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# Multi-Model Machine Learning Based Path Loss Estimation for Indoor 5G Signal Propagation at 12 GHz

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**Abstract:** In recent years, the advent of 5th Generation (5G) wireless communication technologies has led to a boom in network service usage and access of high-quality multimedia services. In order to maintain acceptable Quality-of-Service (QoS), high-frequency 5G communication at frequencies such as 12 GHz have become commonplace. Consequently, in order to account for signal attenuation, accurate estimation of path loss considering both Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) propagation, is critical for successful implementation of such wireless communication systems. The present work therefore outlines a multi-model approach to path loss modelling and estimation using standard path loss models such as Close In (CI) and Floating Intercept (FI) models, in conjunction with machine learning (ML) models implementing Random Forest, Decision Tree and Gradient Boosting regression to accurately estimate path loss. The machine learning models employed allow for generation of accurate estimation even in case of significantly varying and noisy datasets. Of the ML models implemented for generation of path loss estimates, the Random Forest Regressor model is illustrated to offer the most accurate and stable results for the given scenario. The results obtained by the multi-model approach are appreciably close to the real-world experimental results, establishing the efficacy of the proposed methods.

***Keywords:*** *5G, LOS, NLOS, path loss, machine learning, random forest*

## 1. Introduction

The research on attenuation models for Ku, K, Ka and V band signals has increased its importance in recent years, with the advent of 5G technologies which are expected to exploit these bands for successful implementation of 5G communication networks [1]-[3]. Due to the limited channel bandwidth in a 5G network, service providers are compelled to adopt a much higher frequency spectrum. The user experience and overall performance of present generation mobile technologies are improved by using 5G technology. Higher data speeds, less end-to-end delays, and minimum energy usage are some of the most promising features [4]. In order to achieve a common objective, different technologies must be deployed in a way that allows the total network to perform as a single entity. To work together, however, sophisticated technology and communication strategies are required. The increase in requirements for such an effective system is predicted to more users utilizing resources at the same time, necessitating both spectrum acquisition and utilization. Microwave, millimeter wave, multiple radio access technology, massive MIMO, cooperative heterogeneous network and device-to-device (D2D) communication are just a few examples of outstanding technologies that will allow 5G to more efficiently support a huge number of users in a resource-limited environment [5–10].

The present work consequently seeks to focus on effective application of 5G technologies for indoor connectivity by examination of the path loss metric in such environments. Two of the major approaches to mitigate the challenges to accurate estimation of path loss in indoor environments, which have gained importance in recent years due to their applicability to a number of diverse use cases and complex network scenarios, are presented.

First, mathematical model-based approaches are presented and compared with experimental data collected in suitable indoor environments.

Second, machine learning-based estimates are generated using multiple models for accurate prediction of path loss and the results obtained are examined from the perspectives of accuracy as well as root mean square error (RMSE) to determine the stability of the proposed solution.

Findings utilizing both approaches are compared with experimental data gathered from a real-world indoor environment. Since the formulations presented in this paper are based on real-world evidence, it is evident that the results showcased in this work are applicable to a host of real-world scenarios, which other researchers may also utilize in the near future to expand the scope, breadth and general applicability of this particular focus of research concentrated on the accurate estimation of path loss for diverse network scenarios.

The paper is organized in the following manner. A survey of recent relevant literature in presented in Section 2, which follows. The experimental setup utilized in the present work is illustrated in detail in Section 3. Section 4 presents multiple mathematical models employed for estimation of path loss. The results obtained through hardware-based experiments as well as simulations are presented in Section 5, inclusive of results obtained through application of machine learning models for analysis of the data and generation of predictions. The obtained results are also discussed in detail in this section. Finally, Section 6 concludes the work, summing up the results achieved as well as methods to engineer further improvement in this domain in the near future.

## 2. Literature Survey

The possibility of widespread commercial wireless communication in the millimeter wave bands has been explored some years back in a seminal work [1]. Moreover, it is critical to emphasize that, for optimal configuration of such millimeter wave wireless systems involving multiple technologies, the complete frequency spectrum would not be utilized. Initially, a typical user would require microwaves operating between 3 and 30 GHz, or would access a millimeter wave frequency spectrum running generally between 30 and 40 GHz (which could extend up to 300 GHz) [11]. For mission critical services, including those for self-driving cars, healthcare, smart city infrastructure, and many more applications and use cases, there is also spectrum sharing in the frequency spectrum ranging from 60 to 70 GHz [12]. Moreover, these services require a constant high-speed data connection with low latency, consequently shared spectrum technology is an essential enabler that keeps all of these gadgets linked at all times [13].

