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IMPACT OF BUILDING MATERIALS ON WI-FI SIGNAL PROPAGATION AND POSITIONING ACCURACY

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ABSTRACT

Indoor Positioning Systems (IPS) are essential for reliable navigation and location-based services inside buildings. However, construction materials introduce signal attenuation that reduces the accuracy of these systems. This study investigates the propagation of Wi-Fi signals through five different wall materials: concrete, drywall, glass, white-faced hardboard, and wood. The research introduces the Wall Attenuation Factor (WAF) to quantify signal loss and integrates it into Wi-Fi-based localization algorithms. Experimental results demonstrate that incorporating WAF significantly enhances positioning accuracy, reducing errors from 1–2.5 m to 20–50 cm. Coordinate accuracy improved from 0.5–6 m (X) and 1–4 m (Y) to 10–65 cm (X) and 20–30 cm (Y). Concrete walls caused the greatest signal attenuation, while wood and white-faced hardboard allowed signals to pass with minimal degradation. Optimal router placement, within 4 meters of the receiver and with proper alignment, further enhances performance. Future research will explore three-dimensional positioning and test the impact of environmental variables such as humidity and air density.

Keywords: Indoor positioning systems, Signal attenuation, Wall Attenuation Factor (WAF), Wi-Fi localization, Wireless communication.

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1. INTRODUCTION

A positioning system is a decision-making tool that determines the location of an object within an environment. Currently, positioning systems can be categorized into three main types: Global Navigation Satellite System (GNSS), LiDAR Positioning System (LPS), and Hybrid Positioning System (HPS). These systems are useful in both outdoor and indoor applications. GNSS, a satellite-based system, is commonly used for outdoor tasks including positioning (Dow et al., 2009), navigation, vehicle tracking (Abulude & Akinnusotu, 2015), and other spatial science applications. However, GNSS is ineffective for indoor localization due to severe signal attenuation and Non-Line-of-Sight (NLoS) propagation, resulting in positioning accuracies typically limited to approximately 2 to 6 meters (J, Wahab et al. 2022). Indoor localization is further complicated by the presence of barriers that obstruct line of sight, causing signal interference. Although mobile signals are often available indoors, Wi-Fi offers a better opportunity for accurate indoor localization (Aileen, Suwardi et al. 2021, Ekahau 2024).

Wi-Fi–based indoor positioning techniques can be broadly categorised into model-based approaches (e.g., Received Signal Strength Indication (RSSI) path-loss modelling and trilateration), fingerprinting-based methods, probabilistic frameworks, and learning-based approaches such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Among these, Wi-Fi fingerprinting and deep learning–based indoor positioning systems (IPS) have demonstrated improved accuracy under certain conditions, often achieving sub-meter performance in controlled environments. However, this accuracy is typically obtained at the expense of extensive site surveys, dense labelled datasets, and periodic retraining to maintain performance as indoor environments evolve (Lymberopoulos et al., 2015; Zafari et al., 2019; Hernández et al., 2021).

Fingerprinting-based IPS methods rely on the construction of a radio map during an offline phase, followed by online matching during operation. Although effective, their performance degrades significantly when access point configurations, building layouts, or human occupancy patterns change, necessitating costly and time-consuming recalibration (He & Chan, 2015). Similarly, learning-based approaches including CNN and Long Short-Term Memory (LSTM)-based localization techniques require large training datasets and substantial computational resources, which limits their applicability in small-scale deployments and resource-constrained environments (Hernández et al., 2021).

Indoor environments, however, typically contain structural elements such as walls, floors, windows, doors, and corridors that obstruct Wi-Fi signal propagation. Path-loss models are commonly employed to account for these obstructions by estimating the attenuation introduced by each barrier along the signal path (Farid et al., 2013; Hernández et al., 2021). In such models, signal degradation is represented using loss factors associated with walls or floors that interfere with the direct line-of-sight between the transmitter and receiver.

Moreover, Wi-Fi signal propagation is strongly influenced by the type of building materials encountered, as different materials attenuate signals to varying degrees. Numerous studies have examined the effects of materials such as concrete, drywall, glass, and wood on Wi-Fi signal attenuation and transmission characteristics (Dao et al., 2014; Latif & Memon, 2011). Consequently, the impact of building elements and their material properties must be carefully considered when designing and deploying Wi-Fi-based indoor positioning systems, as they can significantly affect system accuracy and reliability.

The Wall Attenuation Factor (WAF)-enhanced trilateration approach is proposed in this study which adopts a lightweight, model-based strategy that avoids fingerprint databases, training datasets, and probabilistic inference. Instead, it explicitly incorporates material-specific signal attenuation into the RSSI path-loss model, thereby improving distance estimation accuracy while preserving the simplicity and interpretability of traditional RSSI-based positioning. Table 1 presents a quantitative comparison between representative IPS techniques reported in the literature and the proposed approach.

Table 1. Comparison of Wi-Fi–Based Indoor Positioning Approaches.

