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Optimized indoor radio signal prediction with 3D ray tracing model at 2.4 and 5 GHz

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ABSTRACT

Channel propagation models are essential in developing efficient wireless communication networks. Indoor propagation relies on the nature of the surrounding environment. Therefore, many researchers have provided different ways for effective propagation modeling and received power prediction. In this paper, ray-tracing-based site-specific propagation models are presented. The actual measurements are obtained using many wireless access points (AP) based on IEEE 802.11 with different technologies a/b/g and n as transmitters and mobile phone with a proposed mobile application used as a receiver to collect the power at different locations called reference points (RPs), these measurements are done without the existence of people movement. The simulation results are obtained using wireless InSite simulator depends on 3D shoot and bounce ray (SBR) method. The simulation measurements are assessed by comparing it with the actual measurements and they analyze statistically such that the correlation coefficient R between them reaches up to 80% which is an indicator to an acceptable agreement. Path loss characteristic affected by the building materials and distance along the receiver's route is evaluated.

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1. INTRODUCTION

The wireless communication systems depend on accurate propagation modeling to understand how radio signals behave in different environments. The complex nature of propagation channels, shaped by interactions between transmitted signals and surrounding objects, drives the need for efficient and reliable modeling techniques. A suitable method for propagation modelling must be specified for analyzing any wireless communication system, which encourages the researchers to develop many efficient ways for evaluating the radio propagation models in the indoor and outdoor environments. The propagation channel between two antennas is affected by a lot of interactions between the transmitted signals with the objects exist in the surrounding environment which can lead to path loss of the signals, where these interactions lead to define the pattern of path loss and shadowing in the field [1]. Commonly, there are many approaches used for evaluating and describing the propagation channel. Stochastic models, which are considered preferential models when the propagation environment is unknown, the best cases to use these models, are in the radio channel modelling in an environment with just a general description like rural, urban and suburban environments. Statistical models, have several limitations, such that low accuracy and inapplicability in many emerging wireless systems like ultra-wide band (UWB) [2], [3]. Deterministic models which are performed by solving Maxwell equations. Ray tracing (RT) models are one of the most famous used models [4]–[6]. The shoot and bouncing rays (SBR) technique combined with the uniform theory of diffraction (UTD) form the RT propagation models which make the 3D SBR efficient propagation prediction tool for simulation [7].

In a lot of cases, especially in indoor environments, the accurate description of the propagation area is an evident need to avoid any confusion. RT methods for site-specific propagation modeling gives helped provide solutions for indoor propagation channel modeling and SBR method is considered a robust method for predicting the received signal strength indicator (RSSI) and path loss with defined parameters like the materials of the building and its geometry. The signal is launched from the transmitter (T_x) and received by a particular receiver (R_x), its quality is affected by the environmental architecture, and it is affected by people's movements and material types in the environment [8]–[10]. Path loss is formed due to the influence of the signal propagation characteristics by different factors like obstacles and wave reflection from objects [11]. SBR method gives accurate results when the interest environment is specified very well.

There are many researchers who have discussed the 3D RT approach, see Table 1, because it is considered a very important topic. Table 1 shows various studies that discussed the 3D RT approach. In this paper, two proposed methods are used for the collection and prediction of the RSSI measurements, such that a proposed mobile application is used to collect real RSSI measurements. In addition, the simulation was performed through 3D SBR for indoor field signal strength prediction with 2.4 GHz and 5 GHz frequencies. The study area is a part of the second floor of the engineering college at An-Najah National University, Palestine. The simulation predictions are compared with the actual measurement values, and a sensible agreement is observed.

Table 1. Recent studies on the 3D RT approach

Ref.	Year	Indoor propagation model	Environment area	Method	Data collection method	Estimation error
[4]	2022	RT model and multiwall model	Three environments: sports hall, office building, and a long corridor	Bluetooth	Actual measurement, wireless InSite simulator	N/A
[12]	2023	Ray-based channel model	Indoor industrial scenarios	Tuning ray-based model	Measurement campaigns/simulations	N/A
[13]	2020	Ray-tracing approach	University building	Wi-Fi	Wireless InSite simulator	N/A
[14]	2020	Ray-tracing approach	Meeting room	Radiation pattern of LEDs	Actual measurement, OpticStudio	MSE=2%

The organization of this paper is as follows: in section 2 a review of the related work is introduced. Propagation channel characteristics are discussed in section 3. Section 4 introduces the proposed approaches for data collection for indoor radio signal prediction measurements. In section 5, the results and validation are discussed, and then conclusions are drawn in section 6.

In recent years, radio frequency propagation models have been one of the major interesting research subjects due to the rapid development of new wireless communication systems. Therefore, many researchers have introduced various studies on this topic. Dama *et al.* [15] introduce the use of shoot-and-bounce ray-tracing techniques for MIMO systems, specifically 2.4 GHz and 5 GHz indoor environments. A 3D SBR simulator was used to stimulate the received power in an indoor environment, in addition to introducing a comparison between the actual and simulation measurements, and a detailed explanation of the effects of the building materials on the signal strength was also introduced [16]. Moreover, according to Sheikh *et al.* [17], RT simulation was executed and the response of the spatial angular impulse of the channel in an indoor environment and the impact of transmitters location on the path loss were analyzed, their results showed a good agreement between the simulated and the measured path loss such that the root mean square error (RMSE) between them is around 2.6 dB and 2.9 dB. Besides, Manan *et al.* [18] used the 3D SBR method for line of sight (LOS) and non-line of sight (NLOS) simulation and investigated the effect of many different frequencies on Wi-Fi system performance in an indoor space, in addition, path loss and received power are used to evaluate the system performance such that path loss will increase in high frequencies whereas the received power drops. Bhatia *et al.* [12], discusses the RT technique in modeling indoor radio wave propagation and verifies the results by comparing the results with measurement data achieving a reduced RMSE. The investigation by Abdulwahid *et al.* [13], has been achieved by using ray-tracing approach-based wireless InSite software and the effect of building material on the utilized 2.4 GHz. Recent studies have examined how human presence affects indoor radio wave propagation, with findings showing that even small movements can lead to significant variations in signal strength. These fluctuations are particularly important because they can cause errors in localization systems that depend on consistent signal measurements [19]. For example, the movement of people within a room can disrupt radio wave patterns, which can affect the accuracy of tracking or positioning technologies. To address these challenges, some researchers have turned to hybrid models that combine traditional RT methods with machine learning techniques. These models offer a promising way to enhance the accuracy of signal predictions while reducing the computational load. By integrating the detailed simulations of RT with the flexibility of machine learning algorithms, they provide a more adaptive approach to indoor positioning systems (IPS), which can adjust in real-time to changes in the environment [20]. Additionally, a well-specified area of interest is considered one of the most critical factors for an accurate propagation model for the location estimation process in an indoor environment. Liao [21], Mohammed *et al.* [22], provide a detailed explanation of the material and environmental effects on Wi-Fi received signal strength, concluding that metal is a significant contributor to signal strength fluctuations, while insulators like wood and plastic contribute to the reduction in signal strength.

