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Performance Evaluation of Current Empirical Path Loss Models for 5G Communication Networks in Mid-Band Spectrum of 3.5 GHz

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Abstract
The rapid deployment of 5G networks in urban environments necessitates accurate path loss prediction models to ensure efficient network planning and optimization. Given the complex propagation characteristics in dense urban areas, selecting an appropriate model is crucial for reliable signal coverage and performance. This dissertation focuses on evaluating the performance of three empirical path loss models—Close-In (CI), Floating Intercept (FI), and Alpha-Beta-Gamma (ABG)—in predicting path loss for 5G networks within Abuja's urban environment. The study analyzed both line-of-sight (LoS) and non-line-of-sight (NLoS) scenarios using field measurement data. The CI model demonstrated the best performance, closely aligning with the measured path loss in both scenarios. It achieved the lowest Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), with values of 3.12 dB, 3.05 dB, and 2.11% in the LoS scenario, and 4.08 dB, 2.68 dB, and 0.79% in the NLoS scenario, respectively. In comparison, the FI model underpredicted path loss more noticeably, and the ABG model consistently underperformed, particularly in NLoS conditions. The study concludes that the CI model is the most reliable for 5G path loss prediction in urban environments. Future work should focus on refining the CI model for greater accuracy and exploring site-specific calibration to improve model adaptability for varying urban landscapes.
Keywords: *5G communication, CI model, FI model, ABG model, Path loss.*

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I. Introduction

Precise path loss estimation is vital for predicting transmitter coverage and improving the efficiency of wireless networks. The ever-changing characteristics of wireless channels, shaped by diversity, temporal variability, and large-scale deployments, reduce the effectiveness of conventional path loss models in addressing these complexities [1]. Identifying the factors that influence radio signal attenuation in communication systems is key to accurately defining the coverage area of a broadcast station [2].

The rapid advancement of communication systems, especially with the emergence of fifth-generation (5G) mobile networks offering higher speeds, has compelled the wireless industry to integrate with earlier generations. This integration presents significant challenges for the planning and optimization of 5G and future communication technologies [3].

Understanding the many radio frequency factors that affect radio signals is important for predicting the coverage that a particular Radio broadcast station may attain [4]. Wireless communication is everywhere, from the Long-Term Evolution (LTE) technology in smartphones to the Bluetooth Low Energy (BLE) chipset in wearables and the WiFi modem in our homes. Despite the widespread availability of cellular and operator-based technologies such as LTE, LoRA, and satellite, many interior industrial regions still lack coverage due to the presence of huge obstructing metallic structures in industrial environments [5].

In Abuja's urban environment, the capital of Nigeria, the effectiveness of 5G path loss models for communication networks is uncertain. The challenge lies in accurately understanding how well these models predict signal loss as they navigate through the city's diverse landscapes with buildings, streets, and varying obstructions. Evaluating the real-world performance of these models is crucial to ensure reliable and efficient 5G network coverage in urban areas like Abuja. This paper aims to investigate the actual performance of these models in Abuja's urban setting, providing insights into their accuracy and suitability for optimizing 5G communication networks within this dynamic environment.

The main objective is to investigate the performance of the three most widely used current empirical models for path loss at the mid-band of 3.5 GHz and recommend the most performed one for the urban environment of Abuja, F.C.T. It starts by conducting an outdoor measurement campaign at the mid-band frequency of 3.5 GHz in the urban environment of Abuja. Subsequently, the prediction of the three chosen current empirical models were evaluated using the measurement campaigns' results. Then, compared the predictions of the selected models against the measured path loss using the standard performance metrics.

The 3.5 GHz frequency band has been widely designated by numerous countries for the deployment of 5G networks. In line with the global emphasis on this priority mid-band spectrum, the Nigerian Communications Commission (NCC) has allocated the 3.4–3.8 GHz range for the implementation of 5G technology in Nigeria. Details of the specific use cases for this spectrum allocation are illustrated in Figure 1.

