBm to -28 dBm. During the measurement campaign, the application has recorded data from 5 APs and 4 BLE devices.



(a) FW-208 Classroom Grid Setup



(b) iFused Fingerprints Data Collector

Fig. 4.6 Physical Environment and the Fingerprints Data Collector

Simulated Radiomap

The second radiomap was constructed using the TruNet simulator. RSS fingerprints were collected according to the procedure used by the authors in [149, 82]. To ensure that the measurement recorded by the iFuse application matches the simulated measurements, 5 APs and 4 BLE were configured according to the antenna radio propagation characteristics in Table 4.2. Furthermore, the building structure and furniture were configured based on the calibration procedure in [150]. As a result, the same 2236 measurement points were generated and defined as receiver cells. At the end of this process, two layers of fingerprints (2 m and 1.5 m high) have been merged merged with the actual measurement radiomap.

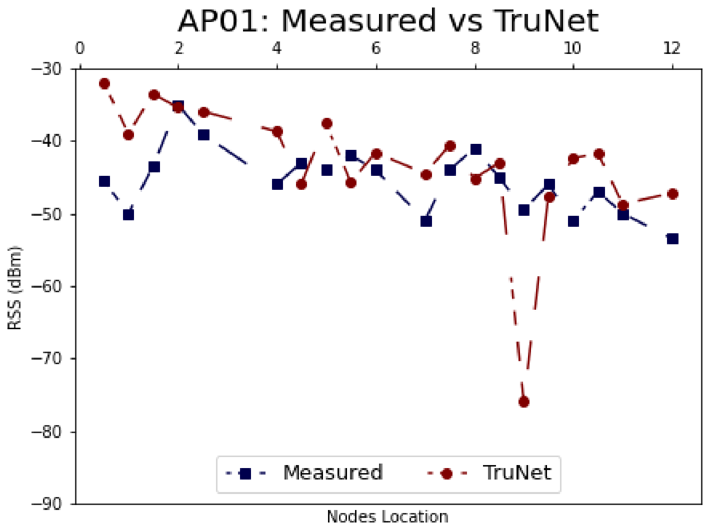
Table 4.2 The BLE and WLAN radio propagation parameters

Parameter	**BLE**	**WLAN**
Rx sensitivity (dBm)	-70	-120
Tx power (dBm)	8	12
Antenna Type	Omnidirectional	Omnidirectional
Max refractions	5	12
Max reflections	5	12
Max diffractions	1	1

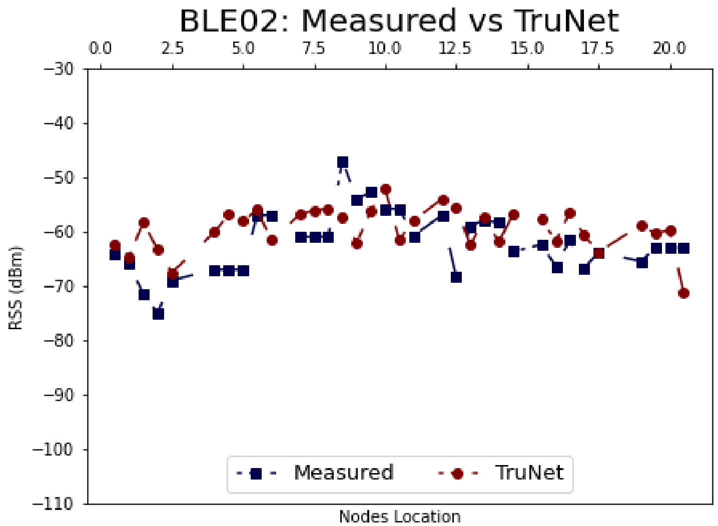
The propagation parameters specified are based on TruNET simulator pre-sets. These have been adjusted as per the available WLAN and BLE chipsets in the market.

The physical Network Behaviour

It is evident that the obtained RSS signal can be affected by noise from the environment. To ensure that the radiomap constructed the simulation is matching with the measurement campaign carried out. As a result, Figure 4.7 shows a strong correlation between the real RSS values and the Trunet measured for access points and BLEs.



(a) Measured vs simulated fingerprints AP 01



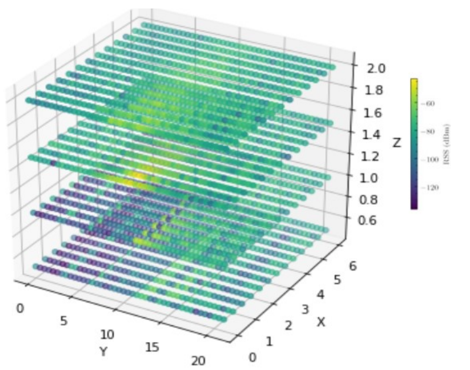
(b) Measured vs simulated fingerprints BLE 02

Fig. 4.7 BLE 02 and AP 01 simulated vs real measurement comparison

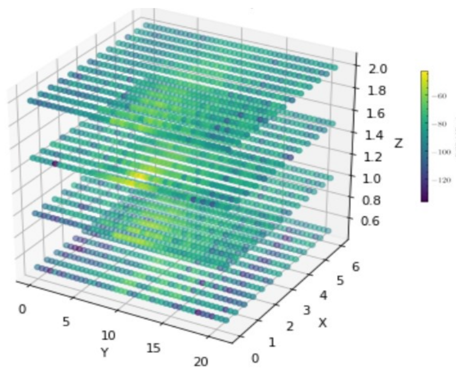
4.3.2 Preprocessing

Multilayered Radiomap Hybridisation

Hybridisation of radiomap refers to the process of merging simulated and real measurements of the same environment but different height levels. This preprocessing technique merges multiple 3D layers from various available sources. In this experiment, we combined two simulated measurements (2m and 1.5m height) with two layers of real measures (0.5m and 1m measures). This technique is novel as far as we know and has not been implemented in previous papers. It can be beneficial for scenarios where complex buildings are in which extensive human resources and time are allocated. To ensure that there is correlation between the simulated and the real measures, we have compared location ids of the same layer belonging to the same BLE and access points. As demonstrated in Figure 4.8, there is a strong correlation between the measurements obtained in the simulation and the actual measures. Furthermore, to prove the feasibility of this technique, we compare the non-fused and fused models along each other at later stage in this chapter.



