Wi-Fi Based Automatic Fingerprinting

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Wi-Fi Based Fingerprinting Data Automatic Generator And Research Tool Development

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1 Introduction

As it has been discussed on the previous chapter, the location fingerprinting technique consist on matching the *fingerprint* of some characteristic of a signal that is location dependent. The characteristic chosen for this work is the received signal strength (RSS) of each Wi-Fi access point available in the mapped area. There are two stages for location fingerprinting: offline stage and online stage (also known as run-time stage). The offline stage consists on performing a survey of the environment where location coordinates and respective signal strengths from nearby access points are collected. Subsequently, during the online stage, a location positioning technique uses the currently observed signal strengths and previously collected information to figure out an estimated location.[1]

1.1 Justification and Objectives

The main challenge to the techniques based on location fingerprinting is that the received signal strength during the offline stage could be affected by several errors committed by the person who does the measurement in addition to measurement ambiguities caused by time and space variability of the environment, type and orientation of used antenna, etc. Besides the potential problems during the measurement, this stage requires the presence of a physical person with technical equipment and experience to measure every coordinate of the mapped area. Furthermore, the data acquired in this stage is discrete and fixed, once it is collected, there is no way of getting more data without a new environment survey. This problem is especially inconvenient when the environment changes after the survey or a higher resolution of data is needed because it would require new data acquisition by an expert with special equipment.

Fingerprinting technique represents a reliable way of getting accurate position information inside Wi-Fi networks but its data acquisition stage makes it slow, static, expensive and hard to scale. In order to fix this disadvantage, a new technique of data acquisition is presented.

The goal of this subproject is to design a system capable of calculate the RSS level of each Wi-Fi access point at every point from a discrete amount of points inside an area.

1.2 Methodology

This section presents the methodology followed in order to achieve the main goal of this project which is, design a system capable of calculate the RSS level of each Wi-Fi access point at every point from a discrete amount of points inside an area:

1. A deep research of how RF signals will be performed, specifically in a frequency of 2,4GHz, performs on indoor environments.
2. From this research the most reliable mathematical models of signal propagation will be obtained and will be tested to retrieve the one that get more accurate predictions.
3. Once the appropriate model is selected, a tool capable of perform every Wi-Fi related functionality of this project will be developed.
4. Once this tool is developed, the selected model will be implemented as a software module inside this tool to, not only get advantage from other modules of this project such as the Map Framework, but also be used as a service framework for this modules too, specially the Fingerprinting Location Framework.
5. Finally, several test will be performed in order to verify the reliability of the implemented module.

2 Indoor Signal Propagation

Predicting the propagation of electromagnetic waves has always been a difficult task. It is influenced by many factors in the environment, and the signal from the transmitter usually reaches the receiver by more than one path, making the prediction more complex. This is most evident in indoor environments where the receiver most likely does not have a direct line of sight to the transmitter, but is reached by a large number of weak rays, making the prediction process extremely difficult [2] It is essential to understand the nature of electromagnetic waves propagation in order to predict some of its values.

2.1 Nature of Signal Propagation

The three main mechanisms of radio propagation are attributed to reflection, diffraction, and scattering. These three effects cause distortions in the radio signal that suffers attenuation due to losses in its propagation [3].

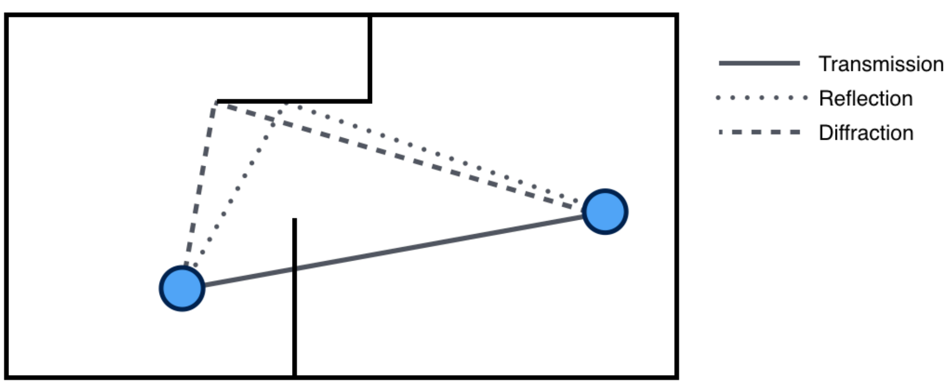

Figure 1 - Transmission, reflection and diffraction representation

2.1.1 Reflection and Transmission

When the medium through which a wave travels suddenly changes, the wave often experiences partial transmission and partial refection at the interface. Reflection and transmission often occur at the same time. Transmission permits the passage of wave, with some or none of the incident wave being absorbed. Reflection is a wave phenomenon that changes the direction of a wave front at an interface, which has very large dimensions when compared to the wavelength of the propagating wave, between two different media so that the wave front returns into the medium from which it originated. The amplitude, phase and polarization of the reflected wave depend on material parameters of the reflecting medium and on the surface irregularity.

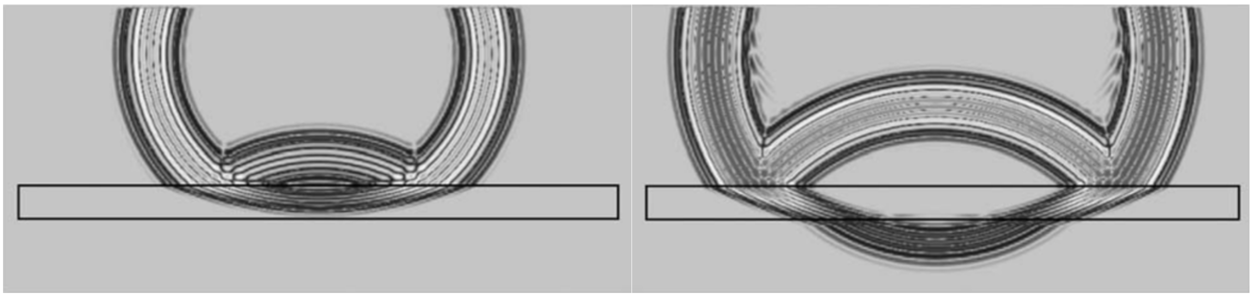

Figure 2 - Wave transmission on a lossy dielectric [4]

2.1.2 Diffraction

The diffraction process in ray theory is the bending of light around the corners of an obstacle or aperture into the region of geometrical shadow of the obstacle. In this case behind the corner of a wall or over office separators. Diffraction phenomenon depends on the size of the object relative to the wavelength of the wave.

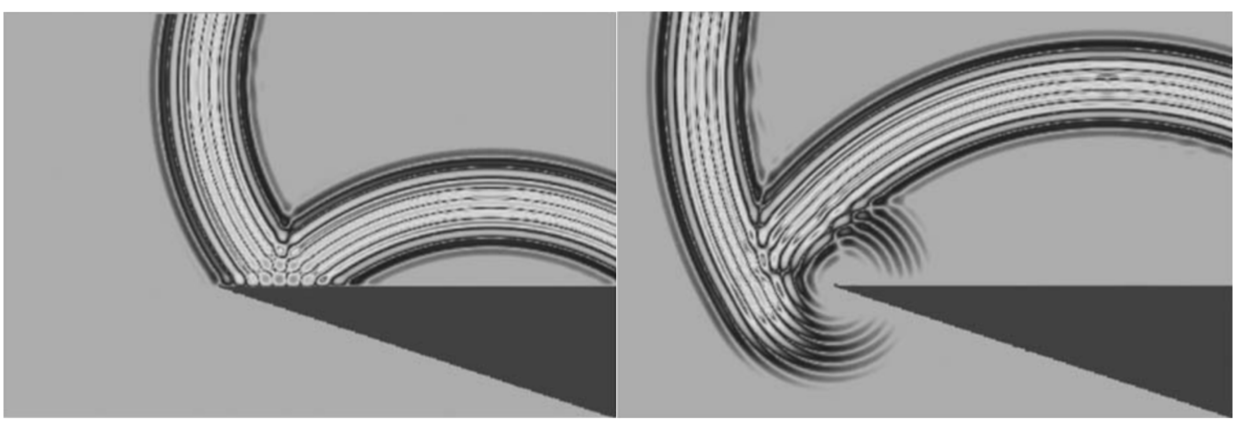

Figure 3 - Diffraction on a lossy dielectric wedge[4]

2.1.3 Scattering

The scattering phenomena is a general physical process where some forms of radiation are forced to deviate from a straight trajectory by one or more paths due to localized non-uniformities in the medium through which they pass. Rough surfaces and finite surfaces scatter the incident energy in all directions with a radiation diagram which depends on the roughness and size of the surface or volume. The dispersion of energy through scattering means a decrease of the energy reflected in the specular direction. [4] Figure 4, shows how electromagnetic radiation and electrons interact comparing scattering phenomena between reflection and refraction.

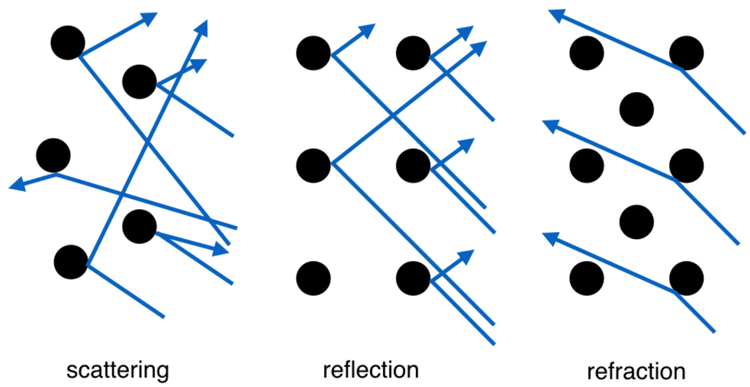

Figure 4 - Scattering effect compared with reflection and refraction

2.1.4 Fresnel Zone

In addition to the three main mechanism, it must be taken into account the different Fresnel zones effect. A Fresnel zone is the locus of points (R) around the source (S) and an observation point (0b) such that the phase on the path S-R-Ob equals the sum of the phase on the shortest distance S-Ob plus an additional constant.[5]

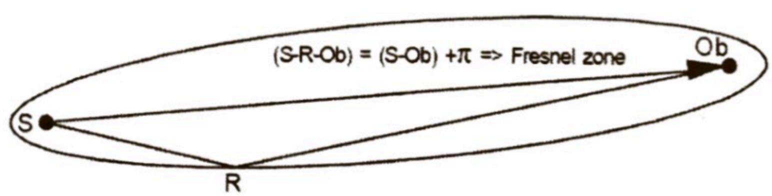

Figure 5 - First Fresnel zone

This effects, together with the multi-path and diffraction caused by the corners, are very difficult to evaluate. However, there are many publications about mathematical models of indoor radio propagation able to evaluate its behavior [6] [7].