The earlier mentioned studies discuss the RT propagation model without introducing big attention to the actual measurements [15]-[18]. On the other hand, in this paper, the contributions in the followings:

a. Two proposed data collection methods for indoor radio signal prediction as follow,
   – A proposed mobile application, such that by the development of information technology, the smartphone have become more and more popular and efficient to be used.
   – 3D SBR simulation method using the wireless InSite simulator.
b. Evaluation of the received power and the path loss is introduced in terms of the building material type and distance in the receiver route.
c. Achieve a good level for two of the most critical requirements in indoor radio signal prediction which are precision and speed.

2. RELATED WORK

2.1. Overview

IPS have become an essential aspect of modern wireless communication networks, particularly in the context of 5G and beyond. Numerous research efforts have been devoted to improving the accuracy and efficiency of these systems. This chapter reviews the relevant literature on indoor positioning and radio propagation modeling, focusing on recent advancements in methodologies such as RT, neural networks, and data-driven approaches.

2.2. Fingerprinting-based indoor positioning systems

Fingerprinting techniques are widely used in indoor positioning due to their robustness in complex environments. Sulaiman *et al.* [10] explored radio map generation approaches for RSSI-based IPS using biharmonic spline interpolation (BSI) and the wireless InSite simulator. Their findings highlight the effectiveness of combining simulation-based methods with interpolation techniques to enhance radio map accuracy. Similarly, Kharmeh *et al.* [23] developed a Wi-Fi beacon dataset using autonomous robots for 3D location estimation, demonstrating the potential of robotic platforms in creating high-quality datasets for fingerprinting applications. Sulaiman *et al.* [24] further examined artificial neural networks (ANNs) for location estimation, leveraging semi-interpolated databases to address data sparsity. This study showcased the advantages of feed-forward backpropagation neural networks and generalized regression neural networks in improving fingerprinting performance.

2.3. Ray tracing for indoor propagation modeling

RT has emerged as a powerful tool for simulating indoor radio propagation. Hossain *et al.* [25], Hossain *et al.* [26] conducted extensive studies on 3D RT methods for predicting radio propagation at 28 GHz and 4.5 GHz, respectively. Their research validated the accuracy of RT models through empirical measurements, emphasizing their applicability in 5G networks. Zhang *et al.* [27] introduced WiSegRT, a dataset for site-specific indoor radio propagation modeling using 3D segmentation and differentiable RT. This approach integrates advanced data processing techniques with RT, providing a comprehensive framework for indoor radio modeling. Li *et al.* [28] proposed a dynamic 3D indoor radio propagation model incorporating wall obstructions. Their work demonstrated the flexibility of 3D RT in adapting to dynamic indoor environments. Additionally, Pyo *et al.* [29] leveraged deep learning techniques to enhance RT accuracy, bridging the gap between traditional modeling and machine learning.

2.4. Enhancements in ray tracing algorithms

Several studies have focused on optimizing RT algorithms for indoor environments. Rautiainen *et al.* [30] compared 3D and 2D RT schemes, highlighting the superior accuracy of 3D methods in channel characterization. Okamura *et al.* [31] utilized 3D point cloud data to reconstruct indoor models for RT simulations, emphasizing the importance of precise environment modeling. Zeng and Shi [32] investigated convergence analysis in 3D RT algorithms, proposing enhancements to improve computational efficiency. Similarly, Louro *et al.* [33] combined building information modeling (BIM) with RT for 5G indoor radio coverage planning, showcasing the potential of integrating architectural models with simulation tools.

2.5. Applications in 5G and beyond

RT techniques have found extensive applications in 5G networks, particularly for millimeter-wave frequencies. Dong *et al.* [34] conducted simulations on 3D beamforming systems, addressing challenges related to co-channel interference and link blockages. Yuji *et al.* [35] explored millimeter-wave propagation in urban multi-cell scenarios, utilizing 3D RT for system-level simulations. In the context of MIMO systems, Kazemi *et al.* [36] modeled indoor propagation at 60 GHz using shoot-and-bounce RT techniques. Their results underscored the significance of precise modeling in achieving accurate MIMO channel characterizations.

2.6. Emerging trends and challenges

Emerging research trends in IPS include integrating machine learning with RT, as demonstrated by Fathollahi *et al* [37], and developing datasets for specific applications, such as Zhang *et al.* [27]. However, challenges remain in balancing computational complexity with accuracy and scalability in large-scale indoor environments.