(a) Access Point 03 Hybrid Radiomap



(b) Access Point 03 Simulated Radiomap

Fig. 4.8 Simulated vs Hybrid radiomap

Features Selection

During the feature selection process, a Pearson correlation test was performed between the BLEs and APs as this was necessary to ensure no redundancy in the information provided to the K-DNN models. Figure 4.9 clearly shows no high positive or negative correlation between the selected BLE and AP used in this experiment.

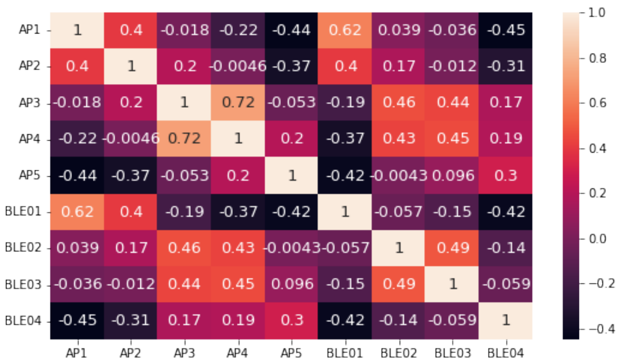


Fig. 4.9 Pearson correlation matrix for the radiomap

Outliers Elimination

Outliers are generally values that lie an abnormal distance from other values in a normal distribution. In the case of RSS-based positioning, these types of values find their way to the radiomap during the measurement campaign when a signal fluctuation occurs or when there is interference, such as human activity. To deal with this quality data problem, we applied the interquartile method introduced by Upton and Cook in [151] as shown in Figure 4.10.

In this work, we have implemented this method to prevent K-DNN from learning extreme RSS values that have been picked up by the receiver during the data collection process. After

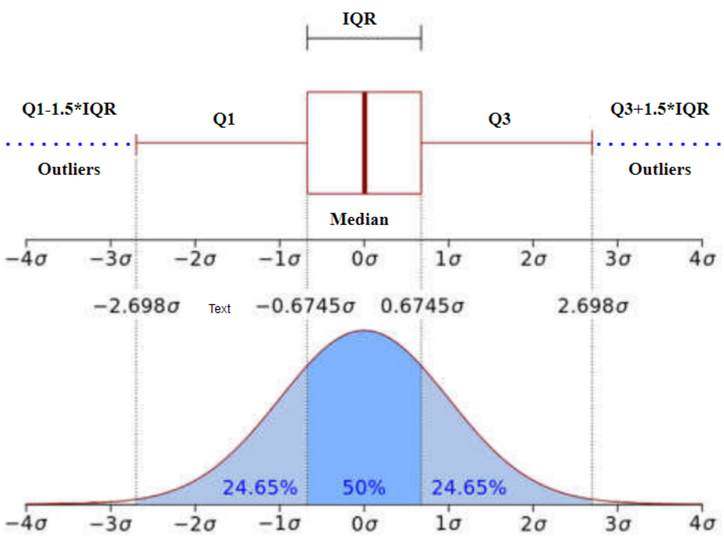


Fig. 4.10 Outliers removal using IQR technique

treating the outliers, 2031 observations have been left to train K-DNN. Table 4.3 shows a summary of the considered features and their minimum and maximum values.

Table 4.3 The features used to construct the fingerprints database

Variable	**Min. Value**	**Max. Value**	**Type**
X	0	6	coordinates
Y	0	21	coordinates
Z	0.5	2	coordinates
AP1	-84 dBm	-28 dBm	RSS value
AP2	-86 dBm	-30 dBm	RSS value
AP3	-84 dBm	-35 dBm	RSS value
AP4	-87 dBm	-32 dBm	RSS value
AP5	-109 dBm	-37 dBm	RSS value
BLE01	-105 dBm	-32 dBm	RSS value
BLE02	-86 dBm	-32 dBm	RSS value
BLE03	-97 dBm	-35 dBm	RSS value
BLE04	-120 dBm	-42 dBm	RSS value

Data Normalisation

To preserve the relationship between the original data values while speeding up the learning process, a min-max normalisation technique was implemented to scale the original values between 0 and 1. The equation used is:

$$\frac{RSS_i - min(RSS)}{min(RSS) - max(RSS)} \tag{4.9}$$

Where $min(RSS)$ refers to the minimum values of the threshold signal in the training signal, that is, -120 dBm and $max(RSS)$ represents the maximum measured value, that is, -28 dBm. Each measurement of the signal that we need to convert is denoted by RSS_i where i is the ith row on the N BLE or Access Point transmitter. For a different scenario, it is preferable to rely on the receiver sensitivity level as the minimum value, while choosing the strongest measured signal value during the offline phase as the maximum value. This process is important for both KNN and DNN models, as it changes the values of each access point and BLE to a common scale, without affecting the differences in the range of values.

One-hot encoding

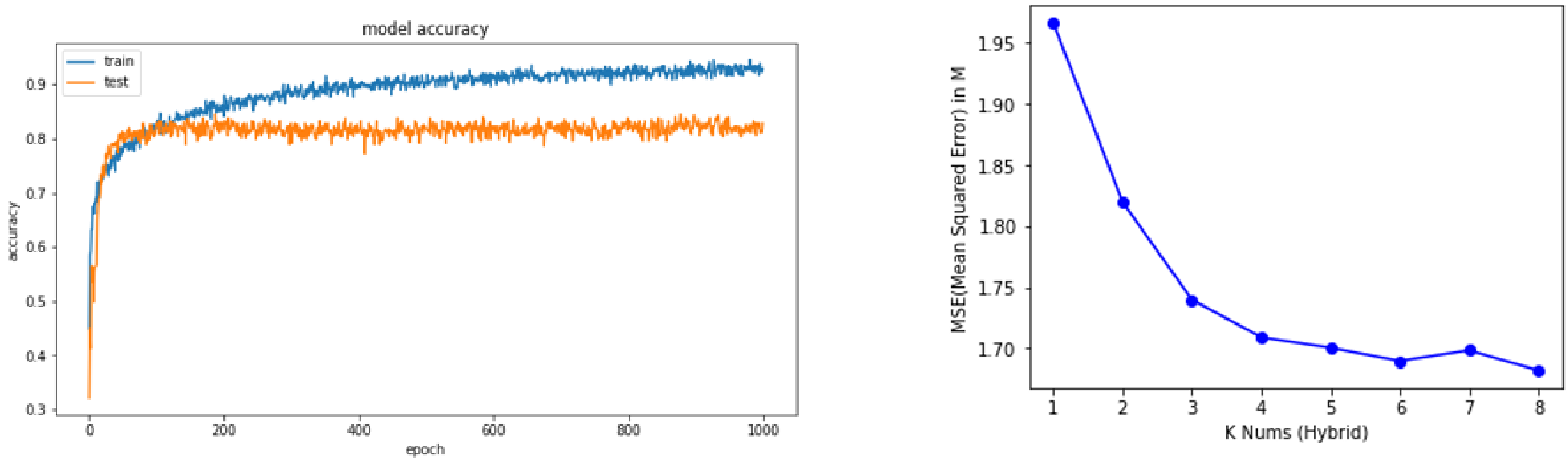
One hot encoding is the process of converting a column of continuous ordinal numeric values to binary columns based on the distinctive values [82] as shown in the Algorithm 4. This process was applied in this experiment to the 1D (Z) values. Mapping the distinctive values 0.5 m, 1.0 m, 1.5 m and 2.0 m to four binary columns was the result of this process.