Method	Typical Accuracy (m)	Training/Survey required	Computational cost
RSSI Trilateration (Path-loss) (Farid et al. (2013); Pahlavan (1998)	1 – 3	No	Low
Wi-Fi Fingerprinting (He & Chan (2015); Liu et al. (2007)	1 – 3	Yes	Medium
Models (Bayesian, Kalman) (Zafari et al. (2019)	0.8 – 1.0	Partial	Medium
Deep Learning (CNN / LSTM) (Hernández et al. (2021); Lymberopoulos et al. (2015)	0.3 – 1.0	Yes	High
Proposed WAF-Based Trilateration	0.2 – 0.5	No	Low

Under controlled indoor conditions, the proposed approach achieved distance and positional accuracies in the range of 0.2–0.5 m, which is comparable to or better than many reported fingerprinting-based and learning-based methods, while maintaining significantly lower deployment complexity and computational overhead. These results indicate that the proposed method is particularly well suited to rapid-deployment scenarios, environments where site surveys are impractical, and applications that require transparent and easily interpretable positioning models.

In this context, the present study focuses on quantifying the impact of various building elements and materials on Wi-Fi signal propagation. By integrating a WAF into the Wi-Fi localisation process, the proposed approach enhances positioning accuracy and robustness while retaining the advantages of a simple and interpretable model-based framework.

2. STUDY AREA AND DATA COLLECTION

2.1 Study Area

The study was conducted at the Faculty of Geomatics, Sabaragamuwa University of Sri Lanka, which consists of various building elements constructed from materials such as concrete, drywall, glass, wood, etc. This variety provides an ideal setting to analyze the impact of different materials on Wi-Fi signal propagation.

Figure 1. The study area is composed of different building elements and materials.

This experiment was intentionally conducted in a controlled indoor environment to isolate the effect of building materials on Wi-Fi signal attenuation. Variables such as building layout, access point configuration, and receiver geometry were kept fixed to ensure that observed variations in signal strength could be primarily attributed to material-specific attenuation rather than environmental randomness.

2.2 Data Collection

Received Signal Strength Indication (RSSI) in Wi-Fi signal was measured at known distances in both open and obstructed indoor environments. Three Access Points (APs) were used, and signal strength was recorded at nine receiver points. Measurements were taken for each wall material, both inside and outside, to determine the Wall Attenuation Factor (WAF).

To address short-term signal variability and ensure repeatability, RSSI measurements at each observation point were recorded with different router angles continuously over a 20-second interval and averaged. This procedure was repeated independently three times at each location and for each wall material, with the router and receiver repositioned to the same surveyed coordinates. The reported RSSI values and derived WAFs therefore represent the mean of multiple independent trials.

3. METHODOLOGY

During data collection, measurements were taken during low-occupancy periods to minimize the influence of human movement and dynamic multipath effects. While this improves internal consistency, it also implies that the reported accuracy represents best-case performance under steady-state conditions.

The flow chart below illustrates the Methodology used in this study.

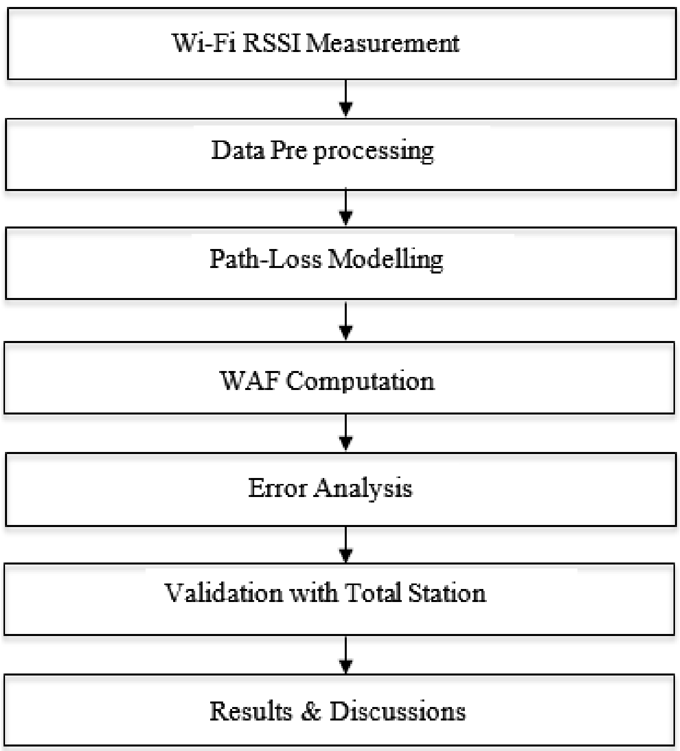


Figure 2. Workflow of the research process showing data acquisition, WAF computation, and positioning accuracy evaluation.

The methodology involved several key steps as follows:

Establishing Observation Points and Access Points (APs) Using a Total Station

Three indoor locations within the faculty were selected, each comprising three Wi-Fi access points and three observation points situated around various wall materials. A closed traverse was conducted from a known reference point to determine precise coordinates. All access points and observation points were accurately positioned using a Total Station to ensure high spatial precision.

Measuring Wi-Fi Signal Strength

Wi-Fi signal strength was measured using the AirPort Utility App in an obstacle-free environment to evaluate the basic signal attenuation characteristics. Signal readings were recorded at six known distances as 1 m, 2 m, 3 m, 4 m, 5 m, and 6 m from each router. These measurements were used to calculate the path loss exponent. Additionally, the orientation of the router antenna was varied to assess its impact on signal strength.