2.7. Summary

This chapter reviewed the state-of-the-art in IPS and radio propagation modeling. From fingerprinting techniques to advanced RT methods and applications in 5G, the literature highlights the continuous evolution of methodologies to meet the demands of modern wireless communication networks. The next chapter will delve into the methodologies adopted for this study, building on the insights gained from this literature review.

3. PROPAGATION CHANNEL CHARACTERISTICS

There exist different reasons that affect the radio signals in the indoor environment, like reflection, diffraction, the people's motion, and the material types of the objects in the surrounding. These reasons lead to a reduction in received power, which is called by path loss. Therefore, the received power and the path loss are very important characteristics to study.

3.1. Path loss models

Path loss is a measure of the attenuation in the signals transmitted from the T_x to R_x. Log-distance path loss model [38], [39] is widely used since it covers the main propagation aspects and gives reasonable results:

$$PL(d) = PL0 + 10nlog(d) \tag{1}$$

where, *PL* is path loss at reference distance usually one meter, *n* is the path loss exponent, and *d* is the distance between T_x and R_x (m). To compute the reference path loss, apply the free space Friis formula [40] as shown in (2):

$$PLd0=20log10(4\pi f/c)+20log10(d0)-GT-GR \tag{2}$$

where f is the frequency, c is the speed of light, GT is the transmitter gain, and Gr is the receiver gain.

3.2. Received power

The received power is the amount of power received by a specific receiver from a transmitter; it can be computed as given in (3), such that it is the power for each ray path combined with the time average received power [18]. This parameter is used in a huge number of applications, such as in the indoor location estimation domains [41], [42],

$$PR = \Sigma Np\, Pi \tag{3}$$

where N_p is the number of paths and P_i is the time average power for the i^{th} path.

4. PROPOSED APPROACH

In this section, two different data collection approaches for indoor radio signal prediction measurements are introduced.

4.1. Actual measurements

RSSI readings are used to derive an important propagation channel characteristic, which is the path loss, that determines the relationship between the received signal power and the distance. During the actual data collection phase, RSSI samples are collected at known positions in a duration of time and then saved in a radio map, these positions are named reference points (RPs). The actual measurements are performed on the 2nd floor of the engineering college building at An-Najah National University.

The physical model is carried out in a square corridor with four routes, divided into 1.35 m space, lead to 64 RP locations for covering all the area. T_x is located 1.5 m above the floor. A mobile phone is used as R_x, it is fixed on a one-meter stand and moved along the corridors. The used mobile phone collects the received power values using a proposed mobile application. Multiple copies of the RSSI sample are collected at each RP from the available access points (AP). The RSSI samples in (dBm) with other related data like section name which is the name of the area containing the RP. AP name is the name of the AP that transmits the power. AP mac address is a physical address used as a unique identifier for the AP. Time is the timestamp when each RSSI sample is collected. Sample number is the number of the recorded RSSI at a specific RP from reachable APs and (x, y) is the coordinates of the RPs are gathered to construct the radio map. Table 2 shows the structure of the recorded radio map.

Table 2. Radio map structure

Section name	Point name	RSSI value	AP name	AP mac address	Time	Sample number	X-Y coordinates
A	a1	$RSSI_{i,1}$	IndA	64:70:02:5d:c0:f5	1/25/2020 8:00:00 AM	1	(1, 1)
	a2	$RSSI_{i,2}$	IndB			2	(1, 4)
	a3					3	
				64:70:02:5d:c1:c7	1/25/2020 11:23:00 AM		
	b1		OutA				
	b2				1/25/2020 12:10:00 PM	1	
				f0:5c:19:47:6e:d0		2	
			Extra C				(3, 1)
				e8:de:27:bc:92:b0			(3, 4)
				60:e3:27:7a:0b:7b		1	
D	d1	$RSSI_{i,n}$	Tplink d				

The study area covers 37×32 m. There are seventeen AP based on IEEE 802.11 a, b, g, and n standards (three of them are dual-band) which are distributed in the study area. The number of RSSI samples can vary a lot between the RPs, such that the maximum number of RSSI samples at each RP is set to be 60 samples from each AP. The stronger RSSI value the more samples are received. Figure 1 shows the relation between the number of samples received from a specific T_x and the average signal strength received from it during a period of time.

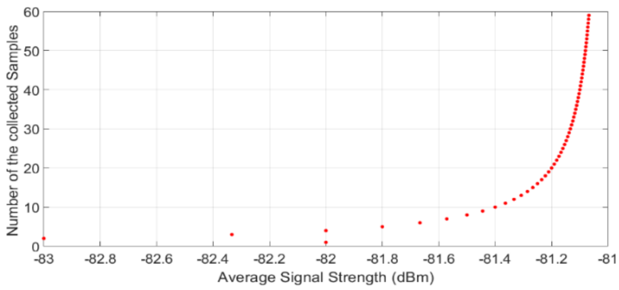


Figure 1. Relationship between the number of samples received from T_X and the average signal strength during a time period

Some processing steps are executed for the radio map to be ready for use in different domains. The purpose of applying these steps is to mitigate the required storage memory of the radio map and to reduce the computational cost when using the radio map for any purpose. Storing only the mean of r_{ij} in the radio map is considered a very common way as a processing method [43].

$$\bar{r}_{ij} = \frac{1}{|r_{ij}|}\sum_{t=1}^{|r_{ij}|} r_{ij}^{t} \quad (4)$$

where r_{ij} is length (r_{ij}), r^t is t^{th} the element of the list r_{ij}.