Algorithm 4: One hot encoding

```
Input   :Column Z ▷ get Z columns
Output :Result matrix of N binary vectors unique values from Z
Dictionary D=[];
Results R={[],[],[],[]};
for i in Z.length do
    if i ∉ D:▷ If value not in dictionary add it
    key=D[i]
    D[i]=Z[i]
end
return D
Map D into results R columns as binary vector {[Z1],[Z2],...,[Zn]}
```

4.4 Performance Evaluation

Testing the performance of K-DNN involved training DNN using the ADAM (ADAptive Momentum) algorithm [134] and KNN using the elbow method [152]. The former is useful for learning highly sparse datasets , while the latter is a technique used to cross-check the model performance against the number of K chosen. Figure 4.11a reveals how DNN has converged in the 1000th training iteration. The KNN achieved the lowest error rate at K = 6, as illustrated in 4.11b.



(a) DNN epochs vs the model accuracy

(b) KNN MSE vs the number of K selected

Fig. 4.11 5G IoT simulated environment radiomap example

Table 4.4 DNN hyperparamters

Hyperparameter	**value**
Learning Algorithm	Adam
Learning Rate	0.001
$\beta 1$	0.9
$\beta 2$	0.999
Dropout	0.35
momentum	0.99
batch size	64
ε	1e-07
number of hidden layers	3
number of hidden layers in each neurons	128

Additionally, it is worth noting that DNN have been trained using the hyperparameters on Table 4.4. In the following section, we evaluate and compare the performance of this model on different radiomaps.

4.5 Results Analysis

4.5.1 DNN Scoring

To assess the impact of the proposed approach, we have trained 4 models using different combinations of radiomaps to compare with the concept proposed in this chapter. The four models have been trained as follows:

- Model 1: Hybrid radiomap (*Proposed approach*).
- Model 2: Hybrid radiomap without information fusion
- Model 3: Simulated radiomap

- Model 4: Simulated radiomap without information fusion.

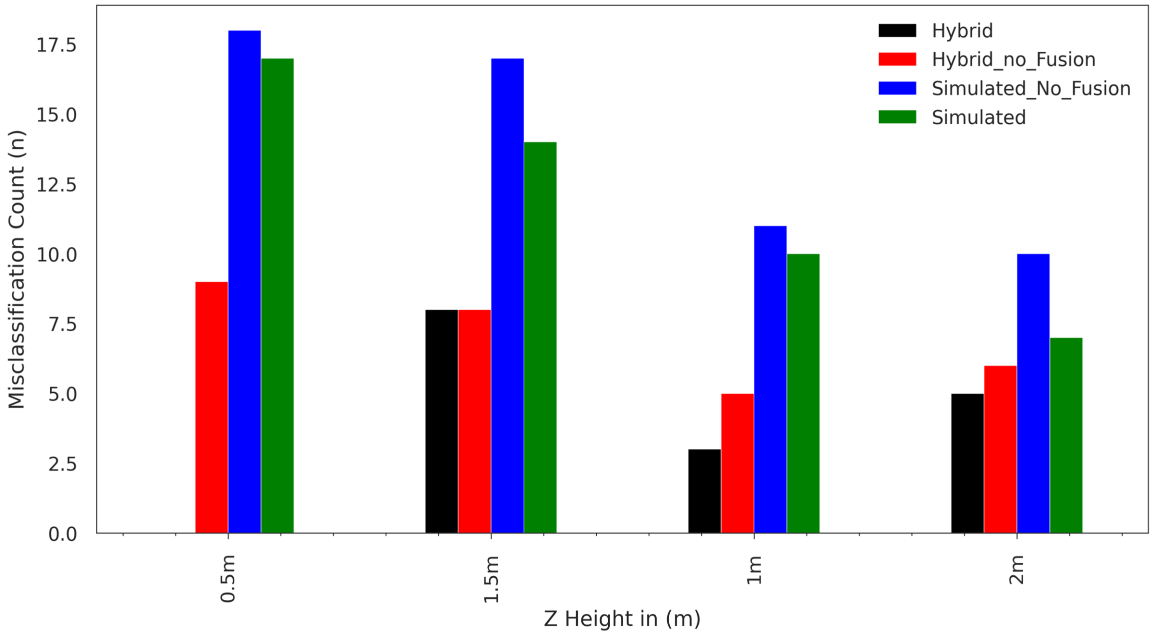


Fig. 4.12 DNN misclassification count results by height

Using 180 random samples as suggested by the authors in [127], we have tested the misclassification performance of each DNN model at various height levels: 0.5m, 1m, 1.5m and 2m as illustrated in Figure 4.12. In the graph, it is clear that the hybrid approach with information fusion has achieved the lowest misclassification count out of the 4 models. As can be seen in Table 4.5, 91% of the samples - cerca 164- have been accurately classified. The model trained using the proposed hybrid approach without information fusion has come second with a classification rate of 87% (152 out of 180 samples). The third model was trained with information fused simulated radiomap, and it has performed badly compared to the two previous models. This model has scored a classification rate of 73% (132 out of 180 samples). The fourth model that was trained using a simulated radiomap without information

Table 4.5 DNN misclassification count detailed results

	Hybrid	Hybrid No Fusion	Simulated	Simulated No Fusion
0.5m	0	9	17	18
1m	8	8	14	17
1.5m	3	5	10	11
2m	5	6	7	10
Total	16	28	48	56

fusion has performed worse with a classification score of 56 out of 180. These results demonstrate how the proposed hybrid approach has outperformed the rest of the training scenarios. Given this, it can be concluded that the hybrid information fusion technique can drastically improve localisation in a 1D environment. Detailed misclassification counts for each height are provided in Table 4.5. The model with the poorest performance is indicated in red, while the model with the highest performance is denoted in blue.