The path loss equation

The distance between observation points and each Wi-Fi access point (AP) was calculated using the path-loss equation (Dao et al., 2014): accuracy assessment of D model

$$P(d)[dB] = P(d_0)[dB] - 10n\log_{10}\left(\frac{d}{d_0}\right) - n_w WAF(p) \quad (1)$$

Where: P(d) is the esteemed signal strength at distance d, $P(d_0)$ is the reference path-loss at distance d_0 and n is the path losss exponent that depends on the indoor parameters, type of building, room size and other factors. n_w is the number of walls WAF is the wall attenuation factor.

To calculate the WAF for different wall materials, the router was positioned 4 meters away from the observation point with a wall in between, minimizing the influence of free-space signal fluctuations (Figure 3). The signal strength was recorded on both sides of the wall:

AVG1: Average signal strength inside the wall (before penetration),

AVG2: Average signal strength outside the wall (after penetration).

Then WAF is calculated as:

$$WAF = | AVG2 - AVG1 | \ (dB) \quad (2)$$

In which RSSI is measured in decibel-milliwatts (dBm). In this analysis, the values of WAF are expressed in the form of positive attenuation losses (dB). In this case, the values of WAF represent the contribution of each material to the reduction of the signal power. For example, a decrease of -40 dBm to -50 dBm is equivalent to a +10 dB WAF. There can be easy comparison of materials under this convention, whereby the higher the WAF values, the higher the attenuation. The attenuation of concrete was the greatest, and that of wood and hardboard the least.

Determining and Comparing Locations

The trilateration method was applied to estimate positioning coordinates based on the measured distances from the receiver point to three access points (Farid et al., 2013; Elashry et al., 2019). The positioning accuracy was assessed by comparing these calculated coordinates with reference coordinates obtained using a Total Station. For data processing and accuracy evaluation, Wi-Fi-based location estimates were analyzed with the WAF model. Accuracy was evaluated by comparing the calculated distances and coordinates while incorporating the WAF values of individual wall materials. The impact of each wall's WAF on signal attenuation was analyzed to determine the most suitable WAF values for accurately modelling distance calculations in environments with mixed wall materials.

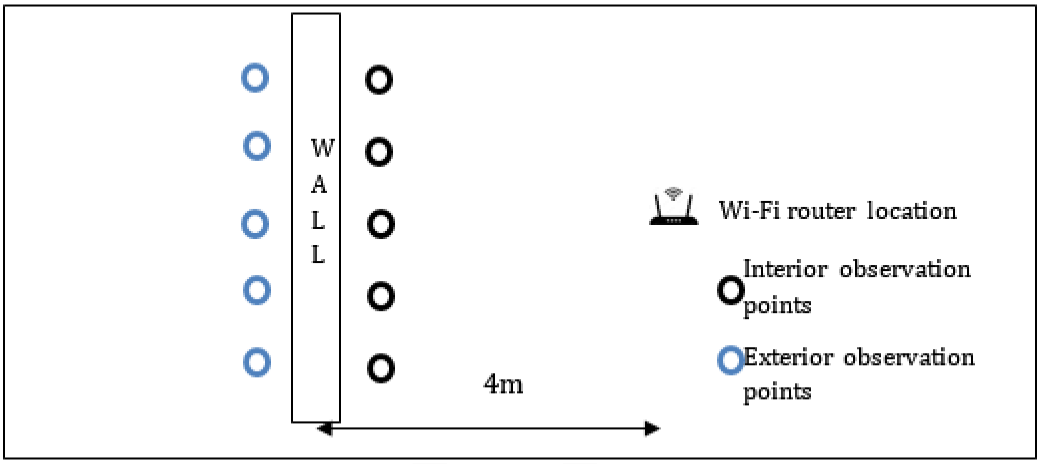


Figure 3. The setup of measuring WAF of wall materials.

4. RESULTS AND DISCUSSION

This section presents the results of Wi-Fi signal propagation analysis with a focus on positioning accuracy. It includes WAF measurements and evaluates the impact of various building materials on the accuracy of indoor positioning. The findings demonstrate the relationship between Wi-Fi signal strength at different distances and the signal attenuation caused by different wall materials, emphasizing how construction elements influence the overall performance of Wi-Fi-based positioning systems. Figure 4 shows the signal strength and distance relationship in an obstacle-free environment.

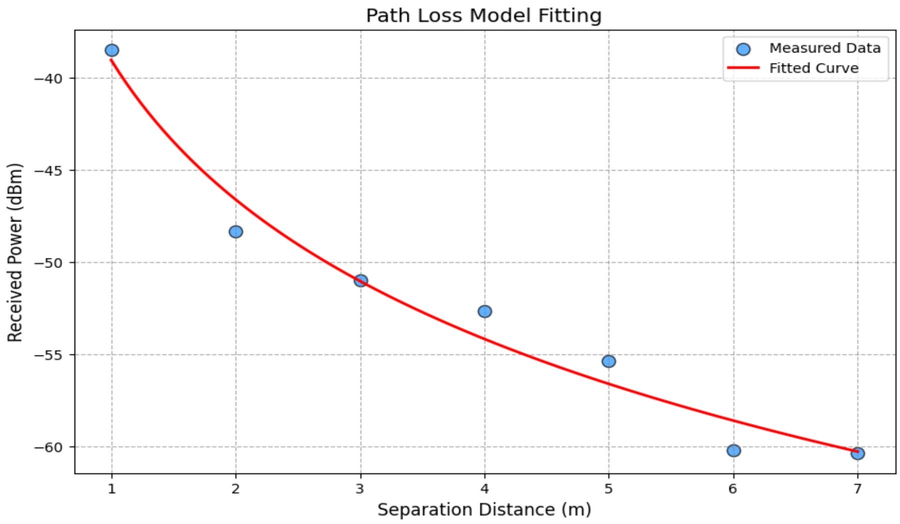


Figure 4. Represents the relationship between Wi-Fi signal strength and range from the Wi-Fi router. The estimated path loss exponent(n)= 2.51.