Due to the possibility to appear some outliers in RSSI samples since it is not a typical environment. It is important to measure the variance of the RSSI samples at each RP. Variance is a statistical measurement that reflects the variation between the collected RSSI samples. Therefore, the radio map also can be extended to store the variance of the RSSI samples such that the variance of r_{ij} is given by (5).

$$\sigma_{ij}^2 = \frac{1}{|r_{ij}|}\sum_{t=1}^{|r_{ij}|} (r_{ij}^{t} - \bar{r}_{ij})^2 \quad (5)$$

4.2. Simulation measurements

Simulation is performed using 3D SBR technique using wireless InSite software [44] for the actual study area. The construction of the simulation model has the same physical characteristics as the actual case clarified in the previous section, as shown in Figure 2. Specification for the area of interest for an accurate indoor radio signal prediction, such that the effect of the building material is considered an important factor affecting the prediction results. Table 3 shows the properties and the types of the materials used in the simulation model [12].

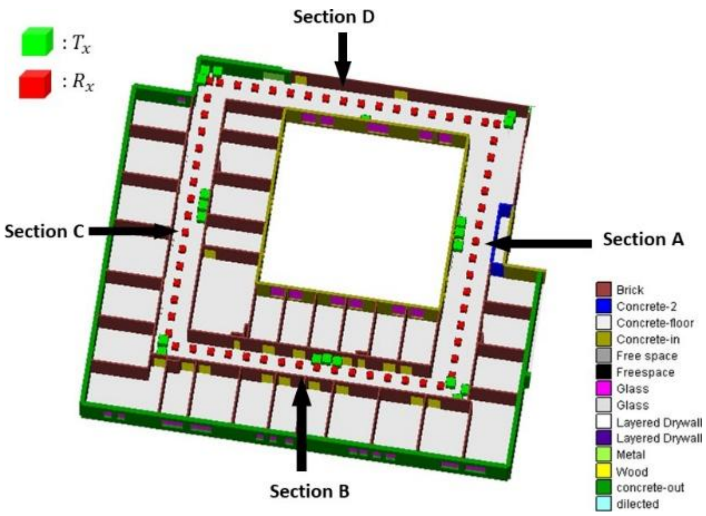


Figure 2. 2D floor layout

Table 3. The used materials in the simulation model

Type	Material	Thickness (cm)	Density (Kg/m^3)	Permittivity	Conductivity
Ceiling, floor	Concrete	30	2400	5.31	0.066
Walls	Brick	28	1500-1800	3.75	0.038
Door	Wood	4.5	500-720	1.99	0.012
Windows	Glass	0.3	2500	6.27	0.012

The receivers are set as a route in the four sections of the corridor (64 R_x), and 17 T_x (3 of them dual band (2.4 GHz and 5 GHz) are distributed as shown in Figure 2, red cubic represent the R_x and the green dots is T_x. The threshold for the receiver's sensitivity is determined to be -250 dBm, the properties of T_x and R_x antenna are illustrated in Table 4.

Table 4. Properties of T_x and R_x antenna

Properties	Omnidirectional	
	T_x	R_x
Waveform	Sinusoid	Sinusoid
Input power (dBm)	20	-
Temperature (K)	293	293
Receiver threshold	-250	-250
Polarization	Vertical	Vertical

5. VALIDATIONS AND RESULTS

After the processing steps are performed to the actual measurements, the average of the collected number of RSSI sample measurements for each RP from each T_x is obtained, and the resulting variance is in the range of (0-3), which is an indicator to the accurate aggregation process. The APs are used at different frequencies, 2.4 GHz and 5 GHz. The actual measurements are compared with the simulation measurements, and a good match between them is obtained. Figure 3 illustrates the relation between the actual and simulation measurements for five of the used APs.

The graphs in Figures 3(a) to (d) are for four of the used APs with 2.4 GHz frequency. Figure 3(e) is for the AP with 5 GHz frequency. The relation between the results is analyzed statistically. The correlation coefficient (*R*) is a numerical measure of the strength of the relationship between two variables. *R* is computed as in (6):

$$R = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{(n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2)(n\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2)}} \tag{6}$$

where x is the actual measurements, y is the simulation measurements, and n is the sample size.