### 2.1. Wireless Network Optimization for LOS and NLOS

Allowing microwave/millimeter wave systems in an extremely dense network may be able to resolve issues with propagation range and channel limitations. However, various problems must be resolved before practical implementations of such systems can be effectively realized. For example, microwave/millimeter wave has considerable penetration losses, resulting in a reduced transmission range [14]. It must also be noted that microwave/millimeter waves are easily absorbed by the atmospheric rain, water vapour, fog and many atmospheric gases, as a result of which meteorological events and concrete structures effectuate significant signal diffusion and absorption. This necessitates the predominance of configuration of line-of- sight (LOS) communication systems for such scenarios [15][16]. The 5G microwave/millimeter wave deployment is predicted to need the use of a huge number of small cells, necessitating the use of highly compact, directional, and high gain antennas. Additionally, because of the small signal wavelength, free-space propagation losses are extremely large [17]. The creation of steerable, high gain, compact antennas in 5G devices is another challenge for microwave/millimeter wave communication. Optimization of the magnitude and orientation of the Poynting vector is therefore found to be crucial for achieving the maximum quality of service performance in non-line-of-sight (NLOS) communication. [18, 19].

The performance characteristics of 5G networks are compatible with these goals of achieving optimal high-quality data transmission for diverse use cases. A conventional 5G communication network includes two data rate benchmarks: 1 Gbps at the cell-edge, which is the area with the lowest performance, and 10 Gbps in the cellular region. [20, 21]. Also, in order to achieve 10 bits per second per Hertz, the spectral efficiency must be improved [22]. Additionally, 5G networks are required to support millions of devices in order to attain higher capacity inside a one-square-kilometer region, including smartphones, wearable devices, smart devices, and vehicles equipped with IoT devices/systems for vehicular mobile connectivity [23]. A system with high mobility and extremely low latency, for instance, must provide end to end service in response to a data request, which needs delivered within five milliseconds (ms), however there should be less than one millisecond of propagation delay between the access point and the device [24]. The Third Generation Partnership Project (3GPP) and the International Telecommunication Union (ITU) were anticipated to establish 5G standards in order to do this; the 3GPP Release-16 were not anticipated until 2020 [25][26]. The major technologies for the 3GPP releases appear to be unique waveform design, multiple radio access technologies and frequency ranges beyond 6 GHz, massive MIMO antenna arrangement, enhanced D2D communication, and flat network hierarchy [24].

In an ideal channel environment, the received signal must ensure an optimum signal to noise ratio (SNR). This is feasible if transmitted signal is received without attenuation beyond a minimal estimated limit. However, when the propagation signal is continually fluctuating, the signaling overhead presents a number of major problems owing to the erratic nature of a channel. The multipath propagation effect, however, offers increased spectral efficiency with a substantial capacity gain when we propagate the signal over large no of antennas. [27].

### 2.2. Model Based Approaches for Path Loss Optimization

Perfect Channel State Information (CSI) is often considered to be present among transmitter and receiver in order to achieve optimum detection (Rx). However, in reality, the channel's impulse response fluctuates because of the communication environment's mobility, necessitating the need for channel estimation. Additionally, the predicted CSI at the transmitter must be signaled through continuous feedback, which consumes a lot of time slots and lowers the system's bandwidth efficiency. In real-world cellular networks, where the majority of users connect to base stations (BSs) through non-LOS channels, exact geometric information on the relative positioning of the BSs and users delivers tremendous spectrum efficiency [28]. As a result, the channel's propagation behavior is critical in this circumstance, because the propagation signal's response can be anticipated [29]. Understanding the propagation channel and its behavior is thus vital for critically analyzing the future generation 5G microwave/millimeter wave wireless network's performance [30]. The purpose of any reliable communication is to provide an excellent noise-compensated transmission link between the transmitter and the receiver [31], which includes compensation for path loss, an essential factor to consider while analyzing various network scenarios [32]. The source and user distance, the frequency of operation, the fading influences, the ambient surface, and the climatic conditions are all elements that influence route loss [33, 34]. Because of the randomness in wireless communication channels, researchers have used a variety of probabilistic approaches to estimate various route losses for noise and interference-limited situations. Experiments and detailed results have provided a variety of datasets, and researchers have built a number of route loss models to anticipate signal attenuation in propagation channels using those studies. Radio channels such as 12 GHz are now being investigated by researchers. Some of the most recent advances in propagation channel research for the 5G wireless network domain are consequently discussed below.