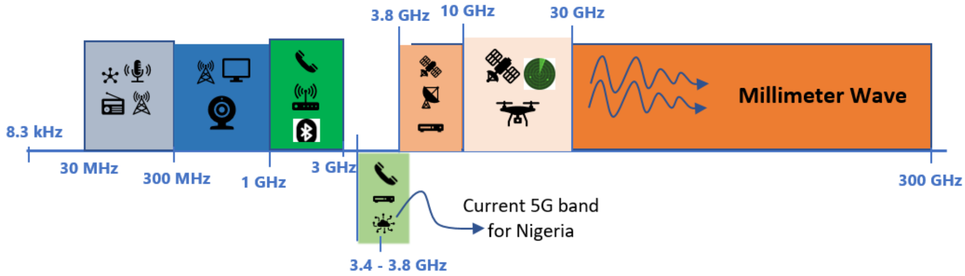

FIGURE 1: Nigeria frequency spectrum.

The main contribution of this paper include:

i. Conducted an extensive evaluation of the CI, FI, and ABG path loss models using real-world measurement data from the 3.5 GHz mid-band spectrum.

ii. Employed standard performance metrics to compare the prediction accuracy of the selected empirical models against measured path loss, providing an evidence-based assessment of their suitability for 5G urban networks.

iii. Identified and recommended the most suitable path loss models for deployment in urban environments based on the evaluation results, supporting more valuable network planning and optimization.

The remainder of this paper is structured as follows: Section 2 presents some of the widely used current empirical path loss models. Section 3 reviews related work on path loss modeling based on empirical models and deterministic models that leveraged on empirical model. Section 4 outlines the methodology used in evaluating the performance of the selected current empirical path loss models. Results and discussion, as well as the validation of the models, are presented in Section 5. Finally, Section 6 presents the conclusion remarks with potential areas for future research.

II. Empirical Path Loss Model

The 5G standard brought significant innovations to accommodate its services and applications. To meet emerging demands, such as the introduction of new frequency bands and beamforming antennas, propagation modeling for 5G has been enhanced, resulting in the creation of improved empirical path loss models.

II.1 3GPP TR 38.901

This model integrates empirical measurements with theoretical analysis of radio wave propagation. It accounts for various factors influencing path loss, such as the distance between the transmitter and receiver, signal frequency, antenna heights, and environmental features [6]. The 3GPP 38.901 path loss model offers a standardized framework for predicting radio wave behavior and serves as a crucial resource in advancing 5G wireless communication systems [7].

i. For Urban Macro and Line-of-Sight (LoS) scenarios.

$$PL_{UMa-LOS} = \begin{cases} PL_1 & 10m \leq d_{2D} \leq d'_{BP} \\ PL_2 & d'_{BP} \leq d_{2D} \leq 5km' \end{cases} \quad (1)$$

$$PL_1 = 28.0 + 22\log_{10}(d_{3D}) + 20\log_{10}(f_c), \quad (2)$$

$$PL_2 = 28.0 + 40\log_{10}(d_{3D}) + 20\log_{10}(f_c) - 9\log_{10}((d'_{BP})^2 + (h_{BS} - h_{UT})^2). \quad (3)$$

ii. For NLOS scenario.

$$PL_{UMa-NLOS} = max(PL_{UMa-LOS}, \quad PL'_{UMa-NLOS})\, for\ 10m \leq d_{2D} \leq 5km, \quad (4)$$

$$PL'_{UMa-NLOS} = 13.54 + 39.08\log_{10}(d_{3D}) + 20\log_{10}(f_c) - 0.6(h_{UT} - 1.5). \quad (5)$$

The equations (4) and (5) hold for shadow fading std, $\sigma_{SF}\ [dB] = 6$; applicability range, antenna height default values of $1.5m \leq h_{UT} \leq 22.5m; and\ h_{BS} = 25m.$

II.2 Close-in (CI) free space reference distance Model

This model provides a straightforward approach to estimating path loss in wireless communication systems. It operates under the assumption that the signal travels through free space without encountering obstacles or reflections and that the transmitter and receiver are separated by a relatively short distance [8]. The CI free space reference distance model is expressed in equation 6.

$$P_L^{CI}(f,d)[dB] = FSP_L(f,d_0) + 10n\log\left(\frac{d}{d_0}\right) + W_\sigma^{CI}, \tag{6}$$

where $FSP_L(f,d_0)$ is the free space path loss in dB at a T-R separation distance of 1m at the carrier frequency, f, 'n' is the path loss exponent, 'd_0' is the initial separating path, of 1m; and W_σ^{CI} is a zero-mean Gaussian-distributed random variable. The equation for free space path loss is given in (7);

$$P_L(f,d_0) = 20\log(d_0) + 20\log(f) + 32.44 \tag{7}$$

where d_0 is the close-in reference distance from the transmitter in km and f is the signal frequency in MHz.