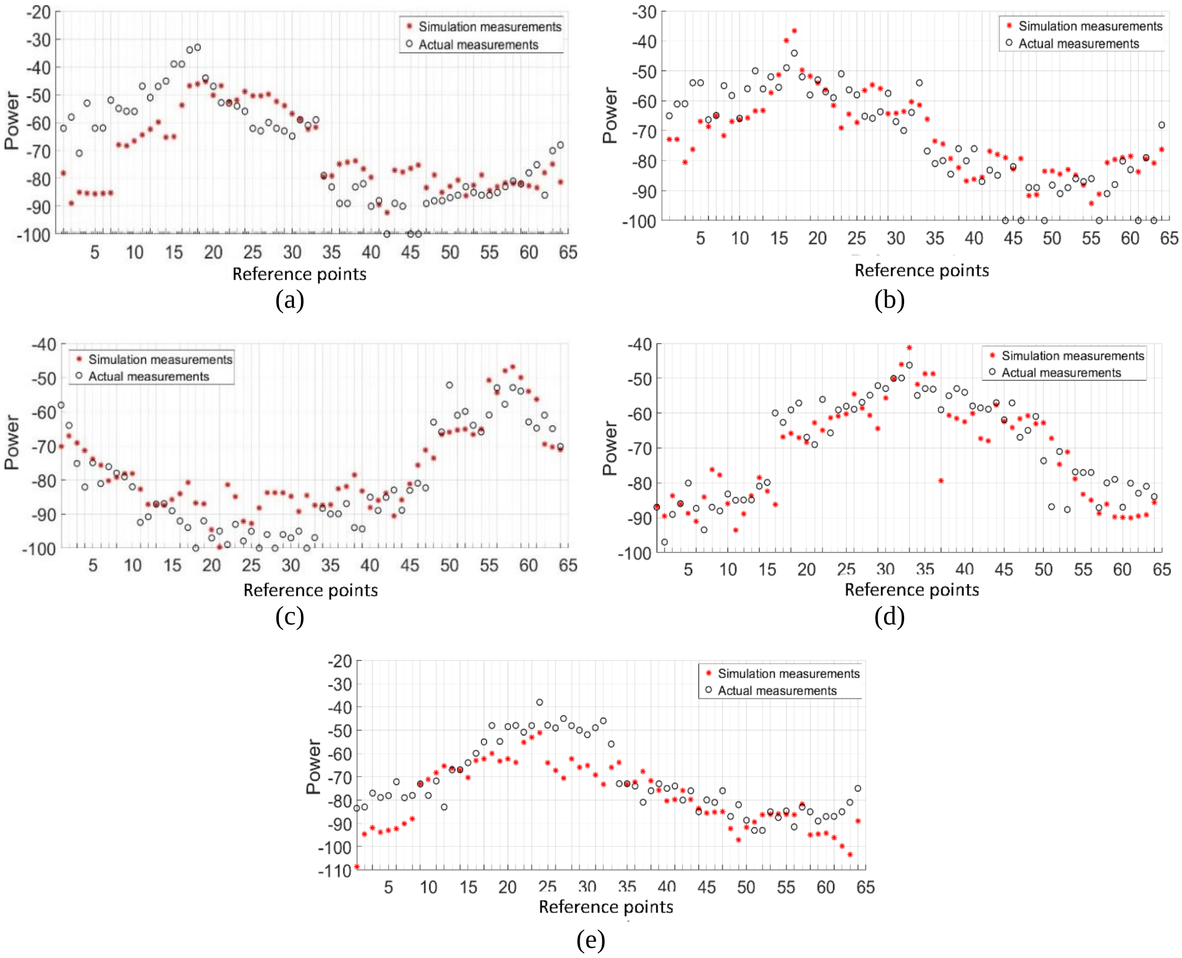


Figure 3. The relation between the actual and the simulation measurements for; (a) AP 1, (b) AP2, (c) AP3, (d) AP 4, and (e) AP with 5 GHz frequency

The correlation coefficient between the actual and simulation measurements in the four APs as shown in Figure 3 is 69%, 80%, 88%, 85%, and 80%, respectively, which is an indicator of an acceptable agreement between the real and simulation measurements. RT [45] and the different effects of the building materials, such that the glass has a small attenuation compared with concrete walls. Ray attenuation increases as wall thickness increases. Figure 4 illustrates the RT in the study area depending on using a T_x in the angle between sections B and C.

It is obvious from the Figure 4 that the shorter paths tend to have higher signal strength, such that the paths with red colour tend to the strongest RSSI and the blue ones point to the longest paths, i.e., highest path loss, which leads to weak RSSI values. Transmitter location affects the received power value by the receiver, such that higher path loss will be generated with a large distance of R_x. small distances lead to reduce the path loss. Figure 5 illustrates the path losses against the distances along the four sections (A, B, C, and D) in the receiver's route.

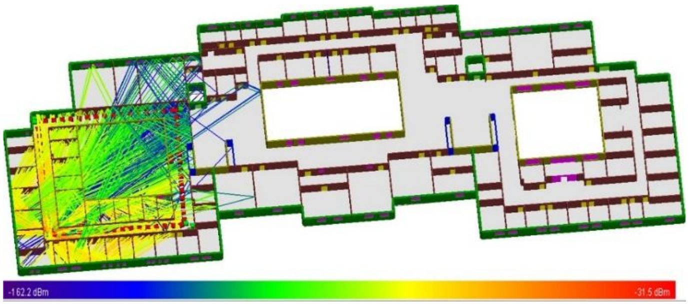
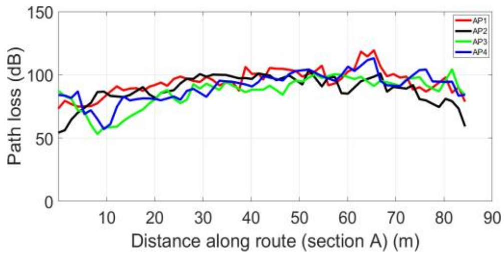
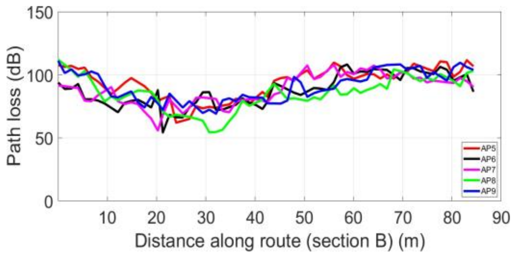


Figure 4. 3D SBR propagation model

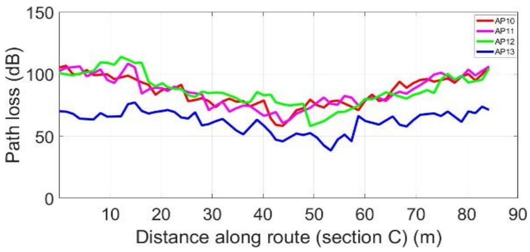
Figure 5(a) illustrates the path loss vs distance along route for 4 of the used APs placed in the corridor (section A), the lowest path loss is approximately from distance 0 to 20 m since the location of these T_x is the closest to the R_x points in this distance. Figure 5(b), shows the path loss in the indoor environment with 5 APs placed in the corridor (section B) such that the lowest path loss is approximately from distances 20 to 40 m since the location of the transmitter B is closest to these points. In Figure 5(c) the distance from 40 to 60 m has the minimum path loss since the points in this space is the closest to transmitters in section C. Finally, in Figure 5(d), the points have distances greater than 60, have the lowest path loss due to its closeness to the transmitters put in section D.