The propagation channel parameters were calculated in this article by calculating the path loss exponents (PLEs) for the 12 GHz frequency range. The simulation results were generated to explore the viability of microwave propagation path loss models such as FI and CI [35]. All LOS and NLOS measurements were taken in an indoor microcell setting with a standard gain horn and an Omni directional antenna. It becomes important to construct models allowing the estimation of 5G signal attenuation in Ku band as well as in K and Ka band signals, for outdoor as well as indoor environments [27]-[29]. The literature surveyed therefore indicates that a research gap exists in terms of validation of a unified attenuation prediction model for Ku, K and Ka band signals for 5G communications. Further, a review of some of the most recent relevant literature indicates the absence of a flexible adaptive machine-learning model for prediction of signal attenuation at the abovementioned frequencies, due to meteorological phenomena such as rain in outdoor environments, and human bodies, obstacles and building materials such as concrete, in indoor environments [30]-[37]. For such environments, mathematical model-based estimation of path loss has proved to be effective for some scenarios [38].

Consequently, the present article outlines an investigation of signal attenuation for 5G scenarios, focusing on indoor environments, to complement similar investigations of rain attenuation in outdoor environments for both slant path as well as LOS scenarios, for 5G signals in the Ku, K and Ka bands, and possibly the V band as well. The studies on Ku band signal attenuation are expected to enable the modelling of rain attenuation for not only the Ku band, but also for K and Ka band microwave and millimeter wave signals respectively. Formulation and implementation of an accurate machine learning model-based approach for prediction of 5G signal attenuation in indoor environments is presented in this work, which may be suitably and easily modified for application to 5G signal propagation in outdoor environments as well.

## 3. Method

The present work outlines a twofold approach where a hardware-based scheme for real-world 5G signal data collection is used to validate mathematical models for indoor propagation 5G signals, for estimation of path loss.

### 3.1. Hardware Setup for Indoor Measurement

The radio signal is propagated between a transmitter and a receiver in a waveguide-like corridor structure on the third floor of the ECE department at Techno International New Town college, in order to assess the characteristics of the transmitted signal. In this experiment, a microwave signal with a frequency of 11.96 GHz is transmitted over a wireless channel using a directional (horn) antenna. Here microwave test bench setup has been used to transmit the signal from the transmitter (Tx) end, whereas horn/Omni directional antenna along with Low noise block converter (LNBC) and Gw-Instek spectrum analyzer (model: GSP-830, frequency range: upto 3 GHz) is used at the receiver (Rx) end, which is utilized to capture the received signal. The channel specifications used in this experiment are displayed in Table 1. Figures 1 and 2 illustrate the schematic diagram and photographs of the experimental setup inclusive of the hardware employed, respectively.

**Table 1.** Specification of the measurement channel

| Parameter (units) | Value |
|---|---|
| Operating frequency (GHz) | 11.96 |
| Transmitted signal Power (dBm) | 10 |
| Transmitter– Receiver configuration | Horn-Horn/Omni |
| Beam width of the Horn Antenna | $18^0$ |
| Mode of propagation | LOS and NLOS |

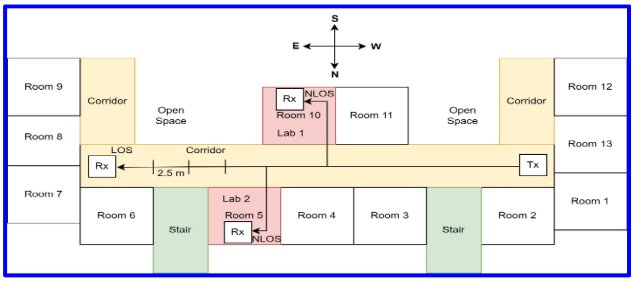



**Fig. 1.** Experimental Setup Schematics

(a) (b) (c)