2.2 Propagation Modelling

Indoor environments present some special difficulties to the investigation of propagation phenomena. This makes indoor propagation modeling one of the most complicated tasks in this field. A reliable indoor propagation model requires a detailed description of an indoor scenario including furnishing, doors, constitutive electrical parameters of used materials, etc. Finding a balanced trade-off between a model complexity (computation time, requirements on input data, etc.) and reasonable accuracy is a challenge.[8]

A propagation model is a set of mathematical expressions, diagrams, and algorithms used to represent the radio characteristics of a given environment [9]. Quite a large number of indoor propagation models can be found. These models can be roughly divided into three categories: empirical, deterministic and stochastic.[8]

Deterministic or semi-deterministic models are primarily based on electromagnetic wave propagation theory being as close to physical principles as possible.

Most of the models known as ray tracing or ray launching are based on geometrical optics. Some simplifications lead to viewing the radio wave propagation as optical rays.

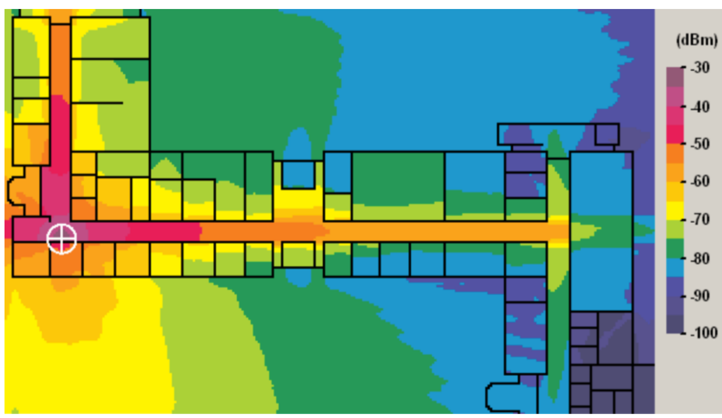

Figure 6 - Coverage prediction by a deterministic model [10]

The outputs of deterministic models show an excellent site-specific accuracy. Figure 6 shows the example of the deterministic model coverage prediction. It can be seen that diffraction and wave-guiding effect of the corridor are considered. Since the multi-path propagation can be fully described, other space-time properties like time delays, angles of arrival etc. can be determined. On the other hand, for a common planning only the propagation loss is sufficient and the cost for the accuracy is enormous. The sophisticated predictions are very time consuming and require detailed description of the scenario (3D geometry, constitutive material parameters), which is not easy to obtain.[8] That is why the deterministic models are not very popular in common praxis. Several deterministic models can be found in literature such as the

FDTD (Finite Difference Time Domain) method [4],SRT (3D Standard Ray Tracing) [11] and IRT (3D Intelligent Ray Tracing)[12]

Stochastic models, on the other hand, model the environment as a series of random variables. These models are the least accurate but require the least information about the environment and use much less processing power to generate predictions.[13]

On the other side, the empirical models are primarily based on statistically processed representative measurements. These models are mainly used to predict the path loss and are easy and fast to apply, and its prediction is usually obtained from simple closed expressions. Empirical models can be split into two subcategories namely, time dispersive and non-time dispersive [14]. The former type is designed to provide information relating to the time dispersive characteristics of the channel i.e., the multipath delay spread of the channel. An example of this type are the Stanford University Interim (SUI) channel models developed under the Institute of Electrical and Electronic Engineers (IEEE) 802.16 working group [15]. Examples of non-time- dispersive empirical models are ITU-R [16], Log-Distance Model [17], Motley Keenan Model [18] and the COST-231 Hata model [19]. All these models predict mean path loss as a function of various parameters, for example distance, antenna heights etc. [13]

2.2.1 Empirical Models

This section describes the features of the main propagation empirical models for indoor environments found in the state of art:

2.2.1.1 Log-Distance Pathloss Model

This is a simple model for prediction of pathloss in an indoor and line-of-sight propagation environment. It shows the linear relationship between the pathloss in decibel and the logarithmic variation of the transmitter and receiver separation [20]. The path loss exponent (n) on which large scale pathloss of random T-R separation depends is a function of the propagation environment while reduced value of n gives lower signal loss. The value of n for free space is 2, it ranges from 1.2 (waveguide effect) to 8 in general.[5]

$$L(d) = L(d_0)_0 + 10n\log_{10}\frac{d}{d_0} + X_\sigma$$

where:

$L(d)$: the average pathloss between transmitter and receiver
$L(d_0)$: path loss at $d_0(dB)$, for a reference distance d_0 at 1 m, and assuming free-space propagation $L(d_0) = 20 \log_{10} d_0 + 20 \log_{10} f - -147{,}55$ where f is in Hz
n: the pathloss exponent, a wider explanation of this variable can be found in the section 2.3.4
d: the separation between transmitter and receiver in meters
$X\sigma$: a normal (or Gaussian) random variable with zero mean, reflecting the attenuation in dB caused by flat fading. In case of no fading, this variable is 0.

2.2.1.2 Propagation Model for Indoor Environments

This model, developed by ITU-R (ITU, 2009), is a radio propagation model for the frequency range 300 MHz to 100 GHz that estimates the path loss inside a room or a closed area inside a building delimited by walls of any form. This model is designed only for indoor environments. The basic model has the following form:

$$L(d) = L(d_0) + N \log_{10} \frac{d}{d_0} + L_f(n)$$

where:[21]

N: distance power loss coefficient
f: frequency (MHz)
d: separation distance (m) between the base station and portable terminal (where d > 1 m)
d_0: reference distance (m)
$L(d_0)$: path loss at $d_0(dB)$, for a reference distance d_0 at 1 m, and assuming free-space propagation $L(d_0) = 20 \log_{10} d_0 + 20 \log_{10} f — 147.55$ where f is in Hz
L_f: floor penetration loss factor (dB)
n: number of floors between base station and portable terminal ($n \geq 0$), $L_f = 0\ dB$ for $n = 0$.

The power loss coefficient (N) and floor penetration loss factor values (L_f), based on various measurement results, are given in Tables 2 and 3 of ITU-R recommendation [21]

2.2.1.3 Motley Keenan Model

This model takes the form of a free space propagation model with attenuation added for each wall, floor, or obstruction encountered along the route. Although this work is focused on 2.4GHz frequency, this site specific model is general enough to accommodate a wide range of frequencies with the appropriate choice of attenuation factors.[22]

This model has the following mathematical form:

$$L(d) = L(d_0) + 10nLog(d) + \sum_{i=1}^{I} k_{Wi} L_{Wi} + \sum_{j=1}^{J} k_{Fj} L_{Fj}$$

where: [18]

$L(d_0)$: path loss at $d_0(dB)$, for a reference distance d_0 at 1 m, and assuming free-space propagation $L(d_0) = 20 \log_{10} d_0 + 20 \log_{10} f — 147.55$ where f is in Hz
n: distance power loss coefficient
L_F: floor penetration loss factor (dB)
L_W: wall penetration loss factor (dB)
k_F: number of floors with the same characteristics
k_W: number of walls with the same characteristics
J: number kinds of floors crossed by the signal
I: number kinds of walls crossed by the signal
f: frequency (MHz)
d: separation distance (m) between the base station and portable terminal (where d > 1 m)
d_0: reference distance (m)

2.2.1.4 COST 231 Multi Wall

The COST 231 Multi Wall Model is considered the most sophisticated empirical model [23]. All walls intersecting the direct ray between transmitter and receiver are considered and, for each wall, individual material properties are taken into account.

This and Motley-Keenan models are very similar due to the fact that they calculate the propagation loss based on path loss in free space added by the loss (attenuation) due to obstacles (walls and furniture).[24] However, his model is differenced form Motley Keenan on how the different floors inside the propagation path are taken into account considering its attenuation as the same value of all the floors present in the area while the second considers every different value.

This model has the following mathematical form:

$$L(d) = L(d_0) + 10nLog(d) + L_F N_F^{\left(\frac{L_F+2}{L_F+1}-b\right)} + \sum_{j=1}^{J} N_{Wj} L_{Wj}$$

where: [24]

$L(d_0)$: path loss at $d_0(dB)$, for a reference distance d_0 at 1 m, and assuming free-space propagation $L(d_0) = 20 \log_{10} d_0 + 20 \log_{10} f — 147.55$ where f is in Hz

n: distance power loss coefficient
L_F: floor penetration loss factor (dB)
k_F: number of floors with the same characteristics
J: number kinds of walls crossed by the signal

N_F: number of floors crossed by the signal
b: floor attenuation factor associated with the floors the signal must cross
f: frequency (MHz)
d: separation distance (m) between the base station and portable terminal (where d > 1 m)
d_0: reference distance (m)

2.3 Model Analysis

All the models analyzed in the previous chapter allows to predict the signal strength level of electromagnetic waves on indoor environments. However, as this project has very specific requirements, not all of them are suitable for it. In this chapter the Log-distance, ITU-R, Motley-Keenan and COST 231 Multiwall Models will be tested to evaluate its suitability for the characterization of propagation in indoor environments. Different characteristics has to be taken into account in order to compare different indoor propagation models, because they have several and different parameters, such as wall's material and thickness, number of floors, etc. Small differences in the parameters values could be reflected in discrepancies on the output values of the different propagation models. To solve this, the following testing methodology has been followed:

2.3.1 Testing Methodology

The methodology followed to test the models defines the different scenarios were the tests will be executed, the equipment used for measuring the signal strength level and the technics used to measure the wall and floor penetration loss factor.