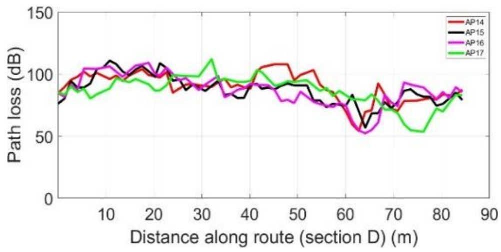
(a)



(b)



(c)



(d)

Figure 5. Path loss vs distance along route for; (a) 4 of the used APs placed in the corridor (section A), (b) 5 of the used APs placed in the corridor (section B), (c) 4 of the used APs placed in the corridor (section C), and (d) 4 of the used APs placed in the corridor (section C)

A comparison between our approach and the different methods used in the state-of-the-art studies is conducted to justify the superiority of our proposed approach.

- Study 1: according to Abdulwahid *et al.* [13], the investigation has been achieved by using ray-tracing approach-based wireless InSite software and the effect of building material on the utilized 2.4 GHz. On the other hand, in this paper, the obtained simulation measurements were investigated by comparing them with the real measurements in addition to utilizing single-band and dual-band APs supported both 2.4 and 5 GHz.

– Study 2: research by Bhatia *et al.* [12], presents tuning of a ray-based channel model for 5G indoor industrial scenarios, focusing on accurate propagation characterization. In contrast, this paper suggests our special mobile application to collect RSSI real measurements and used more than one frequency, which is 2.4 and 5 GHz, with obtaining accurate results as described before.

Unlike other state of art studies, this paper introduces a proposed special mobile application for RSSI measurements collection using single-band and dual-band APs supported both 2.4 and 5 GHz and achieves a high correlation coefficient (R) reach to 80%, and evaluates the proposed simulation model by comparing it with the real measurements.

6. CONCLUSION

This paper introduces a mobile application designed to collect RSSI values and create a radio map with real-world RSSI measurements at different RPs within the study area. Additionally, a site-specific 3D SBR propagation model was implemented, offering a reliable estimation of channel propagation with an approximate error of 2.7. This method reduces computational effort, minimizes labor, and saves time in collecting and predicting RSSI measurements. To assess the accuracy of the model, a statistical analysis was conducted, showing a correlation coefficient (R) between 69% and 80%, which indicates a strong agreement between actual and simulated measurements. The study also examines how building materials and receiver distance affect received power values, contributing to path loss propagation. For future work, this approach could be extended to indoor positioning applications and tested in a larger study area.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

REFERENCES

[1] A. Alarifi *et al.*, "Ultra Wideband Indoor Positioning Technologies: Analysis and Recent Advances," *Sensors*, vol. 16, no. 5, p.