**Fig. 2.** Hardware Setup Employed for Experiments

The experiment was carried out in the Electronics and Communication Engineering department (Techno International New Town). Figure 1 is showing the schematic diagram of the experimental set-up. Transmitter (Tx) and Receiver (Rx) are placed at two sides of the corridor for Line-of-Sight (LOS) measurement. Similarly for Non-Line-of-Sight (NLOS), keeping the Tx position fixed, Rx is moved to labs on both sides of the corridor. All data were recorded at separation distances of 2.5 meters. Figures 2(a,b.c) show the hardware set-up of the LOS and NLOS measurement where Tx and Rx heights are 1.5 m. The Rx is moved 40 m in step sizes of 2.5 m each. It is valid to point out at this juncture that the ECE-TINT building consists of a structure with concrete column beams along with wooden doors and glass window frame structures. With respect to Line-of-Sight and Non-Line-of-Sight measurements, the propagation distances are 5–40 m and 20–40 m, respectively. Humans were not present in the direct signal path (LOS path) during the testing and consequently, no human movement was detected during the experiments.

### 3.2. Mathematical Models for Path Loss Estimation

The wireless channel's propagation characteristics may be thoroughly examined with the help of the path loss models. Here, the physical separation between source and destination as well as the signal frequency have been used to calculate the signal reduction. To achieve its goals, this study employs Free Space Path Loss (FSPL) propagation models such as the Close In (CI) and Floating Intercept (FI) models [39].

A frequency-dependent path loss model, the CI propagation model, focuses on free space propagation loss, $FSPL_{CI}$ $(f,d\_0)$, which is related to the frequency of the carrier signal ($f$, measured in GHz) and the physical separation (d) between transmitter and receiver, with d_0 functioning as a reference distance. With only one parameter, it is simply dependent on Path Loss Estimate PLE($\boldsymbol{\eta_{CI}}$), which is calculated in decibels. The following equation is used to calculate the path loss values for this model [40]:

$$PL^{CI}(f,d)[dB] = FSPL_{CI}(f,d\_0) + 10nlog_{10}(\frac{d}{d\_0}) + \chi_{\_\sigma}^{CI} \quad (1)$$

where, $\chi_{\_\sigma}^{CI}$ is a Gaussian random variable with zero-mean value.

$FSPL_{CI}$ ($f$, $d\_0$), the Free Space Path Loss is defined as

$$FSPL_{CI}(f,d\_0) = 20log_{10}(\frac{4\pi f d\_0}{c}) \quad (2)$$

The $\chi_{\_\sigma}^{CI}$ is the variation of signal at the receiver end which can be written as:

$$\chi_{\_\sigma}^{CI} = FSPL_{CI}(f,d\_0) = 20log_{10}(\frac{4\pi f d\_0}{c}) \quad (3)$$

where, $\sigma^{CI}$, the standard deviation, is defined as:

$$\sigma^{CI} = \sqrt{\frac{\Sigma(\chi_{\_\sigma}^{FI})^2}{N}} \quad (4)$$

N represents the collected path loss data points, and the $\eta_{CI}$ and minimum $\sigma^{CI}$ are determined as:

$$\eta_{CI} = \frac{\Sigma[PL^{CI}(f,d)\ [dB] - FSPL_{CI}(f,d\_0)]\{10log_{10}(\frac{d}{d\_0})\}}{\{10log_{10}(\frac{d}{d\_0})\}^2} \quad (5)$$

$$\sigma^{CI} = \sqrt{\frac{[PL^{CI}(f,d)\ [dB] - PL^{CI}(f,d\_0) - 10log_{10}(\frac{d}{d\_0})]^2}{N}} \quad (6)$$

The FI propagation model is used to get the optimum lowest error fit value using the floating intercept ($\alpha$) and line slope ($\beta$) data [41, 42]. The FI model is computed using the following equation:

$$PL^{FI}(d)[dB] = \alpha + 10\beta log_{10}(d) + \chi_{\_\sigma}^{FI} \quad (7)$$

The $\chi_{\_\sigma}^{FI}$ is the variation of signal at the receiver end which can be written as:

$$\chi_{\_\sigma}^{FI} = PL^{FI}(d)[dB] - \alpha - 10\beta log_{10}(d) \quad (8)$$

where, $\sigma^{FI}$, the standard deviation, is defined as:

$$\sigma^{FI} = \sqrt{\frac{\Sigma[PL^{FI}(d)[dB] - \alpha - 10\beta log_{10}(d)]^2}{N}} \quad (9)$$