2.3.1.1 Testing Scenarios

Three testing scenarios were chosen, which have different configurations and kind of rooms, such as classrooms, bedrooms, corridors and rooms with several electronic equipment. The reason why the last kind of area is chosen is because it has several materials that could affect severely to the signal propagation. These signal disturbances can have at least two consequences: it might work as a wave guide, for example on corridors, or it might become a considerably lossy obstacle. The three scenarios can be seen in Figure 7

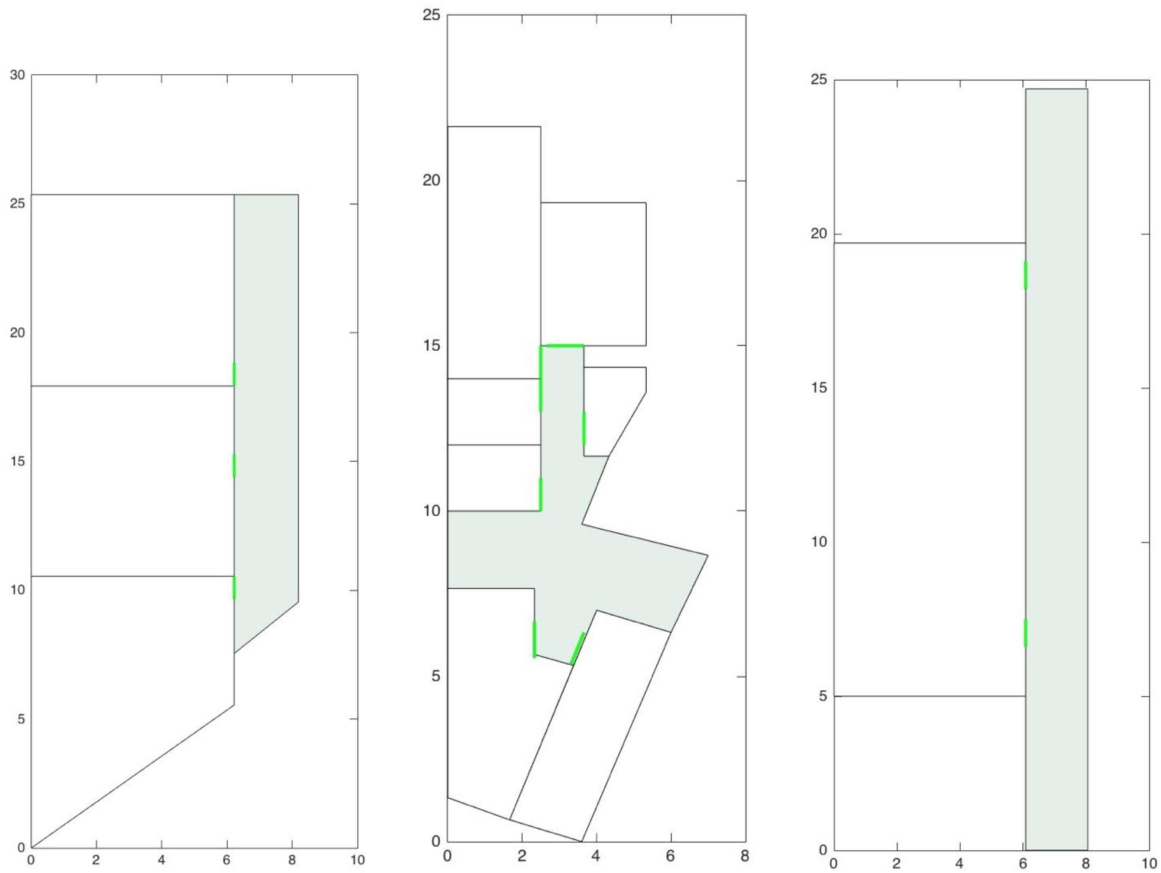

Figure 7 - Three different scenario floorplans

The first one is the section A.1. located on the first floor of FH Campus Wien which is constituted by three classrooms and a corridor. The second is a typical residential floor composed by bedrooms, toilets and a kitchen located on the third floor of a student residence. Finally, the third one is an electrical engineering laboratory constituted by electronic and electrical equipment.

2.3.1.2 Testing Equipment

In order to measure the signal strength level correctly and in a standardized way, a smartphone application has been developed. This application, explained widely on the next chapter, is able to measure the different signal strength levels during time and plot them on a chart and a histogram. This makes possible to see the progress of the signal level over time and get the most accurate level for each position. Besides this, all the tested models has been implemented on a Swift script running on Xcode Playground [25] to calculate all the different model outputs at the same time in order to compare all its results in an easy and fast way.

2.3.1.3 Walls and Floors

The models who consider the influence of walls and floors on the signal propagation needs a loss coefficient value for each wall and floor. Not all of the walls produce the same attenuation in spite of the fact that they are made from the same materials. This variation is produced by the multipath propagation and light of sight effects.

The process of measuring these losses is straightforward. It consists on taking a measure of the signal strength level on the side facing the radio frequency (RF) source and another one in the opposite side. The difference between this two values becomes the loss coefficient of that wall or floor. Unfortunately, this may lead to inaccurate results due to the nature of the signal attenuation.

As the measure instrument, receiver for now on, move away from the RF source, the level of signal received is reduced in a predictable manner. The loss experienced for a 2.4GHz WLAN signal when travelling through free space is shown in the Figure 8.Due to this characteristic, the closer the receiver is to the RF source, the greater is the impact of any errors in distance measurement in the RF readings. However, on a measurement taken at 4 to 5 meters from the RF source, any distance error out at this range will have a much smaller effect in terms of RF level measurements. Because of this, the obstruction should be in a region beyond 4m away from the RF source during the measurement. This provides a reasonable tolerance in terms of the accuracy of the distance measurement.

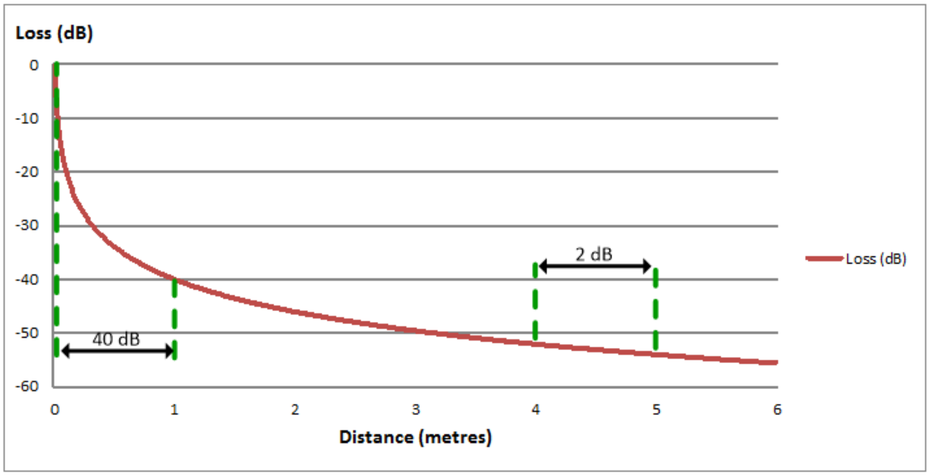

Figure 8 - Variation in rate of loss over distance [26]

2.3.2 Tests

This chapter describes every test made and its results in a standardized way. The aim of these tests is to study and compare every model's result on different situations. The information related to every test consists on a brief description, characteristics of the obstacles of the path, distance between RF source and receiver and the power loss measured compared with the ones obtained from each model. The information and results for the most representative experiments can be found in the appendix 1 in the section 8.1

In this appendix, the path consists on a straight line between the RF source (S) and the receiver (R) and will be represented in the following format:

$$S - d_1 - |n| - d_{(n+1)} - R$$

Were:

S: represents the RF source

R: represents the receiver

d: distance in meters between the point in the left side and the point in the right side.

n: obstacle number. This obstacle's property explanation will be referenced with the same number.

2.3.3 Conclusions

Considering the results of the previous section, the most accurate results were obtained using both Motley Keenan and COST 231 Models. The analysis of the results given by each model

shows that, as expected, Log-distance and ITU-R are not designed to consider wall or floor separation being Log-distance's accuracy great for a clear line-of-sight. Meanwhile, both Motley Keenan and COST 231 Models gives the same results in most of the tests due to its common implementation of free space formula and how they deal with the different wall separation. However, the difference, and key advantage of Motley Keenan Model, lies on how this model handles different floor attenuation. While COST 231 uses the mean of every floor penetration loss factor, Motley Keenan Model considers every different floor's penetration loss factor becoming more accurate with several floor separations.
As a conclusion of this, Motley Keenan Model is the most suitable model for this project.

2.3.4 Test Environment Study

Once the model testing stage has ended, is worth to focus on the pathloss exponent of every scenario. The pathloss exponent can be seen at every model formula as the constant that affects the power loss calculation representing the unconsidered elements of the environment which affects negatively the signal strength. The more chaotic the environment is, the bigger this constant needs to be in order to get more accurate predictions. For the execution of the previous tests, a standardized pathloss exponent has been use. Its value can be found in wireless LAN Network design study [8] in which can be seen different pre-calculated values for each kind of scenario. However, as it doesn't offer a wide variety of values and in order to get the most suitable pathloss exponent for each scenario, a custom study has been carried out for every different scenario.
The main way of doing this study is measuring the most common elements present in each scenario. However, given that the fluctuation of the signal when measuring ranges from X to Y (this range is not fixed but is very representative due to the high amount or measurements done during this project), this method becomes unreliable for measuring attenuations inside this range, in which there are most of the elements present on any of these environments.

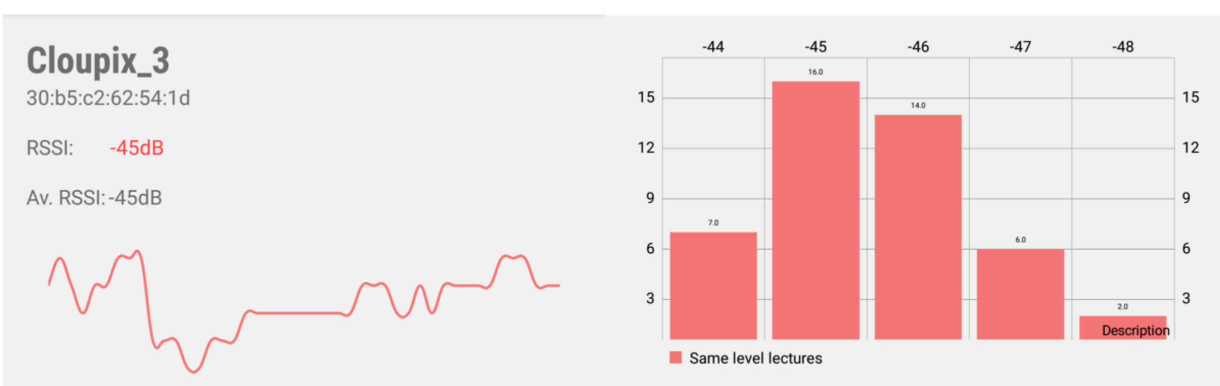

Figure 9 - Fluctuation of signal strength level

To solve this, has been used the implementation of the Motley Keenan Model in the Android app that has been developed for this project. The details of the app and the implementation are widely explained in the chapter 3. This implementation has been used to calculate the predicted signal strength of every Wi-Fi access point at every point of a discretized scenario (See more about this discretization in the section 3.2.1)Using the accuracy score described in the section 3.2.4, it has made several tests to study how the different pathloss exponents affect to every scenario's accuracy. All the test results can be seen in the Table 1.

Pathloss Exponent	Classrooms	Laboratory	Residential
1.0	**8.43**	9.35	15.64
1.1	8.68	8.73	15.37
1.2	9.33	**8.33**	15.20
1.3	10.29	8.35	**15.14**
1.4	11.27	8.63	15.25
1.5	12.56	8.96	15.51

Table 1 - Score values for each pathloss exponent

As this table shows, the values which gives the most accurate results (the highlighted ones) are consistent with the theoretical definition of the pathloss exponent since the complexity of every scenario increases, being the classrooms the simplest one and residential the most complex one.