4.1 Accuracy analysis for distance calculation using Wi-Fi RSSI with and without applying WAF

Table 2 presents the statistical analysis of distance accuracy for Wi-Fi-based indoor positioning, both with and without considering wall materials. When wall materials are not accounted for, the positioning accuracy ranges from 1 to 2.5 meters, based on a 95% confidence interval for the mean received signal strength. In contrast, when WAFs are applied, the mean distance error decreased from 1.77 m to 0.37 m, with a corresponding reduction in standard deviation from 1.37 m to 0.31 m. The non-overlapping 95% confidence intervals confirm that the observed improvement is statistically significant across independent measurements. These results highlight the importance of considering building materials in enhancing the precision of Wi-Fi-based indoor positioning systems.

Table 2. Statistical results of distance calculation without and with applying WAF.

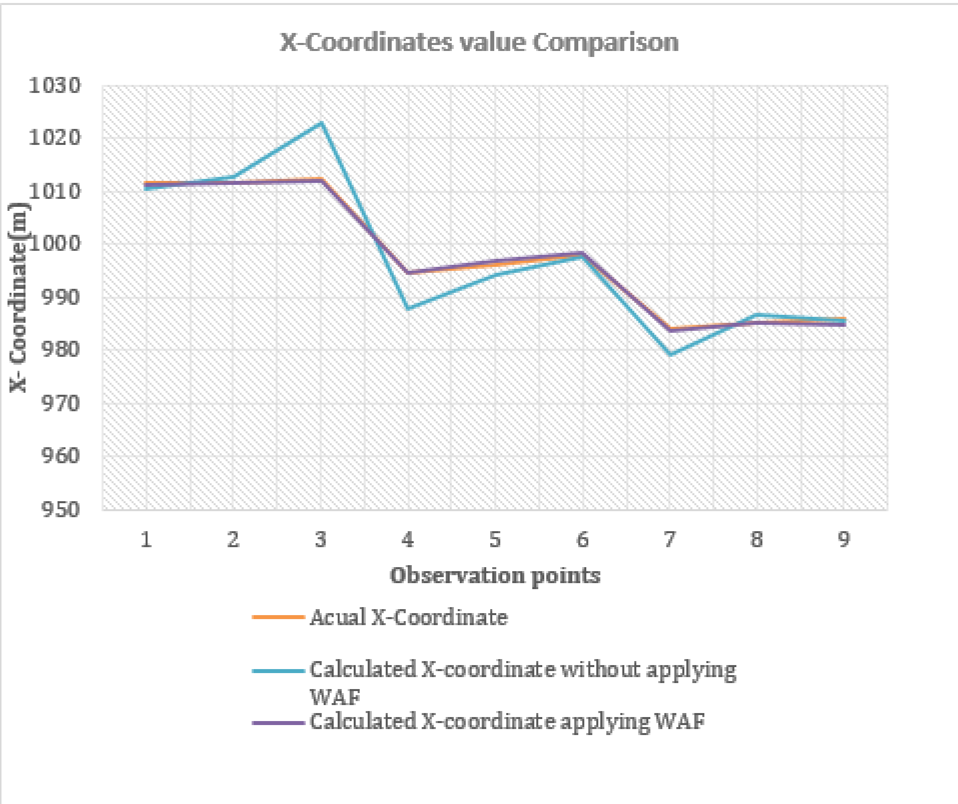
<table>
<tr><th colspan="2"></th><th>Without Applying WAF</th><th>Applying WAF</th></tr>
<tr><td colspan="2">Mean(m)</td><td>1.771</td><td>0.3729</td></tr>
<tr><td colspan="2">Std. Deviation(m)</td><td>1.368</td><td>0.3148</td></tr>
<tr><td rowspan="2">95% Confidence Interval for Mean(m)</td><td>Lower Bound</td><td>1.2298</td><td>0.2484</td></tr>
<tr><td>Upper Bound</td><td>2.3122</td><td>0.4975</td></tr>
<tr><td colspan="2">Range(m)</td><td>5.67</td><td>1.31</td></tr>
</table>

4.2 Positional accuracy analysis with and without considering WAF

Table 3 and Figure 5 illustrate the differences in calculated coordinates with and without the application of WAFs. These comparisons clearly demonstrate the improvement in positioning accuracy achieved when WAF is integrated into the distance estimation model, emphasizing the effectiveness of incorporating material-specific attenuation in Wi-Fi-based indoor positioning systems.

Table 3. Displacements of coordinates with and without applying WAF.