707, May 2016, doi: 10.3390/s16050707.
[2] P. N. Zakharov, R. A. Dudov, E. V. Mikhailov, A. F. Korolev, and A. P. Sukhorukov, "Finite Integration Technique capabilities for indoor propagation prediction," in *2009 Loughborough Antennas & Propagation Conference*, IEEE, Nov. 2009, pp. 369–372, doi: 10.1109/LAPC.2009.5352394.
[3] P. Sharma and P. Khanna, "An upper cut rectangular shaped with f slot ultra-wide band (UWB) antenna," *Power System Technology*, vol. 48, no. 2, pp. 35–46, 2024.
[4] R. Kawecki, S. Hausman, and P. Korbel, "Performance of Fingerprinting-Based Indoor Positioning with Measured and Simulated RSSI Reference Maps," *Remote Sensing*, vol. 14, no. 9, p. 1992, Apr. 2022, doi: 10.3390/rs14091992.
[5] M. Iwasaki, T. Nishio, M. Morikura, and K. Yamamoto, "Transfer Learning-Based Received Power Prediction with Ray-tracing Simulation and Small Amount of Measurement Data," in *2020 IEEE 92nd Vehicular Technology Conference (VTC2020-Fall)*, IEEE, Nov. 2020, pp. 1–6, doi: 10.1109/VTC2020-Fall49728.2020.9348557.
[6] L. Valle, J. R. Pérez, and R. P. Torres, "Characterisation of Indoor Massive MIMO Channels Using Ray-Tracing: A Case Study in the 3.2–4.0 GHz 5G Band," *Electronics*, vol. 9, no. 8, p. 1250, Aug. 2020, doi: 10.3390/electronics9081250.
[7] N. Jeon, C. Lee, N. Kang, and S. Kim, "Performance of Channel Prediction Using 3D Ray-tracing Scheme Compared to Conventional 2D Scheme," in *2006 Asia-Pacific Conference on Communications*, IEEE, Aug. 2006, pp. 1–6, doi: 10.1109/APCC.2006.255882.
[8] S. Kurt and B. Tavli, "Path-Loss Modeling for Wireless Sensor Networks: A review of models and comparative evaluations," *IEEE Antennas and Propagation Magazine*, vol. 59, no. 1, pp. 18–37, Feb. 2017, doi: 10.1109/MAP.2016.2630035.
[9] M. Cheraghinia *et al.*, "A Comprehensive Overview on UWB Radar: Applications, Standards, Signal Processing Techniques, Datasets, Radio Chips, Trends and Future Research Directions," *IEEE Communications Surveys & Tutorials*, pp. 1–1, 2024, doi: 10.1109/COMST.2024.3488173.
[10] B. Sulaiman, S. Tarapiah, E. Natsheh, S. Atalla, W. Mansoor, and Y. Himeur, "Radio map generation approaches for an RSSI-based indoor positioning system," *Systems and Soft Computing*, vol. 5, p. 200054, Dec. 2023, doi: 10.1016/j.sasc.2023.200054.
[11] S. Li, Y. Liu, L. Lin, D. Sun, S. Yang, and X. Sun, "Simulation and Modeling of Millimeter-Wave Channel at 60 GHz in Indoor Environment for 5G Wireless Communication System," in *2018 IEEE International Conference on Computational Electromagnetics (ICCEM)*, IEEE, Mar. 2018, pp. 1–3, doi: 10.1109/COMPEM.2018.8496691.
[12] G. S. Bhatia, Y. Corre, and M. Di Renzo, "Tuning of ray-based channel model for 5G indoor industrial scenarios," *arXiv*, Sep. 12, 2023, doi: 10.48550/arXiv.2309.06101.
[13] M. M. Abdulwahid, M. S. Al-Hakeem, M. F. Mosleh, and R. A. Abd-alhmeed, "Investigation and optimization method for wireless AP deployment based indoor network," *IOP Conference Series: Materials Science and Engineering*, vol. 745, no. 1, p. 012031, Feb. 2020, doi: 10.1088/1757-899X/745/1/012031.
[14] H. B. Eldeeb, M. Uysal, S. M. Mana, P. Hellwig, J. Hilt, and V. Jungnickel, "Channel Modelling for Light Communications: Validation of Ray Tracing by Measurements," in *2020 12th International Symposium on Communication Systems, Networks and Digital Signal Processing (CSNDSP)*, IEEE, Jul. 2020, pp. 1–6, doi: 10.1109/CSNDSP49049.2020.9249565.
[15] Y. Dama, R. A. Abd-Alhameed, F. Salazar-Quinonez, D. Zhou, D. Jones, and S. Gao, "MIMO Indoor Propagation Prediction using 3D Shoot-and-Bounce Ray (SBR) Tracing Technique for 2.4 GHz and 5 GHz," *Proceedings of the 5th European Conference on Antennas and Propagation (EUCAP)*, pp. 1655–1658, 2011.
[16] Y. A. S. Dama *et al.*, "RSSI evaluation for multi-story building," in *2015 Internet Technologies and Applications (ITA)*, IEEE, Sep. 2015, pp. 414–416, doi: 10.1109/ITechA.2015.7317438.
[17] M. U. Sheikh, K. Ruttik, R. Jantti, and J. Hamalainen, "Measurements and Ray Tracing Simulations: Impact of Different Antenna Positions on Meeting Room Coverage at 60 GHz," in *2020 European Conference on Networks and Communications (EuCNC)*, IEEE, Jun. 2020, pp. 63–67, doi: 10.1109/EuCNC48522.2020.9200969.
[18] W. Manan, H. Obeidat, A. Al-Abdullah, R. Abd-Alhameed, and F. Hu, "Indoor To Indoor And Indoor To Outdoor Millimeter Wave Propagation Channel Simulations At 26 Ghz, 28 Ghz And 60 Ghz For 5G Mobile Networks," *The International Journal of Engineering and Science (IJES)*, vol. 7, no. 3 ver. 2, pp. 8–18, 2018, doi: 10.9790/1813-0703020818.
[19] S. Jo, S. Park, and G.-I. Kwon, "Indoor Human Detection from a Building's Exterior Using 433 MHz Wireless Transceivers," *Sensors*, vol. 23, no. 14, p. 6280, Jul. 2023, doi: 10.3390/s23146280.
[20] M. Vasudevan and M. Yuksel, "Machine Learning for Radio Propagation Modeling: A Comprehensive Survey," *IEEE Open Journal of the Communications Society*, vol. 5, pp. 5123–5153, 2024, doi: 10.1109/OJCOMS.2024.3446457.
[21] Q. Liao, "Ray-tracing based analysis of channel characteristics and capacity improvement capabilities of spatial multiplexing and beamforming at 15 and 28 Ghz," Lund University, 2016.
[22] R. A. Mohammed, A. H. Al-Nakkash, and O. N. M. Salim, "A Comprehensive Study of the Environmental Effects on WiFi Received Signal Strength: Lab Scenario," in *Applied Computing to Support Industry: Innovation and Technology (ACRIT 2019)*. . *Communications in Computer and Information Science*, Springer, Cham, 2020, vol. 1174, pp. 455–464, doi: 10.1007/978-3-030-38752-5_35.
[23] S. A. Kharmeh, E. Natsheh, B. Sulaiman, M. Abuabiah, and S. Tarapiah, "Indoor WiFi-Beacon Dataset Construction Using Autonomous Low-Cost Robot for 3D Location Estimation," *Applied Sciences*, vol. 13, no. 11, p. 6768, 2023, doi: 10.3390/app13116768.
[24] B. Sulaiman, E. Natsheh, and S. Tarapiah, "Towards a better indoor positioning system: A location estimation process using artificial neural networks based on a semi-interpolated database," *Pervasive and Mobile Computing*, vol. 81, p. 101548, Apr. 2022, doi: 10.1016/j.pmcj.2022.101548.
[25] F. Hossain *et al.*, "An Efficient 3-D Ray Tracing Method: Prediction of Indoor Radio Propagation at 28 GHz in 5G Network," *Electronics*, vol. 8, no. 3, p. 286, Mar. 2019, doi: 10.3390/electronics8030286.
[26] F. Hossain *et al.*, "Indoor 3-D RT Radio Wave Propagation Prediction Method: PL and RSSI Modeling Validation by Measurement at 4.5 GHz," *Electronics*, vol. 8, no. 7, p. 750, Jul. 2019, doi: 10.3390/electronics8070750.
[27] L. Zhang, H. Sun, J. Sun, and R. Q. Hu, "WiSegRT: Dataset for Site-Specific Indoor Radio Propagation Modeling with 3D Segmentation and Differentiable Ray-Tracing: (Invited Paper)," in *2024 International Conference on Computing, Networking and Communications (ICNC)*, IEEE, Feb. 2024, pp. 744–748, doi: 10.1109/ICNC59896.2024.10556262.
[28] W. Li, W. Zhang, J. Wang, and Y. Liu, "Dynamic 3-D indoor radio propagation model and applications with wall obstructions," *Wireless Engineering and Technology*, vol. 10, no. 02, p. 39, 2019.
[29] C. Pyo, H. Sawada and T. Matsumura, "A Deep Learning-Based Indoor Radio Estimation Method Driven by 2.4 GHz Ray-Tracing Data," in *IEEE Access*, vol. 11, pp. 138215-138228, 2023, doi: 10.1109/ACCESS.2023.3340204.
[30] T. Rautiainen, R. Hoppe, and G. Wolfle, "Measurements and 3D Ray Tracing Propagation Predictions of Channel Characteristics in Indoor Environments," in *2007 IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications*, IEEE, 2007, pp. 1–5, doi: 10.1109/PIMRC.2007.4394431.