2.4 Purpose of the Model

The aim of this model is to fill a map with estimated signal strength levels of the Wi-Fi access points available in the area in order to use them during the fingerprinting location stage. However, as this model allows us to get all the possible distances to an element given a signal strength level, it might be thought that it could be used for trilateration instead of fingerprinting. With 3 or more access points, it could generate a map similar to the one shown in Figure 10.

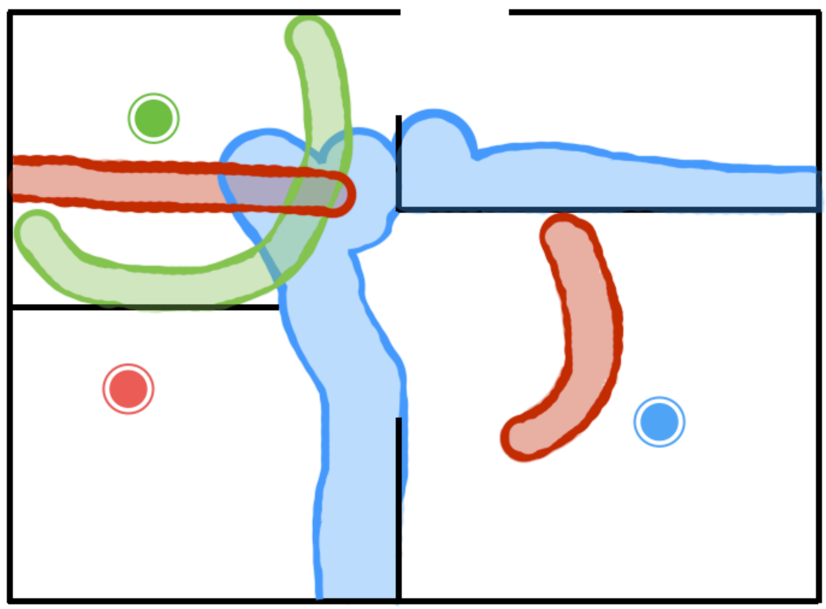

Figure 10 - Location estimation using trilateration technique

Although, this trilateration technique has several key disadvantages that makes it less suitable than fingerprinting for this project. The first and main disadvantage can be found in the amount of computational power is needed in order to get a relative location. [27] The process of getting this location involves the use of several quadratic equations found in the following formula in order to get a location estimation like the one shown in Figure 11.

$$\hat{x} = argmin_{x,y} \sum_{i=1}^{M} [\sqrt{(AP_{x_i} - x)^2 + (AP_{y_i} - y)^2} - \hat{d}_i]^2$$

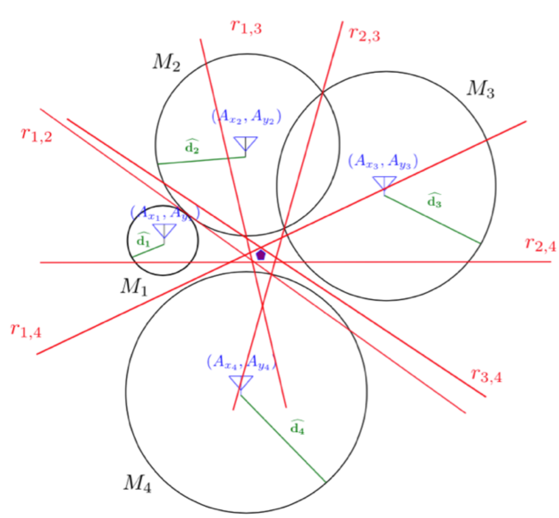

Figure 11 - M quadratic equation nonlinear system representation

Moreover, these quadratic equations needed for trilateration are designed for two dimensional areas. For a three dimensional layouts, even more complex formulas are needed since a spherical area must be calculated. [27]

The second disadvantage can be found in the great fluctuation of the signal strength level that can be get between readings. This variation of values affects in the same way in both fingerprinting and trilateration techniques. However, it has a greater impact on the accuracy for the trilateration technique. [28]
Moreover, while this model allows us to locate an element through trilateration, does not provide any benefit over fingerprinting considering that both techniques needs the same information to get the location.

3 Wi-Fi Location Research Tool

In order to test all the approaches and technology mentioned before, a very sophisticated and specific tool is needed. A portable tool able to provide completely dynamic functionalities to the researchers of this project and the ones who will be involved in the future. Due to the smartphone application development background present in this team, this tool has been developed as an Android [29] application ("app" for now on). Considering this project is focused on developing a system able to provide indoor location positioning on smartphones, building this tool as a smartphone app will provide a closer approximation to the end product making the technology developed easily exportable to the production stage. Even though Android holds 80.7% of worldwide market share [30], the main reason why it has been chosen is because it grants access to the Wi-Fi scanning functionality of the smartphone with a time window between scans of 1 second. Other alternatives, such as iOS [31], has been considered but they has been rejected due to its inability to provide access to any kind of Wi-Fi scanning functionality. The main functionalities this tool offers are surrounding Wi-Fi access point analysis, fingerprinting mapping and real time location.

This tool has been created as an open source project to let other researchers to take advantage of every feature it provides and give them the opportunity of add new ones. The source code of this project can be found in the following referenced GitHub repository [32]

3.1 Wi-Fi Analysis

This section of the app provides Wi-Fi analysis tools to analyze the different parameters of the surrounding Wi-Fi access points. This helps to improve the awareness of how Wi-Fi access points the team is working with works. This awareness will be needed in order to test correctly the different models and approaches mentioned in previous chapters. At the same time, this section is divided in two functionalities:

3.1.1 Access Point List

This section does a Wi-Fi scan every second and lists all the access points detected. Every list row shows access point's SSID, BSSID and current RSSI. Furthermore, it collects all the RSSI obtained and shows it on a chart where X axis represents time and Y axis represents the signal level in dB. This list is constantly sorted by the RSSI showing the access point with a higher level of signal strength at the top of the list.

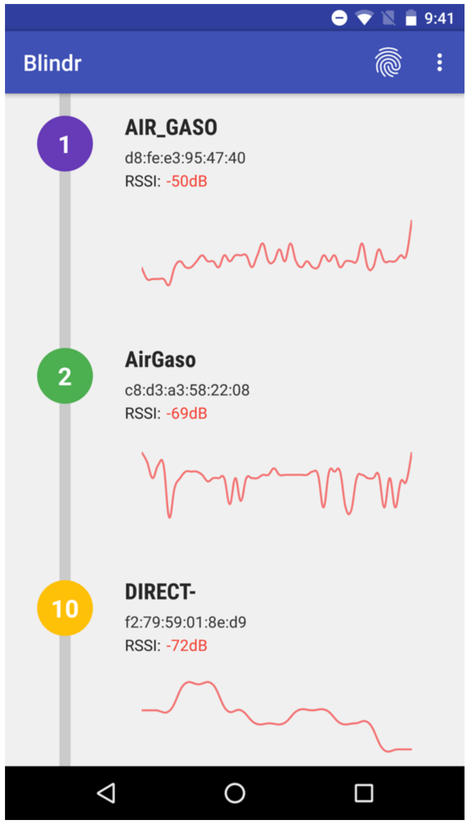

Figure 12 - Access Point List Screenshot

3.1.2 Access Point Detail

The access point detail section shows the information of a specific access point. Besides all the information shown in the list, this section displays the average RSSI and a histogram of all the recorded signal levels. This histogram is updated with every new lecture of signal strength and shows in a clear way. Thus it can be seen the distribution of signal strength level of a single access point providing an easy way to see the fluctuation of this parameter.

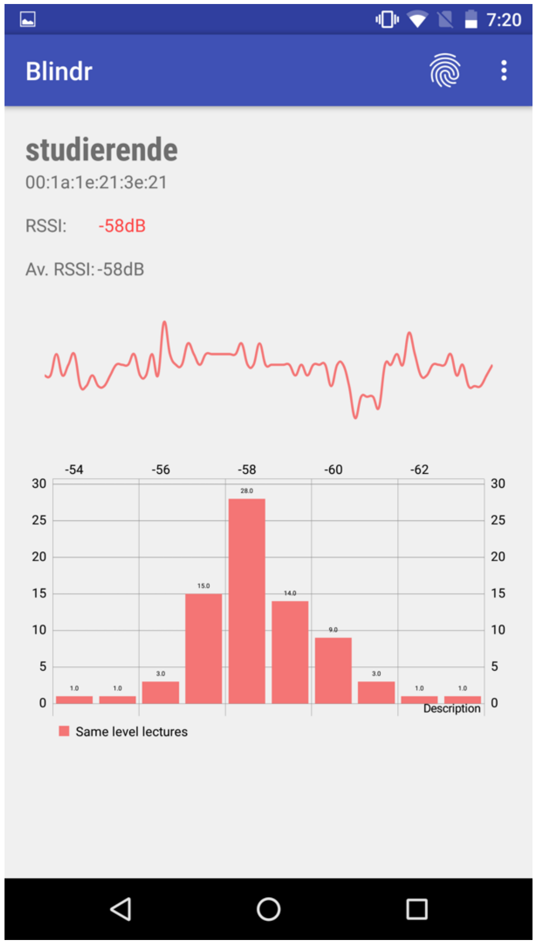

Figure 13 - Access Point Detail Screenshot

3.2 Fingerprinting

This section of the app provides the necessary tools to create indoor maps, fill them with signal strength data and give a real-time indoor location service inside them. The aim of these maps is not to provide any service to the end user but to provide a location assistance during the signal strength data acquisition stage.

3.2.1 Map

This functionality allows the user to create as many custom maps as needed. These maps are placed within a grid where every cell will represent a fragment of the map area. Inside these cells, called "sectors" from now on, the user will be able to draw six possible walls in six different positions. These walls will be represented as four strokes on the outer part of the sector called N, S, E and W and two strokes crossing from one corner of the sector to the opposite called NE_SW and NW_SE (See Figure 14).At the moment, this wall information will only contribute to the visual representation of the map during the fingerprinting stage and will not overlap Map Framework's functionalities. However, this implementation lets the door open to future work to add more features like assigning a wall penetration loss factor to each wall. Furthermore, inside these sectors the user will be able to place the Wi-Fi access points located in the area represented by each sector (See Figure 14). The dynamism of the map will be determined by the resolution of the map, given at the same time by the number of sectors that composes the map.