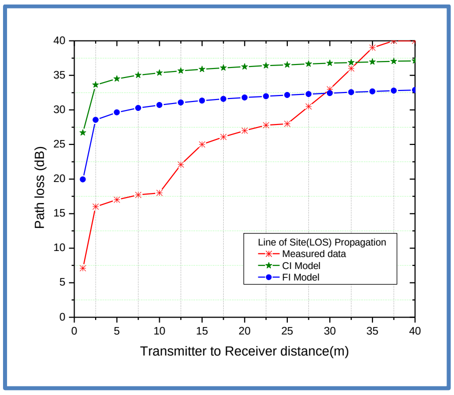
The measured path loss data points are represented by N, and the standard deviation, $\sigma^{FI}$ is reduced using the Minimum Mean Squared Error (MMSE) approach. Consequently, the equations below may be used to compute the following parameters, $\alpha$ and $\beta$.

$$\alpha = \frac{\Sigma 10log_{10}(d)\Sigma 10log_{10}(d)PL^{FI}(d)[dB] - \Sigma\{10log_{10}(d)\}^2 PL^{FI}(d)[dB]}{\Sigma\{10log_{10}(d)\}^2 - N\Sigma\{10log_{10}(d)\}^2} \quad (10)$$

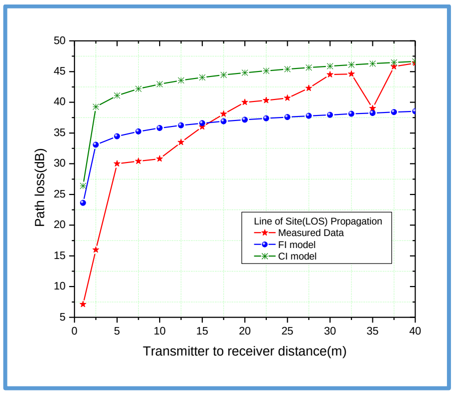
$$\beta = \frac{\Sigma 10log_{10}(d)\Sigma PL^{FI}(d)[dB] - N\Sigma 10log_{10}(d)PL^{FI}(d)[dB]}{\Sigma\{10log_{10}(d)\}^2 - N\Sigma\{10log_{10}(d)\}^2} \quad (11)$$

## 4. Results and Discussion

The radio wave propagation channel modelling parameters are essential for designing more effective next-generation wireless communication systems. These parameters are able to estimate signal attenuation as an electromagnetic signal travels a given distance. The shape and conductivity of the building materials in the corridor scenario controls how the wave travels from transmitter to the receiver side. Multipath reflection, diffraction, refraction, shadowing effects, and penetration loss occurs in the interior corridor propagation environment due to all of which have a significant impact on received signal strength [43]. The received signal is considered to be the total of the reflected and direct waves from the transmitter side due to waveguide effects and multipath refraction. If ray tracing approach is considered within a short distance, a number of existing path loss models are based on scattering refraction as well as free space [44], [45]. In recent times, other researchers have also proposed reinforcement learning-based beam selection techniques for 5G networks considering similar path loss models, for both unmanned aerial vehicles and terrestrial vehicular networks [46][47]. In this experiment, signal transmission and reception at 11.96 GHz has been effectuated, with extensive research and analysis carried out on the obtained results in order to provide findings and make comparisons between line-of-site (LOS) and non-line-of-site (NLOS) environments using various propagation models. The LOS propagation results are illustrated in the following Figure 3.



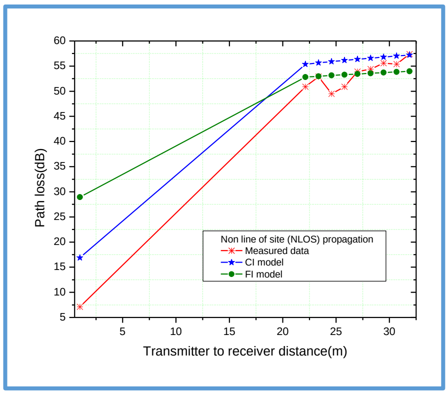

(a)



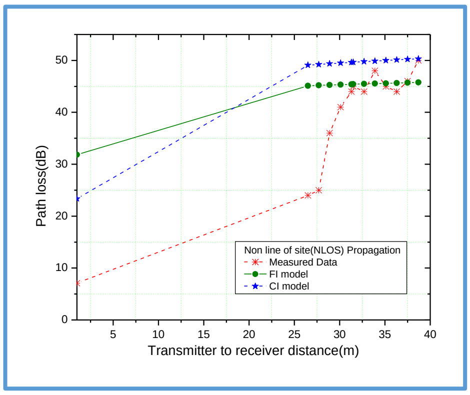

(b)