	Without applying WAF		Applying WAF	
Observation Points	dx (m)	dy (m)	dx (m)	dy (m)
1	1.081	6.317	0.119	0.320
2	1.036	0.624	0.167	0.321
3	10.429	3.449	0.481	0.312
4	6.677	4.223	0.036	0.141
5	1.925	1.808	0.530	0.214
6	0.229	2.427	0.364	0.368
7	4.836	1.484	0.448	0.307
8	1.693	0.932	0.246	0.380
9	0.641	2.268	1.108	0.264



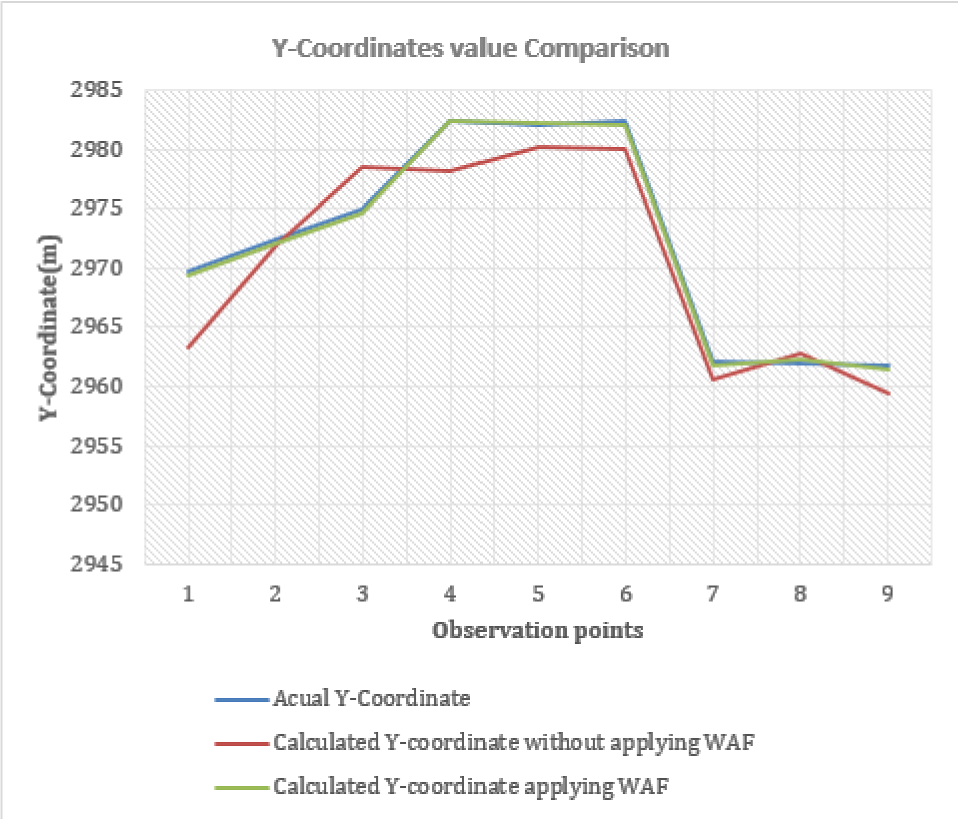


Figure 5. Position variation with and without applying WAF.

Table 4 shows the statistics of the above differences. It shows the clear enhancement of positional accuracy when applying the specific WAF.

Table 4. Statistical information for position calculations with and without WAF.

		Without applying WAF		Applying WAF	
		X Coordinate	Y Coordinate	X Coordinate	Y Coordinate
Mean(m)		3.1719	2.6147	0.3888	0.2919
Std. Deviation(m)		3.4543	1.7982	0.3197	0.0753
95% Confidence Interval for Mean(m)	Lower Bound	0.5166	1.2324	0.1430	0.2340
	Upper Bound	5.8272	3.9969	0.6346	0.3498
Range(m)		10.20	5.69	1.07	0.24

4.3 Distance accuracy analysis in a mixed environment

An actual indoor environment consists of various structural elements made from multiple construction materials. Therefore, it is important to evaluate the positioning accuracy with respect to different building materials prior to deploying a Wi-Fi-based indoor positioning system. In this study, three locations (A, B, and C) featuring diverse building elements: glass, white-faced hardboard, concrete, and wood, were selected within the study area. The corresponding Wall Attenuation Factor (WAF) values for these materials were calculated and are presented in Table 5. Three receivers were positioned behind different building elements relative to the Wi-Fi access points to compare the resulting distance estimations, as illustrated in Figure 6.