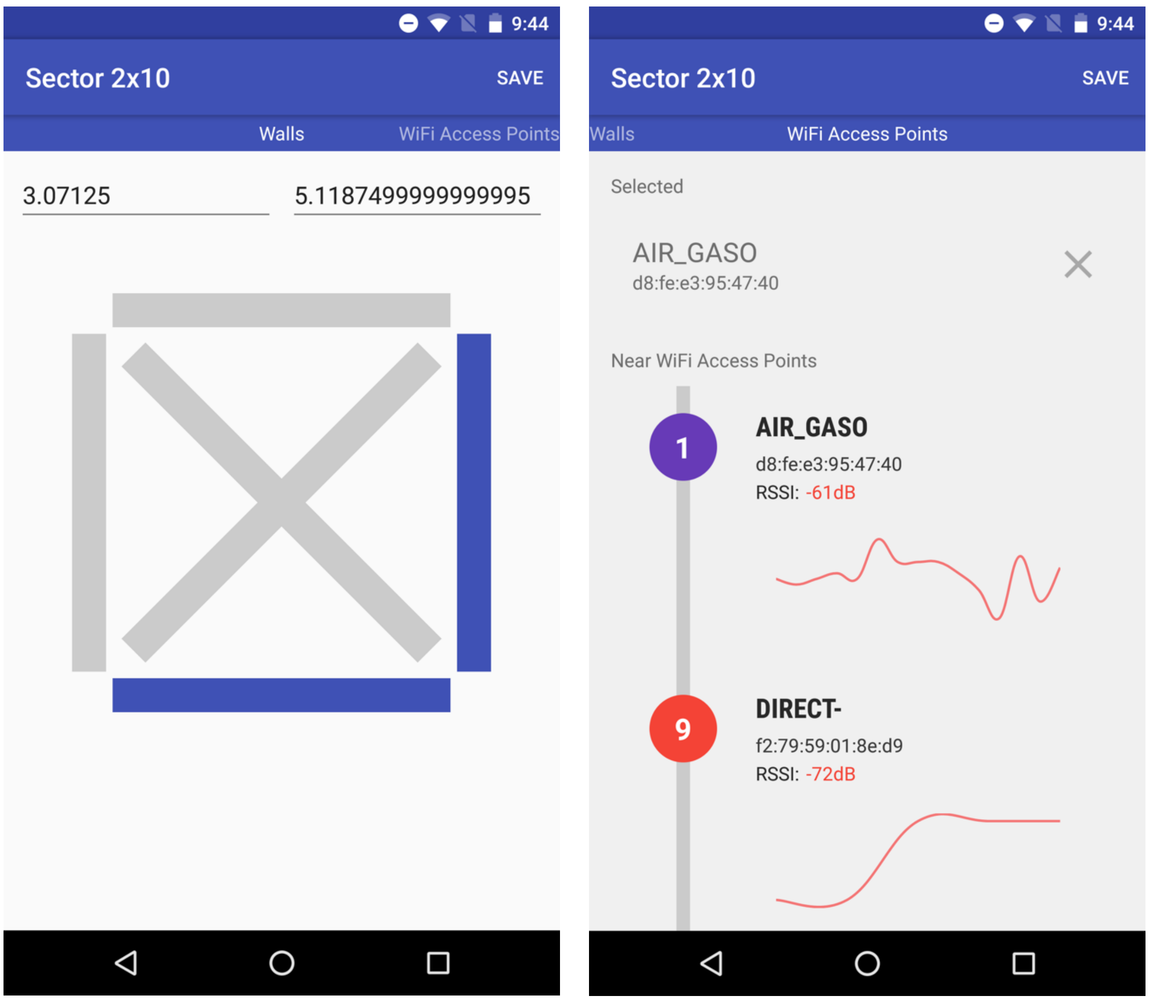

Figure 14 - Sector Configuration Screenshots

This way of representing the maps has both advantages and disadvantages. One of the main advantages is the easiness and speed in which the map is made. However, the lack of precision of the generated map compared with the original area makes the biggest disadvantages of this method. To solve this problem, the user will be able to add each sector's latitude and longitude (in this case, the values for X and Y axis of the Map Framework) associated to the center point of the sector. Knowing that this task could become tedious, has been developed an algorithm capable of generate all X and Y values of the rest of the map sectors once the user has provided these values on the left bottom corner sector. Since every sector's height and width are equal, these values are given by the following formulas:

$$Lat_x = Lat_0 + (H - Y_x) * 2Lat_0$$

$$Lon_x = Lat_0 + X_x * 2Lat_0$$

where:

Lat_x: Value of the Y axis at Map Framework for the sector to be calculated
Lon_x: Value of the X axis at Map Framework for the sector to be calculated
Lat_0: Value of the Y axis at Map Framework for the sector in the position 0,0
H: Height of the map in number of sectors
Y_x: Value of the Y axis at the sector map for the sector to be calculated

Notice that Lat_x requires a conversion of axis due to the difference between Map Framework and the sector map for where the Y axis source point is located.

After several tests, it has been stablished that this method gives a maximum error of 1.2 meters at the most affected sector. This is given by the non-proportionality of the sectors according to the real area. Due to the resolution of dimensions in which this system works, this becomes an acceptable margin of error. However, if this becomes a problem, the system lets to correct every sector's coordinates manually.

3.2.2 Fingerprinting Data Acquisition

Once the map is created, this app offers the possibility of getting and storing all the Wi-Fi signal strength levels form all the access points found in every sector of the map. To do this, the app offers the user a representation of the map where every sector in it becomes clickable. Once the user taps one of the sectors, the app starts getting all the data from the surrounding access points. Due to the RSSI fluctuation between each Wi-Fi scanning lecture and as the signal strength level takes some time until it gets stabilized, several lectures are taken during this process.

All the data acquired during this process is stored in a SQLite database inside the app. The data model can be found in the Figure 15.

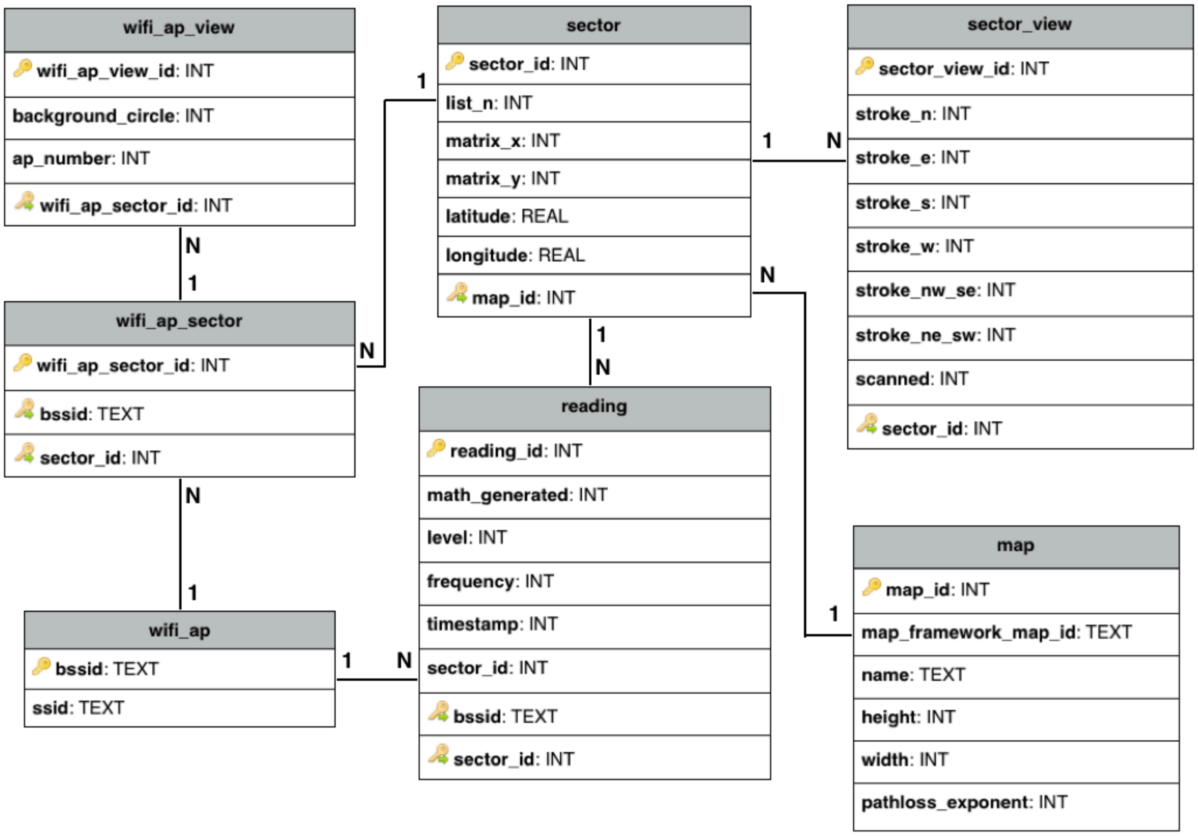

Figure 15 - App Data Model

3.2.3 Mathematically Reading Generation

As it has been explained in earlier chapters, the way the fingerprinting data is acquired is slow, static, hard to scale and the data taken could be affected by several errors committed by the person who does the measurement in addition to measurement ambiguities caused by time and space variability of the environment, type and orientation of smartphone antenna. The following section of the app solves this problem implementing the previously described prediction model in a system capable of fill all sectors with the predicted signal level of the Wi-Fi access points placed in the map.
To achieve this, the Motley Keenan Model has been implemented inside the app to be used on a secondary thread by the reading generator function. Once it is started, this function creates a reading from every Wi-Fi access point present in the map at every sector of the map. Every reading generated here will be marked as math generated reading to be recognized, in the future, by other functionalities of the app. During the process of generation, to satisfy the model's needs, the distance between the Wi-Fi access point and the sector of the reading is calculated. This is a trivial calculation given that every sector's coordinate system is based on

the distance in meters between the center of the sector and the bottom left hand corner of the map which represents the origin of the coordinates. The distance from one sector to another is given by the following formula:

$$d = \sqrt{(x_1 - x_0)^2 + (y_1 - y_0)^2}$$

were:
d: distance in meters
x: value of the x axis of one of the points
y: value of the y axis of one of the points

This method gives one error when it comes to calculate de distance from one sector to the same one. Since the coordinates of every position inside the same sector are the same, the distance obtained is equal to cero. To solve this, the distance obtained will be the half of the distance between the center point of a sector and its corner. At this time, if the distance is shorter than the distance of reference (1m), the signal level will be calculated with the generic free space path loss formula of electromagnetic signal propagation. [7] Once the distance is calculated, the number of walls and floors and its penetration loss factors are needed. To get this information a socket connection is stablished with the Map Framework using the *WALL_LOSS_FACTORS* command of the protocol shown in the section 3.2.7. Unfortunately, the Map Framework does not support 3D mapping therefore none of the floors are considered in this version of the project. Once every data needed is obtained, the predicted signal level is calculated and assigned to the reading.