4.5.2 KNN Scoring

As in the previous subsection, to assess the feasibility of our proposed technique in 2D localisation, 4 KNN models have been evaluated using 180 samples . The trained models are as follows:

- Model 1: A hybrid radiomap with information fusion
- Model 2: A hybrid radiomap without information fusion
- Model 3: A simulated radiomap with information fusion
- Model 4: A simulated radiomap without information fusion

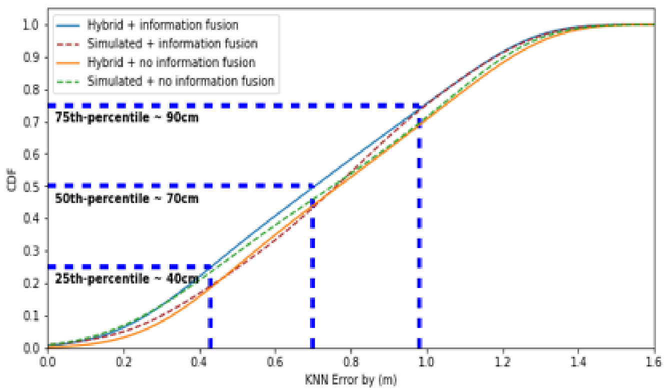


Fig. 4.13 KNN CDF results

Figure 4.13 shows the Cumulative Distribution Function (CDF) of error in meters for each KNN model. At the 75th percentile, it demonstrates that Hybrid with fusion, simulated with information fusion, hybrid and simulated models have achieved 90cm, 1m, 1.10m, and 1.20m errors, respectively. Using CDF as a metric, the proposed 3D multilayered hybrid approach has achieved a submetre accuracy in comparison with the rest of the models. Therefore, given KNN and DNN, it can be strongly argued that the K-DNN proposed method drastically reduces the localisation error.

4.6 Chapter Summary

Chapter 4 of this thesis discussed the development and implementation of a novel algorithm to improve indoor positioning in 5G IoT networks. The chapter begins by highlighting the need for improved 3D indoor positioning, building on concepts discussed in the Chapter 3. However, the primary focus is on the proposed algorithm called K-DNN for enhancing 3D indoor positioning. This approach combines data from Bluetooth Low Energy (BLE) and Wi-Fi (WLAN) signals in a multilayered hybrid radiomap. This algorithm consists of two main models:

- KNN: This model predicts the 2D (XY) location based on the RSS values.
- DNN: This model predicts the 1D (Z) location based on the output of the KNN model and the original input RSS values.

The chapter also explains the 5G IoT physical network environment used for the experiments, including the 5G core network, eNodeB/gNodeB, 5G modems, and wireless access points (APs) for WLAN. The performance of the K-DNN models is evaluated and compared to other models with different combinations of radiomap data. Both DNN and KNN models achieve competitive results, with the hybrid approach outperforming others in terms of accuracy. The chapter concludes by summarizing the findings, highlighting the submeter-level accuracy achieved in 2D positioning and the 91% classification rate in 1D positioning. It also suggests possible future research directions, including azimuth angle data integration and floor-level detection. Overall, this chapter presents a comprehensive exploration of the proposed K-DNN algorithm for 3D indoor positioning in 5G IoT networks, demonstrating its effectiveness in improving accuracy and reducing errors.

Chapter 5

5G Indoor Positioning as a Service

The combination of big data and Artificial Intelligence (AI) are important to improve indoor localisation. It focuses on the use of machine learning probabilistic algorithms to extract, model and analyse live and historical signal data obtained from several sources. In this respect, the data generated by the 5G IoT network is quintessential for precise indoor positioning in complex building environments. In this chapter, we present a new architecture for assets and personnel location management in a 5G network with an emphasis on vertical sectors in smart cities. Moreover, we explain how Big Data and machine learning can be used to offer positioning as a service. Additionally, we implement a new deep learning model for 3D positioning using the proposed architecture. The performance of the proposed model is compared against other Machine Learning algorithms. The rest of this chapter is structured as follows: **Section 5.1** describes a five-tier architecture for positioning concept. **Section 5.2** explains the different functionalities of the proposed knowledge plane. **Section 5.3** deals with a 3D positioning algorithm implemented on 5G emulated environment. **Section 5.4** concludes with an overall summary of this chapter.

5.1 Five Tiers Architecture for 5G Smart cities

There is no doubt that 5G is going to connect IoT device and transform dummy equipment into smart ones. However, smart warehouses, malls and factories are currently facing major challenges managing their assets especially when they are scattered around the entire sites. First, assets such as forklifts, mobile shelving systems and inventory scanning devices are of high value that can be easily lost if the staff either change shifts or forgot to place back equipment's. Second, waste management also represents a challenge especially when the bins are filled with products that can go for days or weeks without being picked up by the waste management teams. To prevent these scenarios from happening, we propose an architecture for positioning as a service for complex environment. In this section, a five tier novel architecture is presented for location management using Big Data and machine learning. Figure 5.1 depicts different components of this architecture. These different components belong to different planes as shown in Figure 5.2.