II.3 Floating-Intercept (FI) Model

This path loss model is commonly applied in wireless communication and radio wave propagation studies. Unlike models with a fixed intercept in their equations, the FI model permits the intercept to change based on specific conditions or influencing factors. This adaptability enhances its utility for analyzing wireless propagation across diverse scenarios [9].

$$L(dB) = A + B\log_{10}(d) + X \tag{8}$$

where; $L(dB)$ is the path loss in decibels (dB), A is the floating intercept. B is the path loss exponent, which quantifies the rate at which the signal strength decreases with distance, d is the distance between the transmitter and receiver, and X represents random or environment-dependent variations in path loss.

II.4 Alpha-beta-gamma (ABG) Model

The ABG model is a popular empirical approach for estimating path loss in wireless communication systems. It employs three key parameters: the distance between the transmitter and receiver, the frequency of the transmitted signal, and the path loss exponent. The path loss exponent indicates the rate at which signal strength diminishes with distance and varies according to the propagation environment [8]. The equation representing the ABG model is provided in (9).

$$PL^{ABG}(f,d)[dB] = 10\alpha\log_{10}\left(\frac{d}{1\,m}\right) + \beta + 10\gamma\log_{10}\left(\frac{f}{1\,GHz}\right) + X_\sigma^{ABG} \tag{9}$$

where d is the 3D transmitter-receiver (T-R) separation distance in meters, f is the carrier frequency in GHz, and X is an optimized offset value for path loss in dB; $PL^{ABG}(f,d)$ represents the path loss in dB over frequency and distance; $\alpha\ and\ \gamma$ are the coefficients showing the dependence of path loss on distance and frequency; β is an optimized offset value for path loss in dB [10, 11].

III. Literature Review

In [12], the researchers introduced empirical path loss models tailored to typical indoor environments at 3.5 GHz for 5G communication. Their study involved large-scale fading measurements conducted under line-of-sight (LOS) and non-line-of-sight (NLOS) co-polar conditions. The equipment used included a real-time spectrum analyzer, a continuous wave signal generator, and two omnidirectional antennas within a building. To achieve more accurate results for both scenarios, extensive measurement campaigns across comparable buildings and the appropriate ITU-R model will be required.

In [13], the authors proposed a path loss prediction method for 5G millimeter-wave (mm-wave) communications using the Grey model. Their approach involved developing a path loss model that utilized distance as input and path loss as output, based on measured data at 28 GHz. This model was compared against four established 5G empirical models\u20145GCM, 3GPP, METIS, and mm-MAGIC\u2014in a dense urban environment. The results highlighted the model's strong predictive capability, particularly for narrow-band frequencies. Additionally, the study suggested incorporating more error metrics beyond the mean absolute error (MAE) to improve performance analysis.

In [14], propagation measurements were carried out at three frequencies; 14, 18, and 22 GHz, covering both line-of-sight (LoS) and non-line-of-sight (NLoS) scenarios. The evaluation included two prominent path loss models: the single frequency floating intercept (FI) model and the single frequency close-in (CI) free space reference distance model. However, the study did not account for the material properties of the surrounding environment, which may have influenced the results due to potential reflection and diffraction effects, contributing to the observed symmetric patterns.