3.2.4 Procedural Mapping Accuracy Calculator

Once every reading at every sector of the map is calculated, a way of quantify its accuracy is needed. To do this, it has designed a new scoring procedure. In this procedure, the Euclidean distance between every amount of mathematically generated readings and manually obtained readings of every sector is calculated. The sectors with no manually obtained readings are ignored due to its impossible reachability during the reading acquisition stage. To match the number of manually acquired readings for each Wi-Fi access point at each sector with the number mathematically generated readings (one per access point and sector), the mean of the different levels associated to the same access point at each sector is calculated. Once every sector's Euclidean distance is calculated, all this distances are added. In order to make the score comparable with other maps with a different amount of sectors, the sum of all this distances are divided by the amount of sectors with at least one manually obtained reading. This method can be represented through the following formula:

$$S = \frac{\sum_{i=0}^{n} d_i}{n}$$

were:
S: accuracy score of a map
n: amount of sectors with at least one manually obtained reading
d: Euclidean distance of a sector

3.2.5 Real Time Location

This functionality lets the user move through the mapped area while the app predicts its location in the map. To do so, the user must tap the “Navigation” button in the action bar of the app while the desired map is selected and full of fingerprinting data in its walkable sectors. In addition to this, this feature offers the possibility of using mathematically generated readings, manually mapped readings or both at the same time to use as fingerprint data for the map. Once the kind of readings is chosen, the app will start taking Wi-Fi readings of surrounding access points and will use the Fingerprinting Based Location Framework to get which sectors the user is more probable to be in. The app will represent this prediction on the map through five colors, red for the most probable sector and orange, yellow, amber and white for the least. At the same time, the app will send every predicted result to the Map Framework through a socket connection using the *WIFI_RESULT_POSITION* command of the protocol shown in the section 3.2.7

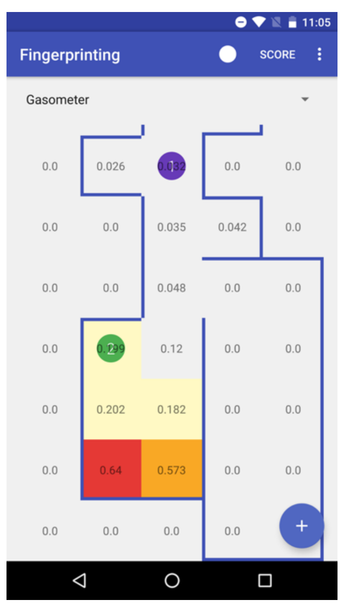

Figure 16 - Navigation Screenshot

3.2.6 Test Recorder

In order to carry out precisely and in an easy way the several tests of this project, a test recording functionality has been developed. This feature allows the user to start the real time location functionality logging every location result obtained using manually mapped readings, mathematically generated readings and both of them at the same time. Every prediction is linked with the timestamp in which has been taken. In order to supervise the prediction results afterwards, the user is able to point on the map in which sector is in at every moment of the test time. At the end of the test, all the data gathered will be exported to the device's root path as a CSV formatted file.

3.2.7 Map Framework Communication Protocol

Due to the fact that in this version of the project, the Map Framework is not a software library able to work locally, an internet communication between the android app and this framework must be stablished. To do so, the following communication protocol has been developed:

Client Command	WALL_LOSS_FACTORS
Server Response	status_code
Client Parameter	map_id
Server Response	status_code
Client Parameter	$x_0;y_0;x_1;y_1$
Server Response	$w_1;w_2;\ldots;w_n$
Server Response	status_code

Table 2 - Wall Loss Factor Protocol Command

Client Command	WIFI_RESULT_POSITION
Server Response	status_code
Client Parameter	x;y;timestamp
Server Response	status_code

Table 3 - Wi-Fi Result Position Protocol Command

Client Command	EXIT

Table 4 - Close Connection Protocol Command

Status Codes

Code	Description
100	CONTINUE
200	OK
206	PARTIAL CONTENT
404	NOT FOUND
500	SERVER ERROR

Table 5 - Protocol Status Codes

4 Test, Results and Discussion

In order to verify the effectiveness of the work described in this subproject, several tests have been carried out. First, given that the mathematically reading generator system is designed to replace the manual reading gathering process, every result of this new system must be compared with the results of the second one in order to get the variation between them. To quantify this difference, the score described in the section 3.2.4 has been obtained in for each studied scenario. As it has already explained, the score represents the sum of all Euclidean distances between the mathematically generated readings and the manually obtained ones at each sector divided between the number of sectors that has, at least, one manually obtained reading. That means, the higher score, the bigger is the difference between the map filled with mathematically generated readings and manually gathered ones. The following table shows the scores of each studied scenario.

Scenario	Score
Classrooms	8.43
Laboratory	8.33
Residential	15.14

Table 6 - Each scenario's scores

However, it must consider the score values could be affected not only by the accuracy of the model or generation method but also by the quality of the manually mapped readings. It might be possible that generated readings were closer to the real readings in each position than the manually gathered ones. In this case, the score of the mathematical generated reading map would represent a worse accuracy that it actually has.

To solve this issue, navigation test has been carried out. This test consists on compare the differences of location prediction results between the ones based just on mathematical generated readings and the ones based on manually obtained readings. In order to do this, the test recorder functionality described in section 3.2.6 has been used. To represent this results in a clear way, several charts have been obtained from the result CSV tables. These charts represent the difference between the location predicted and the actual location in each moment of the test. The blue line represents the accuracy of the fingerprinting method considering manually obtained readings and the red line represents the same accuracy but considering mathematically generated readings. Y axis represents the accuracy through Euclidean distance between the predicted location and the actual location, the bigger the Y value is, the worse is the accuracy (being 0 an excellent accuracy on that prediction). The X axis represents time in milliseconds.

Residential – Test 1

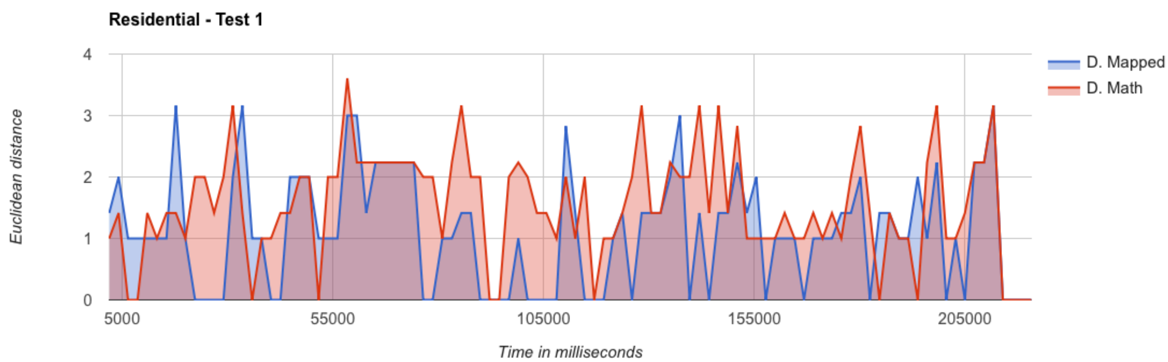

Figure 17 - Residential – Test 1

Path followed in this test available in section 8.2.1
Euclidean distance mean: 1.53
Mean of distance error: 2.29 m
Maximum Euclidean distance: 3.61
Maximum distance error: 5.41 m

Residential – Test 2

Figure 18 - Residential – Test 2

Path followed in this test available in section 8.2.2
Euclidean distance mean: 1.43
Mean of distance error: 2.14
Maximum Euclidean distance: 4.24
Maximum distance error: 6.36