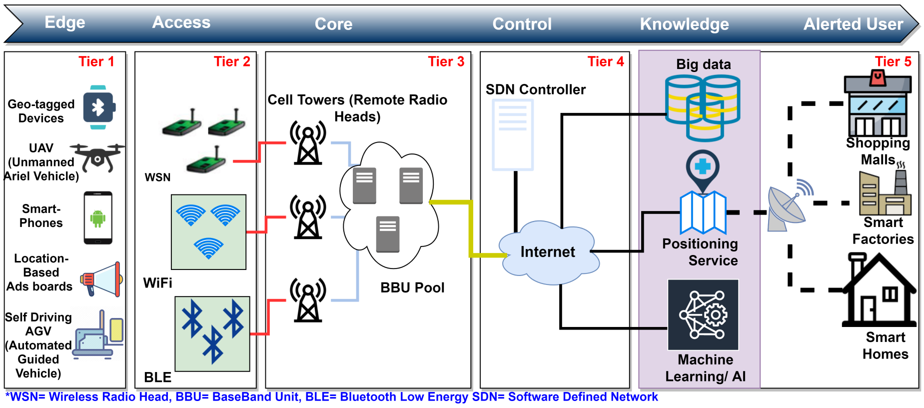


Fig. 5.1 Positioning as a Service for 5G IoT networks

5.1.1 Data Plane

The Data plane, as suggested by 5GPPP [153], works by decoupling the hardware and software components. From an SDN (Software Defined Network) prospective, the aim of this separation is to move certain network functionalities to a distributed softwarized subsystems. Thus, the softwarized programmable networks can be realized. The new 5G C-RAN architecture is one example of this decoupling concept where several RRH (Remote Radio Heads) antennas are deployed and interconnected to a single BBU (Base Band Unit). The architecture suggested in this work follows similar patterns by providing a decentralized positioning as service of massively connected hardware equipment in complex indoor environment. This plane provides data links to connected network hosts.It consists of a set of hardware and software nodes. A software node can either be a virtual switch like Open Vswitch [154] or a cloud-based BBU (Base Band Unit), while a hardware node can be a C-RAN, RRH (Remote Radio Head) antenna, a WSN , a WiFi 6 hotpot, a BAN (Body

Area Network). In Figure 5.2, the data plane represents all elements from tier one to tier three illustrated in Figure 5.1.

Network Edge

the network edge slice compromises of network-connected hosts such as inventory scanning devices, indoor operating vehicles(Autonomous and semi-autonomous) and tagged personnel. The tracked devices usually come with RFID, WiFi or BLE capabilities enabled in them. The slice acts as a signal transmitter for the positioning service in the knowledge plane. Every single node on this edge can be viewed as user equipment that needs to be tracked.

Network Access

In the second tier, network access consists of a set of networks such as Wireless Sensors (temperatures, humidity etc.), BLE and WiFi Networks. These Wireless networks bands in 5G are expected to range between 1Ghz and 6 Ghz. These technologies can either be used together or separately during the radio planning process of the positioning. It is suggested a combination of two or three from these technologies to get better accuracy in [101].

Network Core

The third tier consists of 5G Cloud Radio Access Network. This a unique 5G concept divides the Radio Access Network into two separate entities: an RRH antenna and BBU unit placed on the cloud. An implementation of this concept is mentioned in Section 5.3.

5.1.2 Control Plane

This plane, as proposed by 5GPPP [153], includes Software Defined controllers responsible for orchestrating the network and managing the packets flow. Usually, this plane is reserved for SDN controllers like OpenDaylight [155]. Its functionalities can be further expanded to include event-triggered geo-fencing options through out writing or blocking flows to a specific connected device based on previously defined geographical fences.

Network Control

The Software defined nature of 5G makes it necessary to have a control plane. Tier four includes an SDN (Software Defined Network) Controller responsible for managing network flows and packing matching and blocking. The role of this slice is to patrol the incoming and outgoing traffic in a 5G environment.

5.1.3 Application Plane

From the SDN architecture, an application plane includes an application built on top of the control plane. As shown in Figure 5.2, we developed an application to collect signal data and aggregate them. The functionalities of this application are discussed further in Section 5.2.

5.1.4 Knowledge Plane

This plane has been added to the original architecture to serve the purpose of decentralized positioning. As depicted on Figure 5.2, this plane is made up of four components: Data Aggregation and Standardization Gate, Position Visualizer, Historical Big Data Aggregator and Machine Learning Engine.

The knowledge plane is a member of last tier. Tier five concerns the positioning service or the knowledge plane and the service/alerted users. The knowledge slice consists of three main components: Machine Learning/AI engine that conducts the modeling, a positioning service for both live and historical location tracking and a Big Data component to store both historical data and the positioning model parameters.

The alerted users are the second members of tier 5. They are the system users and they have direct access to the positioning service but no direct access to the Machine Learning engine or the Big Data repository. The alerted users can be systems like a mall management system, a smart factory operation application or a smart home application. The next section covers the functional architecture of this framework and the different interactions between each component.

5.2 Knowledge Plane Framework Components

In this section, as previously mentioned, we have extended the original architecture introduced in [153]. Furthermore, we demonstrate the different components of the knowledge plane and their functionalities. The plane collects and store signal data from various 5G IoT sources using client collector to provide positioning as a service. Figure 5.2 illustrates the proposed plane along with its interconnections with data, control and application planes.