**Fig. 3.** 11.96 GHz LOS large scale path loss on (a) 16/08/2022 and (b) 23/08/2022 for ECE-TINT building corridor with transmitter receiver both side horn antenna

In case of LOS propagation environment, 17 data points are used, distributed over the total range of 1-40 m. On the other hand, for NLOS, 13 data points are used. However, the reference distance (1 m) is the same in both environments. These data show how signal propagation changes when the Tx-Rx spacing varies. The corresponding results for NLOS experiments are illustrated in Figure 4, which follows.




(a)




(b)

**Fig. 4.** 11.96 GHz NLOS large scale path loss on (a) 23/08/2022 and (b) 20/12/2022 for ECE-TINT building corridor with horn antenna at the transmitter and Omni directional antenna at the receiver side

### 4.1. LOS and NLOS Path Loss Models

The LOS path loss model's results are shown in Fig. 3 (a, b). It is clear from figure that the path loss values are very close to FI model predictions on both the experimental days but CI model-based value estimates differ from measured data. Both the models offer divergent estimates when the separation between transmitters to receiver is increased. Fig. 3a & 3b show the 11.96 GHz results, where the day 2 (23/08/2022) LOS case produces more uniform results than day 1(16/08/2022) in this scenario. The PLE (η_CI) values for 16/08/2022 and 23/08/2022 at the said frequency are found out to be 0.268 and 0.613 for LOS environment, respectively. However, the shadowing factors are 7.63 dB and 6.37 dB for the respective days of experiment. Similarly, in the case of NLOS study, for day 1 (23/08/2022) the measured results exactly follow the trend predicted by CI and FI models for all separation distances, as depicted in Fig. 4(a). However, the path loss shows a huge deviation at lower separation distances for day 2 (20/12/2022) but at higher separation distances the measured results are again found to follow the CI and FI model trends as shown in Fig. 4(b). The η_CI values are 1.15 and 0.751 for both the days of measurement, respectively. However, the shadowing factor decreases slightly to 2.875 dB in the case of the NLOS scenario for day 1 (23/08/2022), but increases slightly to 9.36 dB for day 2 (20/12/2022). The signal clearly deteriorates more in the LOS region as compared to the NLOS region for day 1 but the trend is reversed for day 2. In order to illustrate the propagation effect, the results of the FI path loss model have been presented in Figures 3 and 4. For LOS measurement, the signal rapidly deteriorates on day 1 for both the lower and higher separation distances, as shown in Fig. 3(a). However, on day 2, measured results are found to closely follow the FI model estimate curve over all distances as shown in Fig. 3(b). In LOS environment, the α values are 19.26 & 27.39 and the β values are 0.351 & 0.45 respectively, on the other hand in case of NLOS, the α attains its value to 31.268 & 27.76 and β are 0.714 & 0.388 as shown in Fig. 4(a, b).

These numbers indicate that the signal's performance in terms of LOS measurement is significantly better and is also dependent on surrounding environmental conditions, which inference is expected to hold for a number of diverse indoor microenvironments similar to the present experimental setup, which makes such an use case extremely relevant for high-speed indoor communication. In comparison, the penetration losses are found to continuously rise as the transmitter and receiver separation increases. The results are summarized in Table 2, which follows.

**Table 2:** Summary of the CI and FI Path Loss Models

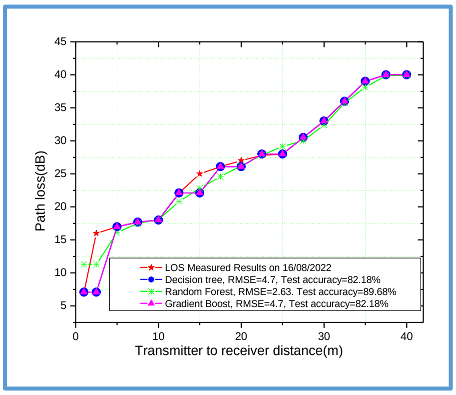
| Frequency (GHz) | Measured parameters | LOS Scenario | | NLOS Scenario | |
|---|---|---|---|---|---|
| | | 16/08/2022 | 23/08/2022 | 23/08/2022 | 20/12/2022 |
| | $\eta_{CI}$ | 0.268 | 0.613 | 1.15 | 0.7512 |
| | $\alpha$ | 19.26 | 27.39 | 31.268 | 27.76 |
| 11.96 | $\beta$ | 0.351 | 0.45 | 0.714 | 0.388 |
| | $\sigma^{CI}$ (dB) | 7.63 | 6.37 | 2.875 | 9.36 |
| | $\sigma^{FI}$ (dB) | 7.52 | 58.68 | 11.94 | 11.83 |