Classrooms – Test 1

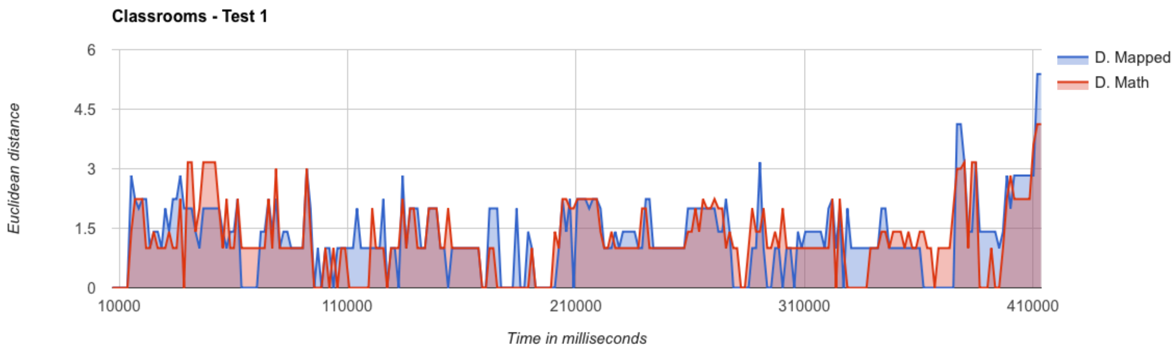

Figure 19 - Classrooms – Test 1

Path followed in this test available in section 8.2.3

Euclidean distance mean: 1.22

Mean of distance error: 2.43

Maximum Euclidean distance: 4.12

Maximum distance error: 8.25

Classrooms – Test 2

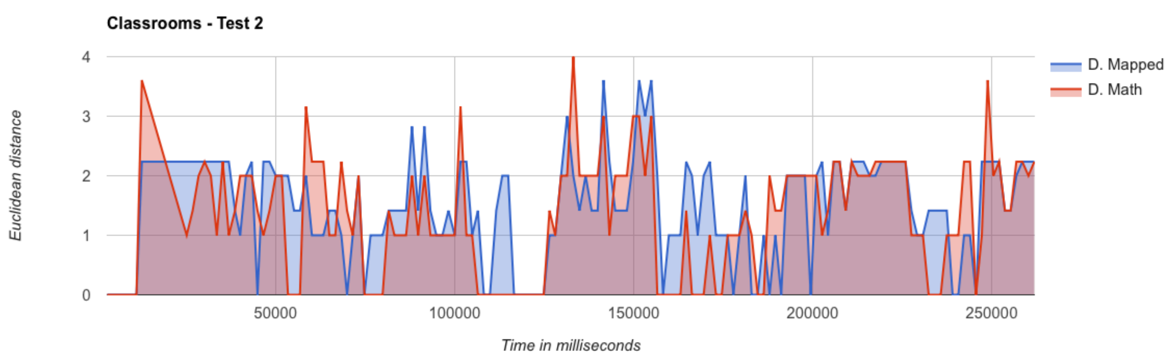

Figure 20 - Classrooms – Test 2

Path followed in this test available in section 8.2.4

Euclidean distance mean: 1.29

Mean of distance error: 2.58

Maximum Euclidean distance: 4.00

Maximum distance error: 8.00

Laboratory – Test 1

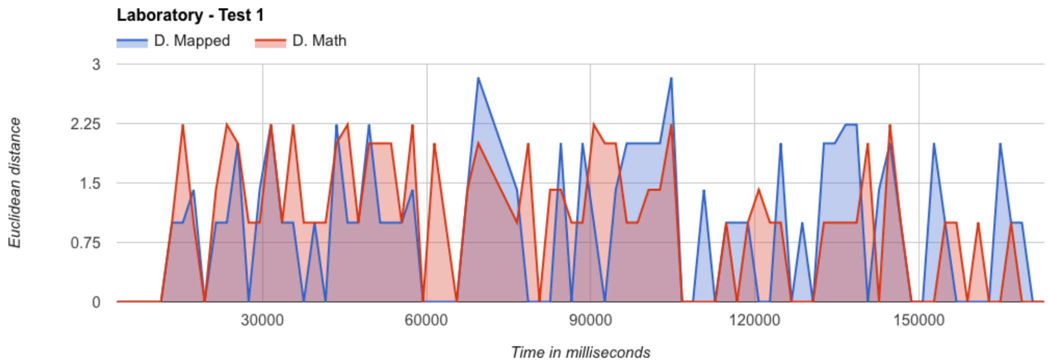

Figure 21 - Laboratory - Test 1

Path followed in this test available in section 8.2.5

Euclidean distance mean: 0.98

Mean of distance error: 1.95

Maximum Euclidean distance: 2.24

Maximum distance error: 4.47

Laboratory – Test 2

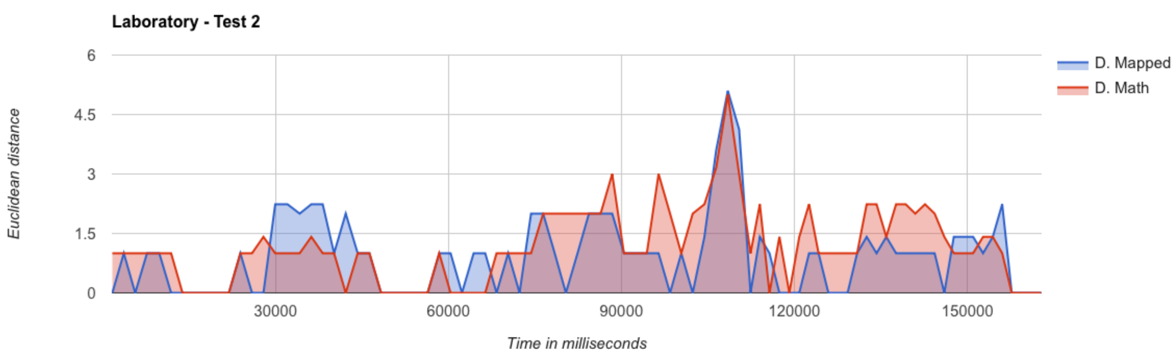

Figure 22 - Laboratory - Test 2

Path followed in this test available in section 8.2.6

Euclidean distance mean: 1.17

Mean of distance error: 2.33

Maximum Euclidean distance: 5.00

Maximum distance error: 10.00

Annotation: In this chart we can see a significant lack of accuracy present at the highest peak of the chart. Due to the similarities between the result of the two source of readings in this accuracy error, and considering that these readings are not related with each other, it can be determined that this inaccurate prediction is given by a reading error during the location stage.

This shows how, even if the fingerprint readings are correctly generated or obtained, there can be errors during the location stage due to a bad reading gathering.

As it can be seen at every test chart, the area difference between blue and red lines in the Y positive axis constitutes an accuracy difference between the location based on mathematically generated readings and manually obtained ones. To quantify this difference, the accuracy improvement of mathematically generated reading based location predictions over the manually obtained ones has been calculated.

Test	Accuracy Improvement
Residential – Test 1	0.722
Residential – Test 2	0.979
Classrooms – Test 1	1.048
Classrooms – Test 2	1.254
Laboratory – Test 1	0.927
Laboratory – Test 2	0.791

Table 7 - Test accuracy Improvements

These results show how the accuracy of the system is not affected severely when mathematically generated readings are used. Moreover, as it shown in the results of the tests one and two of the classroom scenario, mathematically generated readings can improve the accuracy of the location system up to 25%. Analyzing this results becomes clear that the more complex is the environment, the less accuracy the system will have.

5 Conclusions

5.1 Achieved Goals

This subproject was set to design a system capable of calculate the RSS level of each Wi-Fi access point at every point from a discrete amount of points inside an area in order to fix the problems related to the manual gathering of RSS levels. To do this, it has analyzed the nature of RF signals in order to get a clear vision of its behavior. Given this knowledge, four signal propagation models have chosen and studied in order to find the most suitable one for this project. This subproject also describes the development of a tool able to provide all the functionalities needed by the researchers of this project whose work is related with the Wi-Fi area. Finally, has shown the design and development of the system that satisfies the main goal of this subproject.

5.2 Empirical Findings

The models chosen for this study were, Log-Distance, ITU-R for Indoor Environments, Motley Keenan and COST 231 Multi Wall models. After several test performed in different conditions, it has concluded that, Motley Keenan is the most suitable model for this project. This model has proven its accuracy being the one with the best results at every test performed and provides a reliable formula which considers every main aspect of the signal propagation that influences in the signal strength prediction.

The system developed is able to calculate the RSS level needed for the fingerprinting data base in less than thirty seconds. Comparing to the manual technique of data gathering, this method saves a significant amount of time providing a 72% of the accuracy obtained with manually gathered readings for the worst cases and an improvement of 25% for the best cases.

5.3 Implications

The system developed in this subproject provides a reliable method for creating fingerprint data maps. This will supplant the functionality of the manual data gathering during the offline stage of the fingerprinting technique providing a big scalability and suppressing all the potential errors related to this methodology in addition to the big amounts of time needed.

6 Future Work

Although the results presented here have demonstrated the effectiveness of this approach, it could be further developed in a number of ways:

6.1 Study new ways of getting the loss penetration factor of walls and floors

In this approach, once the loss penetration factor is obtained from every wall and floor of an area, there is no need in the future of making any study of the environment. However, the methodology proposed here in order to get these values involves the work of an expert. This becomes the main gap of this approach because it is an inaccurate, expensive and time consuming method. To solve this, future researchers must study the impact of thickness and materials of walls and floors on the signal propagation.

6.2 Add a reliability score to predicted signal values

The accuracy of the models becomes weaker with every wall and floor present in the calculated path. As a result, this predicted signal values are less reliable than the ones that has less walls and floors between the source and analyzed point. Due to this, it is proposed to develop a reliability score which considers the amount of walls and floors in this path in order to consider its potential error. This will give less weight to signal level values with a high potentiality of error during, for example, the real time location stage.

6.3 Consider multi path and wave guide effects

As it can be seen in performed tests, signal propagation effects such as wave guides and multi path influences in the final signal strength. At the moment, these effects are not considered in the signal prediction model. For this reason, it is proposed to study this influence of the geometry of the area on the signal through these effects.

6.4 Improve android app maps

While the android app map engine do not overlap any of the Map Framework's functionalities, there is so much to be done in order to provide to Wi-Fi related researchers with a complete set of functionalities. First of all, as it has described in previous chapters, the possibility of introduce or calculate every wall penetration loss factor must be implemented. Furthermore, this data must be synchronized with Map Framework's wall and floor characteristics in order to provide an easy and fast method of configure this elements in the end maps. Second, the current map rendering engine is highly inefficient making the user interface refresh rate highly slow when the resolution is more than 10 sectors wide. This is why the rendering engine for this maps must be changed or optimized.

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8 Appendix

8.1 Model Tests

8.1.1 Test 1

Scenario	Classrooms
Description	A.1.05, Clear Line-of-sight, no obstacles above 0.73cm
Path	S—4.0—R **Distance:** 4m
PL Measured	47 dB
Log-distance	46.83 dB
ITU-R	71.67 dB
Motley Keenan	46.83 dB
COST 231	46.83 dB

8.1.2 Test 2

Scenario	Classrooms
Description	From A.1.05 to A.1.03, thin wall
Path	S—5.81—|1|—0.10—R **Distance:** 6.04m **Wall 1:** Thickness = 0.13m Penetration loss factor = 1.2dB
PL Measured	49 dB
Log-distance	47.94 dB
ITU-R	76.95 dB
Motley Keenan	49.14 dB
COST 231	49.14 dB

8.1.3 Test 3

Scenario	Classrooms
Description	From A.1.05 to corridor, thick wall
Path	S—5.30—|1|—0.10—R **Distance:** 5.98m **Wall 1:** Thickness = 0.58m Penetration loss factor = 10dB
PL Measured	57.3 dB
Log-distance	48.94 dB
ITU-R	77.95 dB
Motley Keenan	58.94 dB
COST 231	58.94 dB

8.1.4 Test 4

Scenario	Classrooms
Description	From A.1.05 to A.1.01 Two walls in between.
Path	S—2.90—|1|—7.60—|2|—2.10—R **Distance:** 13.06m **Wall 1:** Thickness = 0.23m Penetration loss factor = 6.58dB **Wall 2:** Thickness = 0.23m Penetration loss factor = 6.58dB

PL Measured	66 dB
Log-distance	53 dB
ITU-R	87.08 dB
Motley Keenan	66.16 dB
COST 231	66.16 dB

8.1.5 Test 5

Scenario	Classrooms
Description	Corridor wave guide effect. We expect to have better signal than predicted.
Path	S—13.06—R **Distance:** 13.06m
PL Measured	50 dB
Log-distance	53 dB
ITU-R	87.08 dB
Motley Keenan	53 dB
COST 231	53 dB

8.1.6 Test 6

Scenario	Laboratory
Description	No obstacles, room full of electronic equipment. Let's see how all this equipment affects to the predictions.
Path	S—4.10—R **Distance:** 4.10m
PL Measured	46.5 dB
Log-distance	46.96 dB
ITU-R	71.98 dB
Motley Keenan	46.96 dB

COST 231	46.96 dB

8.1.7 Test 7

Scenario	Classrooms
Description	One floor
Path	S—1.70—|1|—0.0—R **Distance:** 2.4m **Floor 1:** Thickness = 0.7m Penetration loss factor = 30.83dB
PL Measured	75 dB
Log-distance	44.17 dB
ITU-R	65.01 dB
Motley Keenan	75 dB
COST 231	75 dB