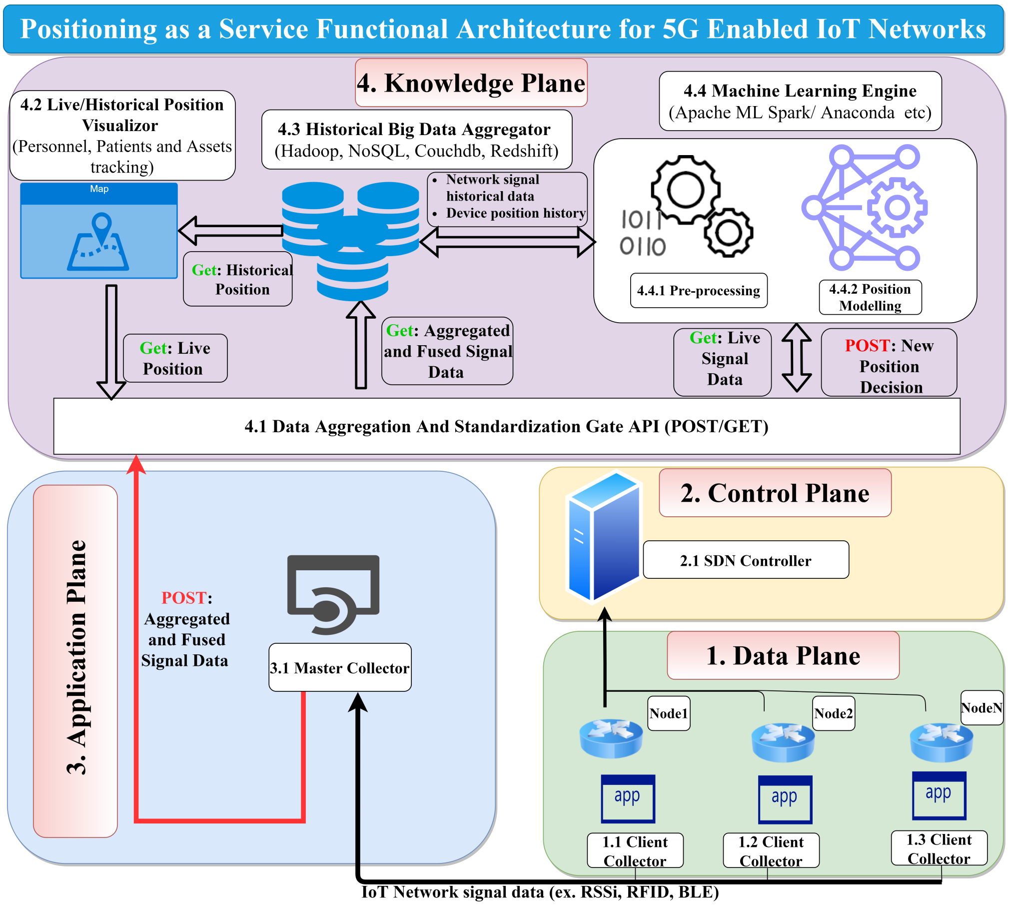


Fig. 5.2 Positioning as a Service architecture for 5G IoT network

5.2.1 Clients Collector

This application is deployed on the UE (User-Equipment) on the edge of the network with the purpose of collecting wireless signal data and send it to the master collector periodically. It runs as a daemon while establishing a reliable secure shell connection with the Master Collector application as show in Figure 5.3 . An example of a UE can be either a handheld scanning devices that supplies personnel with the necessary information about the inventory status or a Wearable Tagging device deployed to locate the staff within buildings. The main function of this component is sending RSS and other signal data to the Master Collector to be aggregated. The following subsection explains thoroughly this client application.

5.2.2 iFuse: RSS Signal Collector for Bluetooth and WiFi

As a Proof-of-Concept (PoC), an application has been developed from scratch to perform measurements for various scenarios and radio technologies in this research. As shown in Figure 5.3, iFuse stands out as a hybrid RSS (Received Signal Strength) signal collector, designed to seamlessly operate with both Bluetooth and WiFi technologies. This application was developed in Java programming language using Kootlin Android application framework. iFuse is equipped with a plethora of features, making it very useful for signal gathering and analysis. The following are the key features incorporated:

1. **Dual-Mode Connectivity:** iFuse supports both Bluetooth and WiFi, ensuring versatility in signal collection across diverse wireless communication protocols.

2. **Real-time Signal Monitoring:** The device provides instantaneous monitoring of RSS signals, enabling users to promptly assess signal strength variations and fluctuations.

3. **Extended Range Coverage:** iFuse leverages advanced signal processing capabilities to extend its range coverage for both Bluetooth and WiFi signals, ensuring a comprehensive understanding of signal behavior.

4. **Data Logging and Analysis:** iFuse includes robust data logging capabilities, facilitating the recording and analysis of signal strength data over time for long-term monitoring and trend analysis.

5. **User-Friendly Interface:** With an intuitive and user-friendly interface, iFuse ensures accessibility for users of all expertise levels, facilitating easy navigation through the configuration and data extraction processes.

6. **Battery Efficiency:** Unlike GPS based signal collectors,iFuse is designed with energy efficiency in mind, it optimizes battery usage, extending its operational lifespan—particularly crucial for applications requiring prolonged usage.

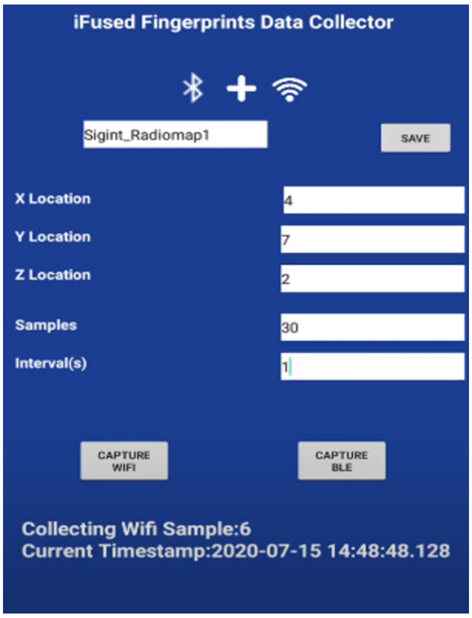


Fig. 5.3 Client collector android application

In summary, iFuse presents itself as an effective RSS signal collector, offering features tailored for both Bluetooth and WiFi technologies. Its dual-mode connectivity, real-time monitoring capabilities, extended range coverage, and user-friendly interface, make iFuse as a powerful tool for signal analysis and optimization in various wireless communication environments.

5.2.3 Master Collector

The Master Collector receives RSS signal data from several IoT application collectors. First, it establishes and maintains a reliable and secure (TCP, SSH) connection with one or multiple client collector on the Data plane. Second, it aggregates the fetched data and stores centrally for location estimation and visualization at the knowledge plane level as demonstrated in Figure 5.4.

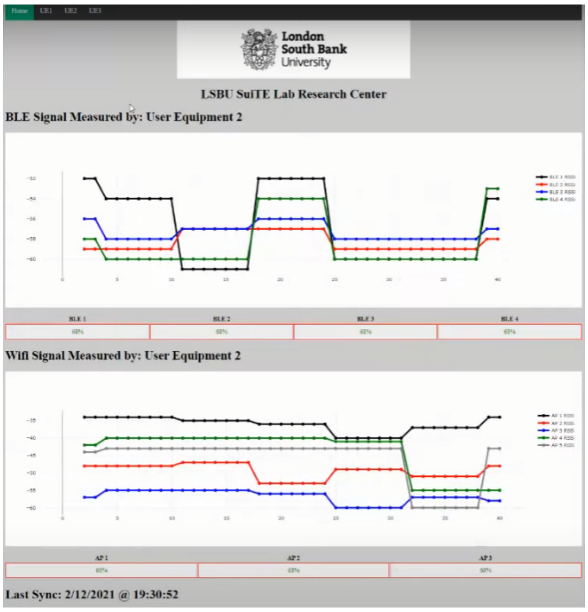


Fig. 5.4 Master collector web application

5.2.4 Data Aggregation and Standardization Gate

To ensure the data received as standardized and unified, an API (Application Programming Interface) platform has been created to service data in a structure manner to the different components of the knowledge plane. The platform has been created used Flask web-server on Python version 2.7. The API acts as a link between the application plane and the positioning knowledge plane. This component receives data via a POST request and serve the available data via a GET request.