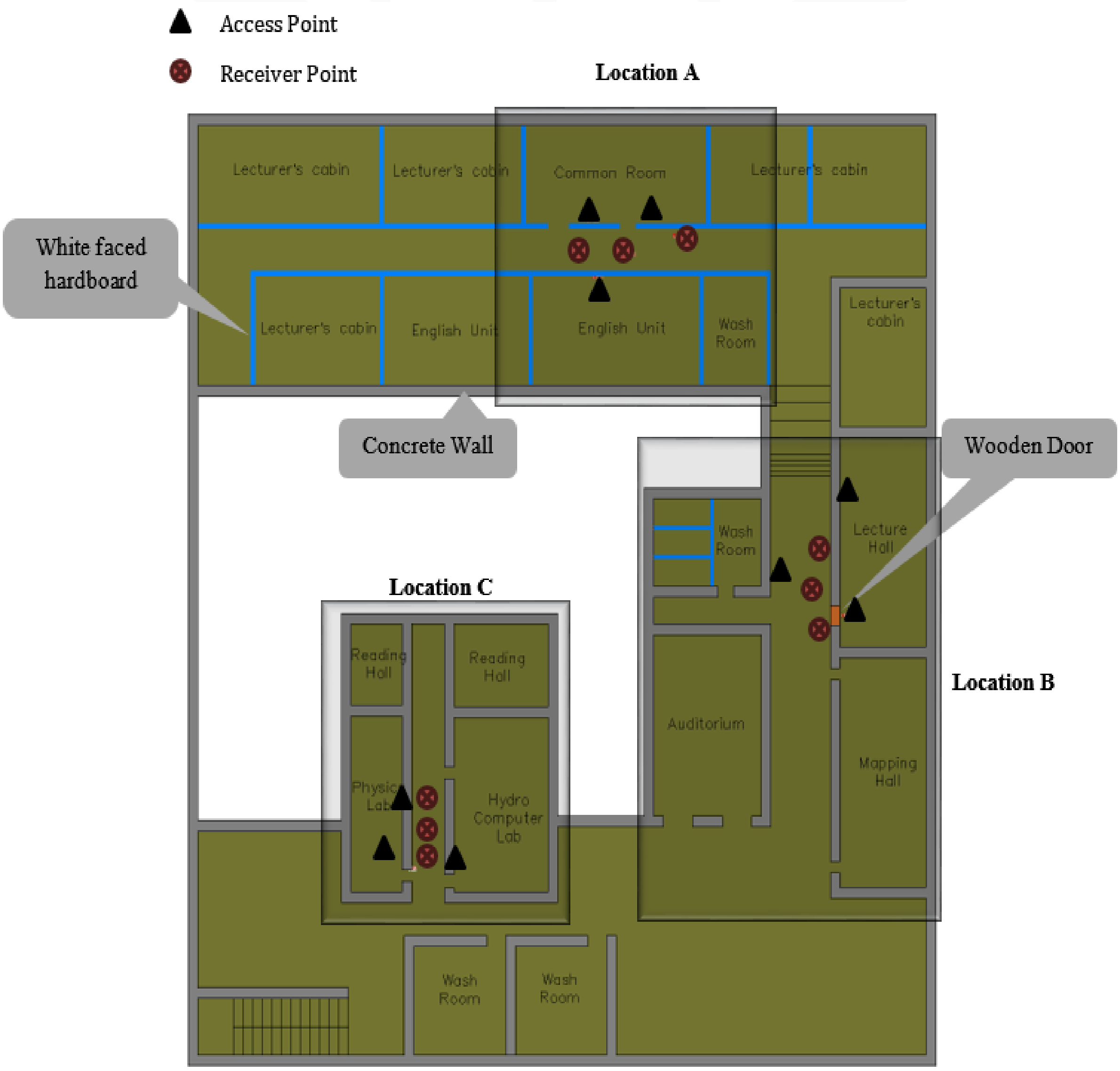


Figure 6. The experimental layout illustrates the faculty floor plan, the placement of different materials at relevant locations, and the positions of access points and receiver points at each location.

Table 5. Calculated WAF values of materials.

Materials	WAF
White Faced Hardboard	-10.4
Concrete wall	-5.1
Glass	-0.4
Wooden Door	-2.8

Initially, the distances were calculated by applying the actual Wall Attenuation Factors (WAF) corresponding to the specific materials encountered along the signal path. For example, at Location A, the WAF for signals from AP1 to R1, R2, and R3 was based on white-faced hardboard, while the WAF for AP2 and AP3 to the same receivers was based on concrete, as illustrated in Figure 6. This approach resulted in a total of nine distance estimations (3 access points x 3 receivers), each utilizing the appropriate WAF for the material in question. The differences between these estimated distances and the actual measured distances were calculated, and the statistical analysis is presented in Table 6. The results demonstrate that the method is capable of achieving sub-meter level accuracy in distance estimation, highlighting the importance of incorporating material-specific WAF values in indoor positioning models.

Table 6. Statistical analysis of the displacement in distance between the Access Point and Receiver after applying the WAF of the material present between them.

<table>
<tr><th colspan="2"></th><th>Location A</th><th>Location B</th><th>Location C</th></tr>
<tr><td colspan="2">Mean(m)</td><td>0.5640</td><td>0.2940</td><td>0.4213</td></tr>
<tr><td colspan="2">Std. Deviation(m)</td><td>0.6352</td><td>0.2510</td><td>0.3510</td></tr>
<tr><td rowspan="2">95% Confidence Interval for mean(m)</td><td>Lower Bound</td><td>0.1490</td><td>0.1300</td><td>0.1920</td></tr>
<tr><td>Upper Bound</td><td>0.9790</td><td>0.4580</td><td>0.6510</td></tr>
<tr><td colspan="2">Range(m)</td><td>2.0533</td><td>0.6725</td><td>1.0287</td></tr>
</table>

Subsequently, distances were calculated using a variety of WAF values for each material, regardless of the actual material present along the signal path. This mixing of WAF values simulates arbitrary conditions and demonstrates how distance accuracy varies when incorrect or generalized attenuation factors are used, as illustrated in Figure 6. The estimated distances were then compared with the actual measured distances, and the degree of matching was expressed as a percentage, presented in Table 7. The results reveal that the highest matching percentages occur when the actual WAF values of the materials are used in the calculations. This confirms that accurate positioning in Wi-Fi-based indoor systems strongly depends on applying the correct material-specific WAF values.

Table 7. The matching percentage between estimated and actual distance values after applying different WAF values. Negative values indicate that the calculated distances are greater than the actual distances.