### 4.2. Discussion of Model Based Estimation Results

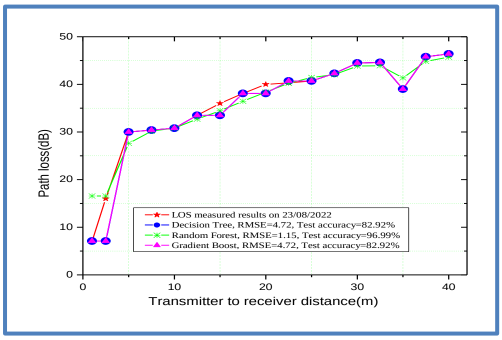
Table 2 summarizes the comparison of significant variables based on multiple days of experiments in LOS and NLOS conditions for the FI and CI models. In case of LOS study, the $\eta_{CI}$ are 0.268 & 0.613 for the respective days of experiment. On the other hand, for NLOS case, the $\eta_{CI}$ values are 1.15 & 0.7512 respectively. It is clear from the above table (Table 2) that, the highest PLE value of 1.15 is observed for NLOS study on 23/08/2022 however the lowest value, 0.268 has been found in the case of LOS study on 16/08/2022. These values indicate that when the separation between transmitter and receiver increases, signal degradation is found to increase correspondingly, and vice versa. Due to interference from a variety of irregular items, such as the iron structures above the corridor railings, column beams, and several wooden doors and glass windows, which make this results frequency dependent. Furthermore, the shadow fading standard deviation $\sigma^{CI}$**(dB)** in LOS scenarios are 7.63 & 6.37 respectively, however the $\sigma^{CI}$**(dB)** values in case of NLOS scenarios are 2.875 & 9.36 respectively. It is observed in the NLOS scenario that the lowest and highest values of $\sigma^{CI}$**(dB)** are 2.875 and 9.36 dB, however no such significant difference is observed in the LOS scenario. The different results observed in the context of NLOS suggest that the significant changes in received signal intensity from various concrete column structures, wooden doors, and iron railings are directly proportional to the power received. Table 2 summarizes the FI model results as well. Here, the $\sigma^{FI}$**(dB)** values for LOS are 19.26 & 27.39 respectively at 11.96 GHz, however in case of NLOS, the $\sigma^{FI}$**(dB)** values are 31.26 & 27.76 respectively at the same frequency. It is to be noted here that the minimum $\alpha^{FI}$ value is obtained for LOS study but is maximum for NLOS. This reveals that the FI model estimates are less accurate for scenarios where the signal undergoes significant attenuation with path loss, which is observable from the NLOS study. Furthermore, in the LOS case, the line slope ($\beta$) values are 0.351 and 0.45, respectively. In contrast, the $\beta^{FI}$ values are 0.714 & 0.388 in the NLOS case. Like the $\alpha$ values, here, it is also seen that the minimum $\beta$ value obtained for LOS case, however the maximum $\beta$ can be found for NLOS case scenario, which corresponds to the results observed for $\alpha$ value. Moreover, the $\sigma^{FI}$ values for the LOS case study are 7.52 & 58.68 respectively, whereas the $\sigma^{FI}$ values are 11.94 & 11.83 in the NLOS case at 11.96 GHz. Here, the maximum $\sigma^{FI}$ value of 58.68 is achieved in the LOS scenario and the minimum $\sigma^{FI}$ value of 7.52 is measured in the same LOS case scenario but the NLOS values are approximate same, 11.94 and 11.83.

### 4.3. Discussion of Machine Learning Results

In order to account for the significant difference of actual values with estimates for significant path loss, machine learning models were employed to generate more accurate path loss estimates in order to model the channel more accurately than otherwise possible. In the present scenario, three separate regression algorithms were employed, namely Random Forest Regressor, Decision Tree Regressor and Gradient Boosting Regressor. The models were used to estimate path loss for LOS scenarios (Figure 5).