5.2.5 Machine Learning Engine

This component performs data pre-processing, offline and online training. It builds positioning model capable of locating several assets and personnel within the designated environment. The end results is an accurate location for each tracked device. The tasks involved in this components are: Pre-processing, offline training, online training, positioning modeling.

- Pre-processing: In this sub-component, a staging area is created for the model the training units. It performs data acquisition, data quality checks and validations, imputing and standardization. Typically, 70% of the overall process time is spent on this phase.

- Offline Training: Once the pre-processing tasks are completed, the offline training starts by dividing the data into training, validation and testing for the machine learning model.

- Online Training: This sub-component validates the positioning accuracy of the model built during offline training. This can be in the form of real-time signal data fed from the client collector of the IoT devices.

- Position Modelling: positioning modelling constructs a model using a machine learning library such as Keras, Pytorch or Tensorflow [130]. It learns from the fed dataset, and generates a model for online position estimation. There might exist several models if the localization area consists of complex set of buildings.

5.2.6 Historical Big Data Aggregator

In this plane, Big Data supports two use cases. On one hand, it stores offline training and prediction performed by machine learning engine in a data repository. Network signal data collected from the Aggregator API are processed into a individual time-series and stored centrally. On the other hand, the repository provides the historical visualizer with time-stamped locations of the devices connected to the positioning service. A Cloudera-HBase server is used for this purpose.

5.2.7 Live/Historical Position Visualizer

A web-based data visualization / dashboard tool has been developed to have a global view of assets tracking. The main two services offered are the following: live location and historical location of people and devices. Position visualizer makes use of the data aggregation API to get the live location of the tracked device while it uses Big Data Aggregator to show the historical position of each device.

5.2.8 The System Workflow

As presented in Figure 5.2, the steps followed to achieve positioning as a service are the following:

Step 1: The client collector sends RSS signal collected from the surrounding network.

Step 2: The Master Collector receives the data after establishing a connection with the Client Collector and post it to the data aggregation API.

Step 3: The data aggregation API sends the aggregated signal data to the big data aggregator.

Step 4: Machine learning engine requests the signal data from the API platform and returns a set of 3D position points and their corresponding IoT device ID to the data aggregation API.

Step 5: The machine learning engine stores the received signal data and the estimated 3D position for each IoT device into the big data repository.

Step 6: The live/historical position visualizer gets the current position for each IoT device.

Step 7: The live/historical Position visualizer sends GET request to the data aggregation API for the current position of each IoT medical device.

Step 8: The live/historical Position Visualizer requests historical data stored by the machine learning engine into the big data repository to be presented in a graphical form.

5.3 Indoor Positioning for complex environment: Implementation and Results.

In this section, we explain the steps followed to set up the simulation environment for 5G IoT Network and the 3D positioning model implementation.

5.3.1 Network Setup

The network setup provided in this experiment consists of a set of hardware and software components put together to emulate an IoT network in 5G environment. The setup is used to leverage signal data for the purpose of 3D positioning.

5G Wireless IoT Network

In this test environment, we consider an outdoor to indoor 5G wireless network, emulated by typical IoT network with Zolertia RE-Mote Revision B nodes as illustrated in Figure 5.5. This WSN is a typical network found in a smart buildings as illustrated in tier 2 Figure 5.1. The Zolertia devices measure the temperature of the rooms, the pollution level, the humidity etc. We have deployed five nodes in this testbed. We have constructed a radiomap from this environment following the steps mentioned in [156]. The database of RSS signal with corresponding location reference points will be used to create a positioning model in the Machine Learning Engine component.

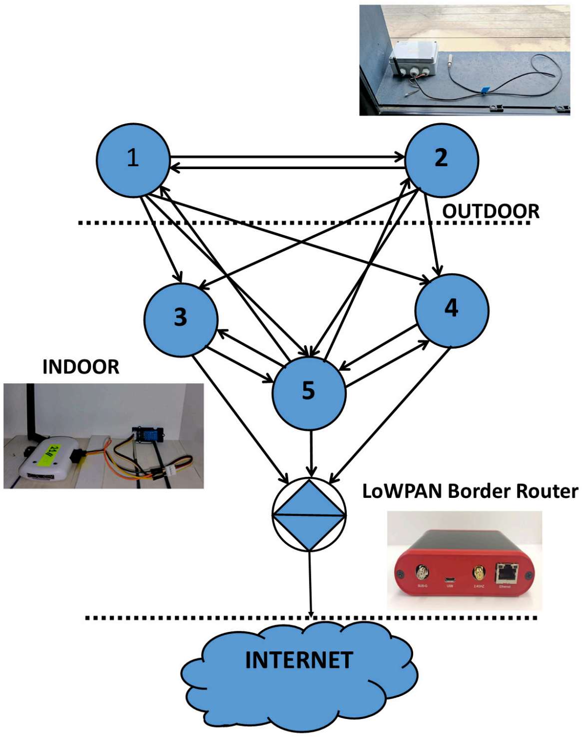
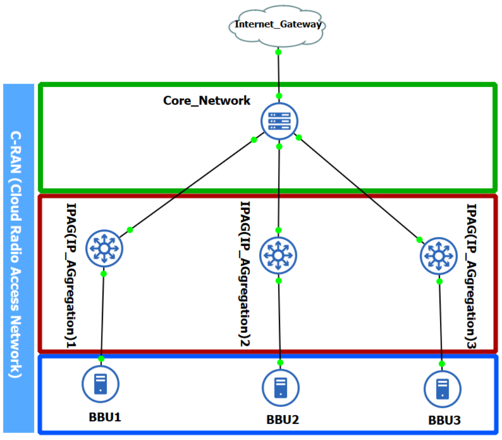


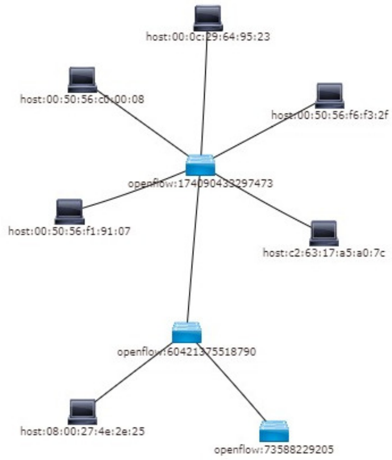
Fig. 5.5 Network setup topology

5G C-RAN on GNS3 Emulator

5G C-RAN is made up of two main components: A RRH (Remote Radio Head) and a BBU (BaseBand Unit). The former is responsible for handling the analogue signal processing functionality while the later performs digital packets processing. To build this concept, we have used GNS3 version 2.2.6 [157], an open source network emulator. The latter, as shown



(a) 5G emulated C-RAN testbed on GNS3



(b) WSN and GNS3 emulated 5G C-RAN connected on OpenDaylight

Fig. 5.6 5G C-RAN setup on GNS3 and WSN connected to OpenDaylight SDN controller

on Figure 5.6a, the BBU component is placed on a cloud environment connecting it to the core network.