		From AP1 to (%)			From AP2 to (%)			From AP3 to (%)		
		R1	R2	R3	R1	R2	R3	R1	R2	R3
Location A	Glass	97.3	18.5	-17.3	-25.6	49.6	44.7	73.9	75.8	43.3
	White Faced Hardboard	41	72.5	86.8	90.2	60.1	61.1	50.4	49.6	62.6
	Concrete Wall	66.7	82.1	58.8	53.4	97.7	99.3	81.9	80.7	98.2
	Wooden Door	82.4	54.4	25.7	18.9	79.3	77.4	98.8	99.7	74.3
	Without applying WAF	93.5	11.7	-25.4	22.2	43.9	41.5	69.1	71.1	37.5
Location B	Glass	92.3	93	87.2	66.3	60.5	48.83	31.7	52.2	9.2
	White Faced Hardboard	36.9	42.8	45.1	53.4	55.7	60.4	67.2	59.1	76.2
	Concrete Wall	61.1	70.8	74.7	88.5	92.3	99.9	88.6	97.8	73.7
	Wooden Door	74	85.9	90.5	92.7	88.1	78.7	64.9	81.4	46.9
	Without applying WAF	95.7	89	82.9	61.3	55.3	43.2	25.4	46.6	2.1

Location C	Glass	-62.1	-27.8	-5.5	74.4	-16.6	70.4	-14.3	15.9	-80.3
	White Faced Hardboard	95.3	91	82.1	29.7	86.5	51.8	85.6	73.6	87.9
	Concrete Wall	69.5	86.5	97.6	37	92.2	64.5	93.3	91.7	60.4
	Wooden Door	-10.3	17.3	35.1	59.7	26.2	96	28.1	52.3	-24.9
	Without applying WAF	-12.2	15.5	33.6	77.1	-24.7	65.5	-22.3	9	-90.8

4.4 Repeatability and Robustness of the WAF Model

To evaluate repeatability, WAF-derived distance and position estimates were analyzed across multiple observation points and material configurations. Consistent reductions in both mean error and variance were observed for all tested materials when WAF was applied, indicating that the improvement is not limited to a single access point–receiver geometry. Although the experiments were conducted within a single building, the consistent performance across different materials and spatial configurations suggests that the proposed WAF-based correction is robust under controlled indoor conditions.

4.5 Suitable angle of the antenna

The orientation of the Wi-Fi router can significantly influence the received Wi-Fi signal strength. To identify the most suitable angle that maintains a clear line-of-sight connection to the receiver, an experiment was conducted to observe signal strength variations at different router orientations. The instrumental setup used for this test is shown in Figure 7, while Figure 8 illustrates the variation in signal strength with respect to both distance and router orientation angle. These observations help in determining the optimal router alignment for improved signal reception and positioning accuracy. θ: the angle measured from perpendicular to the router and the angle increased towards the receiver direction. d: Distance from receiver to Wi-Fi router. The figure represents router antenna angle change towards the signal receiver device.

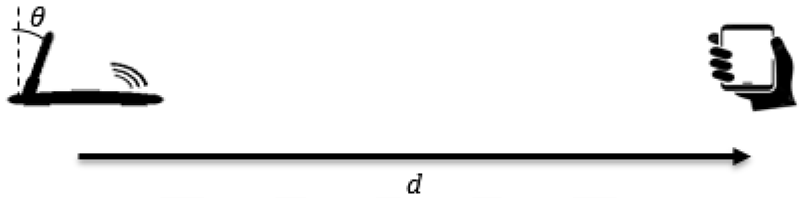


Figure 7. Instrumental setup for finding Signal Strength variation with distances and receiver angle.

To determine the influence of antenna orientation on the signal strength, the transmitting antenna of the router was turned about the vertical axis in set angular steps. The point at which the antenna was facing the receiver perpendicularly (in the direction of the receiver) was set as the reference direction.

The antenna was tilted in 10-degree increments forward and backwards, with the horizontal orientation held constant using a digital protractor (or manually marked angle scale on a rotating stand). Receivable Signal Strength Indicator (RSSI) was measured at the following distances: 1 m, 2 m, 3 m, 4 m, 5 m, and 6 m at every orientation.

This was done in order to make sure that any variation in signal level was only attributed to the radiation pattern and polarization of the antenna and not to the distance or environmental differences. The received RSSI data was then plotted against the angle and distance to determine the most appropriate antenna orientation that was optimal for receiving the maximum signal. The findings (Figure 8) showed that the signal strength was highest at around 60 degrees, which means that at this angle, there was the most preferable propagation path in indoor settings.