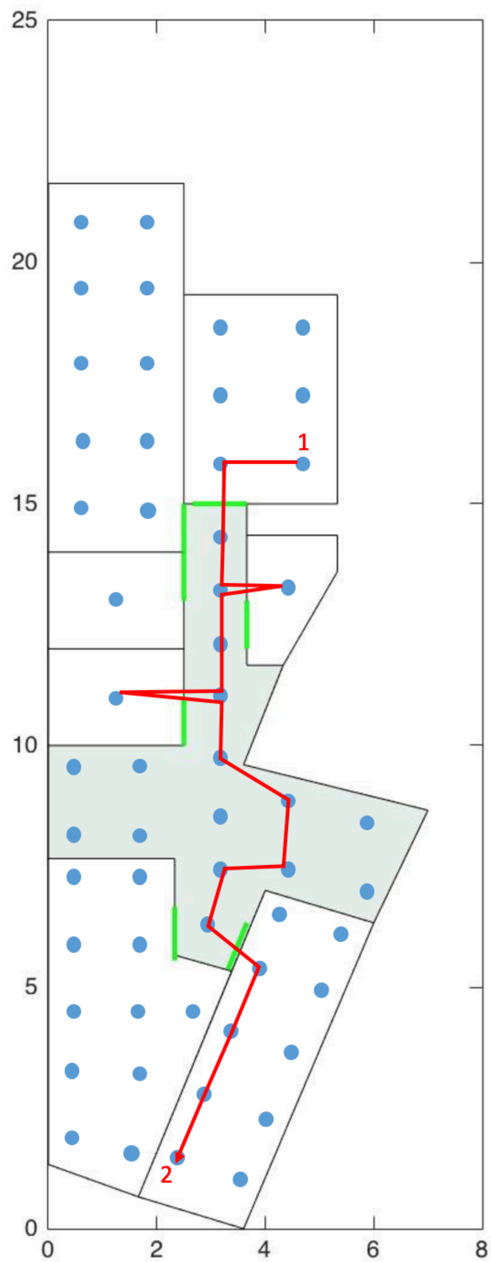
8.1.8 Test 8

Scenario	Classrooms
Description	Two floors
Path	S—1.70—|1|—2.8—|2|—0.0—R **Distance:** 5.2m **Floor 1:** Thickness = 0.7m Penetration loss factor = 30.83dB **Floor 2:**

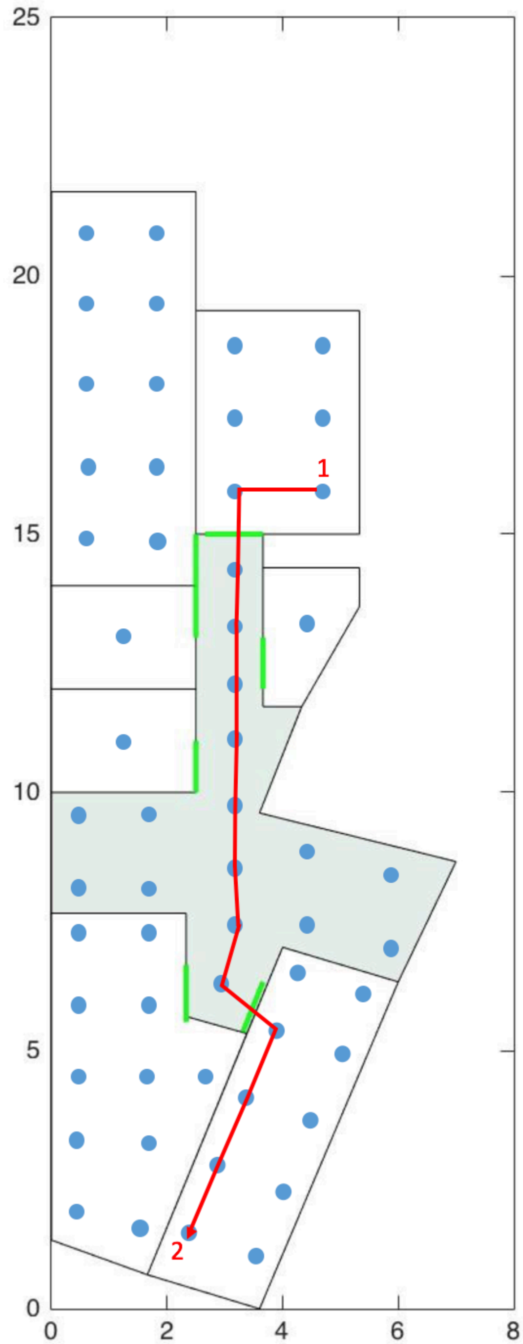
	Thickness = 0.7m Penetration loss factor = 28.53dB
PL Measured	- dB No signal
Log-distance	44.17 dB
ITU-R	65.01 dB
Motley Keenan	103.53 dB = No signal ∵ >100dB
COST 231	99.64 dB

8.2 Test paths

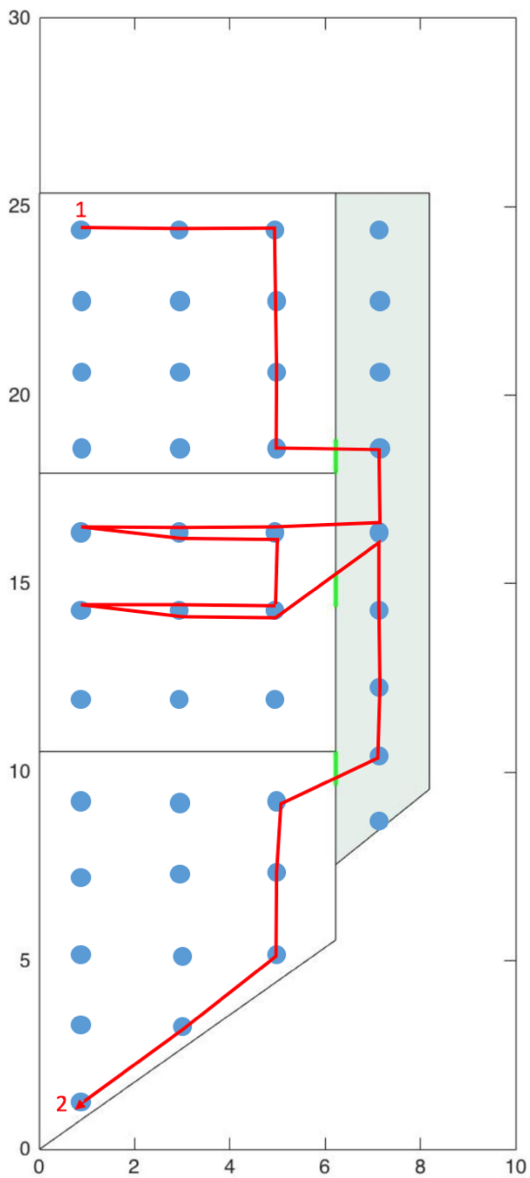
8.2.1 Residential – Test 1



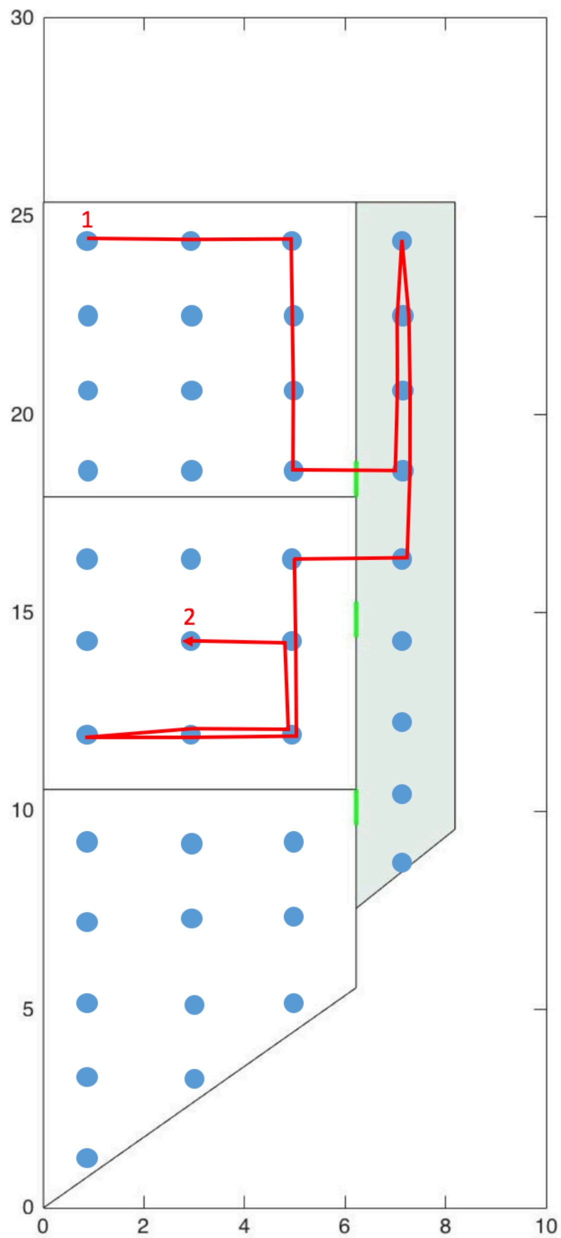
8.2.2 Residential – Test 2



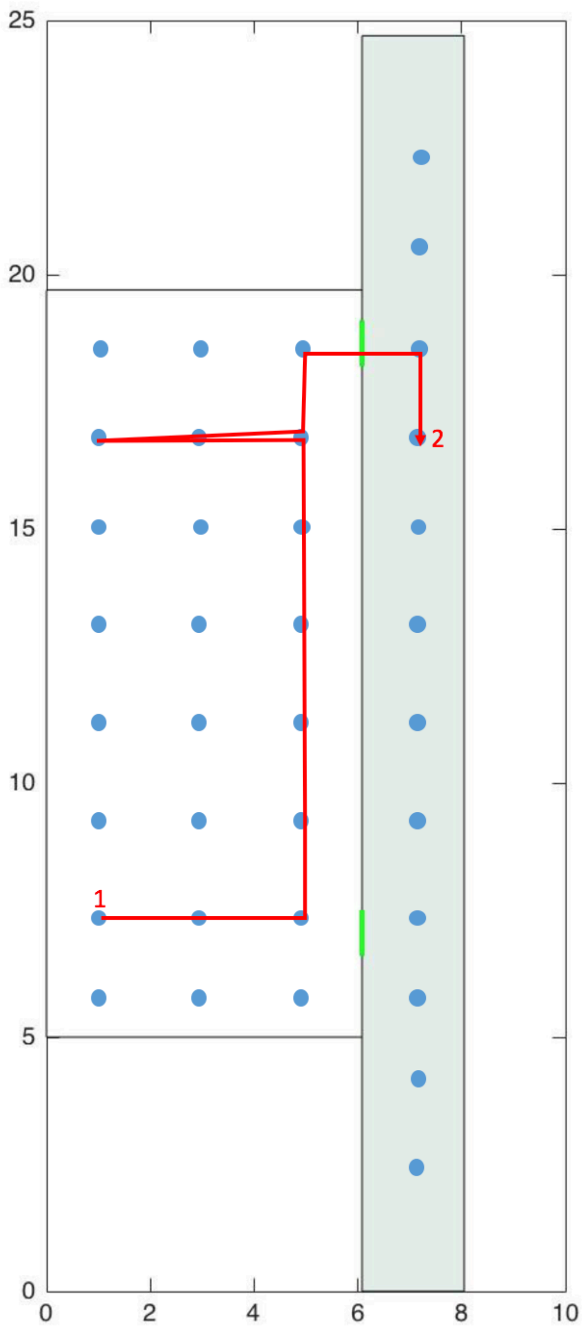
8.2.3 Classrooms – Test 1



8.2.4 Classrooms – Test 2



8.2.5 Laboratory – Test 1



8.2.6 Laboratory – Test 2