OpenDaylight Controller

The OpenDaylight [155] is a controller used to patrol the incoming and the outgoing traffic in a network. To make the testbed support a SDN (Software Defined Network), each node has Open vSwitch [154] installed on it. Each Open vSwitch on the C-RAN is connected to the OpenDaylight controller via the openflow port number 6633. Figure 5.6b shows how a group of 5 Zolertia RE-Mote Revision B node is connected to the C-RAN in blue. The interface shown is from the controller topology view of OpenDaylight.

5.3.2 3D positioning simulation

The concept of Indoor Positioning can be implemented on various types of environments and usage scenarios involving both person and asset tracking in complex building environment, such as: locating the personnel during their shift and monitoring the assets arrangement inside the building. In this 3D positioning simulation, a DNN and RSS fingerprint-based localization approach has been implemented in a 5G IoT setup testbed as previously discussed in Section 3.2 of Chapter 3.

5.4 Chapter Summary

Chapter 5 introduces a novel architecture for providing positioning services in complex indoor environments. The primary motivation for this architecture is to address the challenges facing smart warehouses, malls, and factories in managing their assets and ensuring efficient waste management in large, scattered sites. The proposed architecture is designed to leverage big data and machine learning for location management in 5G IoT networks.

The key components of this architecture are organized into five tiers.The workflow of the system involves data collection from client collectors, aggregation, machine learning modeling, and visualization. A 3D positioning model is created and trained using DNNs, allowing for accurate location tracking.

The chapter also presents a simulation setup for the 5G IoT network and the results of the 3D positioning simulation. It discusses the data collection, pre-processing, modeling, and analysis, showing that the proposed 3D model outperforms other models like KNN and SVM.

In conclusion, the chapter introduces a comprehensive architecture for indoor positioning as a service in 5G IoT networks, addressing complex indoor environments. The proposed architecture leverages big data, machine learning and 5G IoT signal data to provide accurate location management, and the simulation results demonstrate its effectiveness. Future work may involve extending this concept to cover more outdoor-to-indoor positioning scenarios and heterogeneous data sources.

Chapter 6

Conclusion and Future Work

Accurate indoor positioning for both people and assets is a crucial factor for provide a variety of improved location-based services to the military and civilian sectors. These services include real-time tracking of friendly and enemy forces, addressing threats and managing crises, coordinating first responders during natural disasters, and serving various civilian applications in fields like healthcare, transportation, marketing, finance, commerce, energy, and more.

In the age of 5G IoT, rapid and technological advancements have made 3D indoor positioning a prominent and continuously evolving research area where the primary challenge lies in improving accuracy and ensuring reliable performance. In this regard, researchers have explored aspects such as self-improvement, adaptation to environmental changes, minimising energy consumption, and reducing runtime complexity. These studies are carried out in a landscape characterised by heterogeneous wireless technologies and a wide range of radio and nonradio parameters.

Among the prevailing wireless technologies used for indoor localisation in 5G IoT networks, IEEE 802.11 and IEEE 802.15 stand out due to their popularity and cost-effectiveness. Regarding the dominant indoor localisation technique, fingerprinting occupies a prominent position, as concluded by the research outlined in Chapter 2. This has been the rationale behind the positioning techniques and technologies adopted in this thesis.

In Chapter 3, we have proposed a novel approach for 3D Indoor Localization using DNN cooperative networks algorithms implemented on 3D multi-layer radiomaps. To emulate 5G infrastructure IoT indoor Scenario, an IoT network is interconnected to an experimental 5G C-RAN. Using only an offline fingerprint database, we have also demonstrated how the proposed model has outperformed industry traditional models such as KNN. We have accurately implemented this model to the indoor environment. If the steps shown in Figures 3.1 and 3.7 are properly followed, a reliable and fast 3D localization can be achieved. This concept can also be further developed to cover more complex indoor positioning scenarios, involving radio data from heterogeneous network (HetNEt) such as 5G microinfrastructure (Microcells, femtocell, picocells,etc.). Finally, the proposed DELTA model works very well with RSS based IoT and WSNs. Thus, a possible extension of this work could be improving the model by including information fused from other networks such as WiFi and BLE as explored in Chapter 4. Another research direction could be experimenting with more vertical layers. and adding floor level detection for buildings with multiple floors.

In Chapter 4, we have proposed a novel algorithm for improved indoor positioning in 5G IoT networks. The proposed approach uses IQR to deal with outliers and hybrid radiomap to reduce the labour cost incurred during the data collection phase. Additionally, we have demonstrated how cooperative machine learning localisation can be implemented on top of this technique. Using this approach, we have shown how information fusion implemented on 3D multilayered radiomaps can be used to reduce the localisation error to submeter in 2D, and 91% classification rate in 1D. This result can be achieved in similar environment if the steps in Figure 4.1 is followed. This concept has the potential for expansion into more intricate indoor positioning scenarios, encompassing diverse radio data sources from a heterogeneous network like 5G microinfrastructure (including microcells, femtocells, picocells, etc.). Additionally, our proposed K-DNN model demonstrates strong performance with RSS-based IoT and WSNs. As a result, our future endeavours will focus on enhancing the model by integrating data from different azimuth angles (45 °, 90 °, 180 °, and 360 °). Another avenue of research could involve incorporating floor-level detection for buildings with multiple stories.

Throughout Chapter 5, we have concluded our contribution to body knowledge by introducing the knowledge plane to provide PaaS for the 5G IoT network in an indoor environment. We have also demonstrated how this can be implemented in the use case of localisation for complex buildings. This concept can also be implemented in other smart city use cases such as stadiums, malls navigation systems and indoor AGV(Automated Guided Vehicle) control. As for future work, other radio technologies can be implemented to extend the data plane of this architecture. lastly, implementing localisation rules like smart geofencing is also be a potential research direction.

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