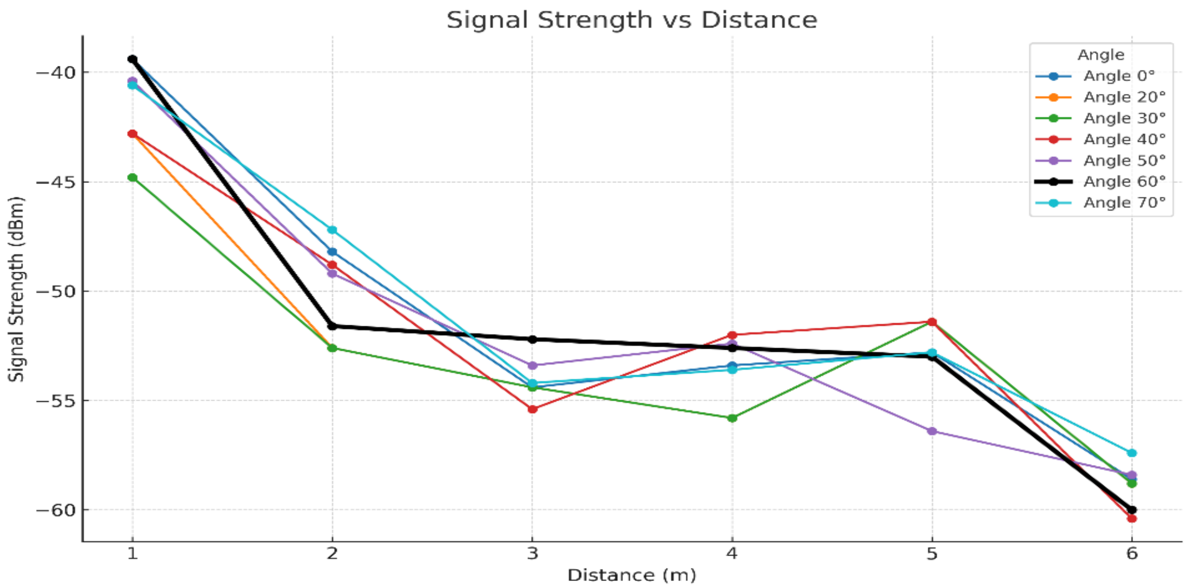


Figure 8. Signal strength changes with the various distances and angles.

According to Figure 8, a clear deviation in signal strength is observed at an angle of 60 degrees. At this orientation, the signal strength remains more stable across varying distances compared to other angles. Therefore, it can be concluded that the optimal angle for the router antenna, in relation to the signal strength measuring device, is 60 degrees from the vertical axis. This orientation provides more consistent signal reception, which is beneficial for accurate distance estimation in Wi-Fi-based positioning systems.

5. LIMITATIONS AND FUTURE WORK

Although this study has been able to show the influence of building materials on the propagation of Wi-Fi signals and positioning accuracy, it has a number of constraints. To begin with, the experiments were performed in one building design and on one floor in an indoor environment. As a result, quantitative evaluation of factors like multi-floor signal propagation and vertical attenuation was not done. Second, the analysis has been conducted with a single type of Wi-Fi router on a fixed transmission power and antenna properties. Various router types, antenna gain, or frequencies (e.g., 5 GHz and 6 GHz bands) might affect the attenuation characteristics and positioning characteristics. Third, the experiments were carried out under a controlled environment, where there was no substantial human movement. In practice, human presence, body blockages and dynamic obstacles may introduce the short-term variations of the signal and multipath effects that were not explicitly modelled in this work. This analysis should be further generalized and confirmed by extending it to multi-floor contexts, mixed router setups, and dynamic conditions with human interactions to achieve further generalization of the suggested WAF-enhanced positioning model.

Direct experimental benchmarking against fingerprinting or deep learning–based IPS methods was not conducted in this study, as such techniques require extensive labeled datasets and site-specific training, which was beyond the scope of this controlled experimental investigation. However, a quantitative comparison with representative results reported in the literature has been included to contextualize the proposed method within the broader IPS research landscape.

6. CONCLUSIONS

This study examined how different building materials affect Wi-Fi signal propagation and indoor positioning accuracy using an LTE wireless router (ZLT S10) and the Airport Utility application. Experiments were conducted in nine locations across three scenarios involving concrete walls, white-faced hardboard, glass, and wooden doors. Signals were measured at 2.5 GHz to reduce reflection errors and improve penetration through barriers.

The Wall Attenuation Factor (WAF) was calculated for each material and position. Without applying WAF, distance accuracy ranged from 1 to 2.5 m. After applying WAF, accuracy improved significantly to 20-50 cm. Coordinate accuracy also improved from X = 0.5-6 m, Y = 1-4 m to X = 10-65 cm, Y =

20-30 cm after applying WAF.

The results clearly show that building materials significantly affect Wi-Fi performance, with concrete walls causing the most attenuation. In contrast, white-faced hardboard and wooden doors had minimal impact. This study demonstrates that incorporating material-specific WAFs can significantly improve Wi-Fi-based distance and position estimation in controlled indoor environments.

Additional experiments were conducted to evaluate the significance of incorporating actual WAF values and ensuring proper router orientation for achieving precise indoor positioning. The results, expressed as matching percentages, clearly indicate that selecting the correct WAF for each building material is crucial for accurate distance estimation. Furthermore, a router orientation of 60 degrees was found to provide optimal and consistent signal strength, reinforcing its importance in enhancing the reliability and performance of Wi-Fi-based indoor positioning systems. However, some errors were caused by signal reflection and interference from nearby people during data recording. The best signal propagation angle was 60 degrees, and optimal accuracy was achieved when the receiver was within 4 meters of the router.

While learning-based IPS techniques may achieve comparable accuracy, they incur significantly higher deployment and maintenance costs. The proposed WAF-based trilateration approach offers a practical trade-off between accuracy, complexity, and deployability, making it well suited for real-world indoor environments where rapid setup and interpretability are required. Finally, this study provides quantitative evidence of the impact of building materials on Wi-Fi signal propagation and positioning accuracy. Future work could explore more materials, higher frequencies, and environmental conditions such as humidity and air density.

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