[31] W. Okamura, K. Sugiyama, G. S. Ching, Y. Kishiki, K. Saito, and J. Takada, "Indoor Model Reconstruction using 3D Point Cloud Data for Ray Tracing Simulation," in *2022 IEEE 33rd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, IEEE, Sep. 2022, pp. 1–5, doi: 10.1109/PIMRC54779.2022.9977926.
[32] P. Zeng and D. Shi, "Convergence Analysis in Indoor 3D Ray Launching Algorithm," in *2020 International Symposium on Electromagnetic Compatibility - EMC EUROPE*, IEEE, Sep. 2020, pp. 1–4, doi: 10.1109/EMCEUROPE48519.2020.9245798.
[33] J. S. Louro, T. R. Fernandes, H. Rodrigues, and R. F. S. Caldeirinha, "3D Indoor Radio Coverage for 5G Planning: a Framework of Combining BIM with Ray-tracing," in *2020 12th International Symposium on Communication Systems, Networks and Digital Signal Processing (CSNDSP)*, IEEE, Jul. 2020, pp. 1–5, doi: 10.1109/CSNDSP49049.2020.9249503.
[34] M. Dong, W.-M. Chan, T. Kim, K. Liu, H. Huang, and G. Wang, "Simulation study on millimeter wave 3D beamforming systems in urban outdoor multi-cell scenarios using 3D ray tracing," in *2015 IEEE 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, IEEE, Aug. 2015, pp. 2265–2270, doi: 10.1109/PIMRC.2015.7343675.
[35] L. Yuji, L. Bo, Q. Yani, S. Hao, M. Ziyu, and D. Lei, "Research on Indoor 5G Millimetre Wave Coverage Based on 3D-Radiometric Tracking Method," in *2023 IEEE 6th International Conference on Computer and Communication Engineering Technology (CCET)*, IEEE, Aug. 2023, pp. 1–6, doi: 10.1109/CCET59170.2023.10335157.
[36] M. J. Kazemi, A. Abdipur, and A. Mohammadi, "Indoor propagation MIMO channel modeling in 60 GHz using SBR based 3D ray tracing technique," in *2012 Second Conference on Millimeter-Wave and Terahertz Technologies (MMWaTT)*, IEEE, Dec. 2012, pp. 25–28, doi: 10.1109/MMWaTT.2012.6532159.
[37] A. Fathollahi, A. Mehrabi, and M. Dianati, "A ray-tracing-aided machine learning approach for indoor localization using mmWave signals," in *2021 IEEE International Conference on Communications Workshops (ICC Workshops)*, IEEE, Jun. 2021, pp. 1–6.
[38] A. J. Motley and J. M. P. Keenan, "Personal communication radio coverage in buildings at 900 MHz and 1700 MHz," *Electronics Letters*, vol. 24, no. 12, pp. 763–764, Jun. 1988, doi: 10.1049/el:19880515.
[39] M. F. Mosleh and A. K. Daraj, "Indoor Localization Improvements Based on Average RSS Samples," *IOP Conference Series: Materials Science and Engineering*, vol. 1105, no. 1, p. 012024, Jun. 2021, doi: 10.1088/1757-899X/1105/1/012024.
[40] S. R. Saunders and A. A. Zavala, *Antennas and propagation for wireless communication systems*. West Sussex, England: John Wiley & Sons, Inc., 2008.
[41] M. Elbes, T. Alrawashdeh, E. Almaita, S. AlZu'bi, and Y. Jararweh, "A platform for power management based on indoor localization in smart buildings using long short-term neural networks," *Transactions on Emerging Telecommunications Technologies*, vol. 33, no. 3, pp. 1–16, Mar. 2022, doi: 10.1002/ett.3867.
[42] S. Khandker, J. Torres-Sospedra, and T. Ristaniemi, "Analysis of Received Signal Strength Quantization in Fingerprinting Localization," *Sensors*, vol. 20, no. 11, p. 3203, Jun. 2020, doi: 10.3390/s20113203.
[43] J. Du, J.-F. Diouris, and Y. Wang, "A RSSI-based parameter tracking strategy for constrained position localization," *EURASIP Journal on Advances in Signal Processing*, vol. 2017, no. 1, p. 77, Dec. 2017, doi: 10.1186/s13634-017-0512-x.
[44] Z. Abbas, F. A. Abed, N. J. Alhyani, and M. F. Mosleh, "Performance Enhancements of the Indoor Localization System Based on Dynamic ToA and RSS Mechanisms," in *Lecture Notes in Networks and Systems*, Cham: Springerr, 2022, pp. 521–532, doi: 10.1007/978-3-030-85990-9_42.
[45] U. R. Kamboh, U. Ullah, S. Khalid, U. Raza, C. Chakraborty, and F. Al-Turjman, "Path loss modelling at 60 GHz mmWave based on cognitive 3D ray tracing algorithm in 5G," *Peer-to-Peer Networking and Applications*, vol. 14, no. 5, pp. 3181–3197, Sep. 2021, doi: 10.1007/s12083-021-01101-w.

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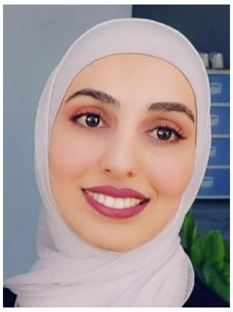

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