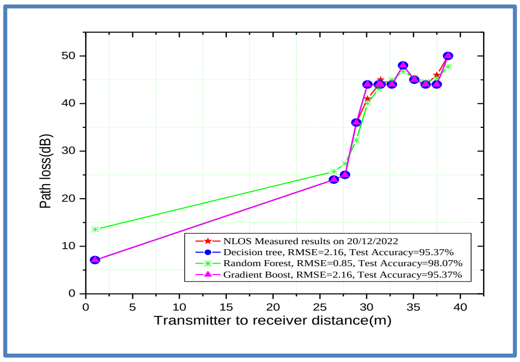

(a)



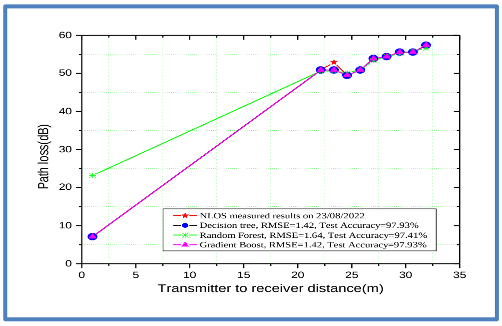

(b)

**Fig. 5.** Machine learning analysis of LOS results on (a) 16/08/2022 and (b) 23/08/2022

Corresponding results for NLOS scenarios could also be estimated using the same methods. The corresponding results obtained for NLOS scenarios are consequently presented in Figure 6, which provides the illustration for comparative results using mathematical modelling-based approaches as well as machine learning based estimate generation, with the actual experimentally obtained value set acting as the set of true values, against which the machine learning model-generated estimates are compared to obtain the different metrics focusing on the accuracy and stability of the models generating such estimates. For the present scenarios, the parameters deemed to be important are accuracy and root mean square error (RMSE), since the machine learning problem can be thought of as a regression problem where the path loss estimates are generated using the set of available feature variables and historical data.




(a)




(b)

Fig. 6 Machine learning analysis of NLOS results on (a) 20/12/2022 and (b) 23/08/2022

It was observed that the Random Forest Regressor model generated the most accurate predictions in almost all of the scenarios (Figures 5a, 5b and 6a) with suitably low root mean square error (RMSE) indicating stability of the results, even in Figure 6b, the RMSE and accuracy of the Random Forest Regressor model is found to be comparable to the Decision Tree and Gradient Boosting models. Another feature of interest is the fact that the Decision Tree and Gradient Boosting models have very similar prediction performances, which can however be attributed to the comparatively small test sample sets examined in this work. However, the Random Forest model is expected to give largely stable performance for other similar scenarios due to its consensus-based estimation method being less prone to inherent data bias present in such sample sets.

### 5. Conclusion

Modelling of a 5G wireless communication link has been performed in an indoor environment with employment of standard propagation model-based estimation to accurately capture the variation in path loss characteristics. The experimental results obtained are found to largely agree with simulation estimates for LOS propagation scenarios, however there can be significant deviation from expected estimates for NLOS propagation.

To tackle this issue, machine learning-based estimation models have been effectively employed to generate accurate estimates for all scenarios, with excellent results (accuracy of approximately 98 % with approximate RMSE less than or equal to 1.4) achieved especially for NLOS propagation of the 5G signal. In future, multi-model estimation, or the employment of neural networks may further improve the estimation performance of the proposed models and allow further improvements in accuracy for estimation of channel and signal parameters for wireless 5G communication.

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**Author contributions**

**Md Anoarul Islam:** Conceptualization, Methodology, Field study, Investigation, Writing-Original draft preparation **Manabendra Maiti:** Conceptualization, Methodology, Software, Validation., Field study, Writing-Reviewing and Editing **Ardhendu Shekhar Biswas:** Methodology, Software, Field study, Visualization, Investigation, Writing-Original draft preparation **Vivekananda Mukherjee:** Conceptualization, Methodology, Software, Data curation, Field study, Writing-Original draft preparation **Judhajit Sanyal:** Data curation, Writing-Original draft preparation, Software, **Quazi Md Alfred:** Conceptualization, Methodology, Visualization, Writing-Reviewing and Editing.

**Conflicts of interest**

The authors declare no conflicts of interest.

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