In their research, [15] used a 3D ray-tracing approach to simulate a 5G communication testbed operating at 28 GHz on Lagos Island. They analyzed five different path loss scenarios: path loss, free-space path loss with and without antenna patterns, and excess path loss with and without antenna patterns, focusing on an urban environment. To identify the most suitable path loss model for Lagos Island, the study employed the Floating Intercept (FI) model, the Close-In (CI) model, and root mean square error (RMSE) for modeling and evaluation. Although no field measurements were conducted at 28 GHz under line-of-sight (LoS) and non-line-of-sight (NLoS) conditions for comprehensive validation, the findings revealed that the FI model achieved a lower RMSE value than the CI model across the examined scenarios.

In [16], a comprehensive measurement campaign was carried out in a campus pond area at 28 GHz, aiming to develop a path loss model that accounted for factors such as water surface reflections and building diffraction. The study also explored other channel characteristics, such as the power delay profile and the root-mean-square delay spread.

In [17], a detailed measurement campaign took place in two rural areas in southern Finland during the summer, focusing on the 26 GHz frequency band. Path loss measurements were conducted with a crane-mounted setup at transmit antenna heights of 30m, 50m, and 70m. To determine the most appropriate path loss model, three models were tested: the Third Generation Partnership Project (3GPP) rural macro (RMa) model, the Alpha-Beta-Gamma (ABG) model, and the Close-In (CI) model, under Line-of-Sight (LoS), Obstructed-LoS (OLoS), and Non-Line-of-Sight (NLoS) conditions. While no indoor measurement comparisons were made, the CI model showed promise for modeling different antenna heights in an RMa setting.

In [18], different scenarios were examined to assess the propagation of millimeter-waves and sub-terahertz frequencies in outdoor Urban Microcell (UMi) environments. The study indicated that channels operating at 38 and 73 GHz show significant resistance to challenging environmental conditions, while those at 60, 100, and 120 GHz are more vulnerable to such factors. However, no physical measurement campaigns were carried out for the channels under consideration.

In a different study by [19], wideband measurements in a street environment were used to develop path loss models for frequency bands of 1.8, 3.5, and 28 GHz. The measurements were carried out under stable environmental conditions, with no wind.

In [20], the authors investigated path loss to ensure precise signal estimation in Malaysia, concentrating on outdoor microcellular environments at 38 GHz over a 300-meter path. The study involved continuous monitoring of a short-path link operating at 38 GHz with horizontal polarization for one year. Rain attenuation data was obtained from the received signal level and analyzed statistically.

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In another study by [22], five distinct empirical models - FSPL, SUI model, Ericsson model, Okumura model, and COST-231 Hata model - were evaluated against empirical data measurements to determine the most suitable model for predicting path loss in the urban setting of Cologne, Germany, operating at 2.5 GHz. The findings revealed that the COST-231 Hata model exhibited the best fit, achieving a minimum RMSE of 5.27 dB. However, it was noted that further refinement of the COST-231 Hata model is necessary to accommodate the specific characteristics of the urban environment, which includes a mix of old and modern buildings.

IV. Materials and Method

4.1 Study Area

The central area of the Federal Capital Territory of Nigeria is one of the fastest-growing cities in Africa, supported by rapid population growth, making it clustering and suitable scenario for path loss investigation and evaluation of the best path loss model that will perfectly characterize the impact of urban environment on path loss within the mid-band channel. The study area for the path loss modeling in the Federal Capital Territory, Abuja, is presented in Figure 2.

FIGURE 2: Measurement Campaigns Study Area for Path Loss Modeling

Table 1 provides the transmitter information parameters, detailing key specifications for the two broadcast transmitting stations considered during the measurement campaigns for path loss modeling.

Table 1: Transmitter information parameters

SITE ID	SITE NAME	Latitude (º)	Longitude (º)	Environment	Frequency (GHz)	Tx Power (dBm)	Antenna Gain (dB)	Antenna height (m)
FC0125	Transcorp, Hiltop	9.0876	7.4803	Urban	3.5	20.0	41.30	35
FC3112	FOMWAN Basic School	9.1003	7.4811	Urban	3.5	15.0	37.30	30

4.2 Measurement Campaigns

An outdoor measurement campaigns were conducted at the mid-band frequency of 3.5 GHz in the urban environment of Abuja. The measurements were carried out around Maitama, where a 5G broadcast transmitting station, identified by ID FC0125, operates on a live 5G network. The campaign began by taking measurements at a reference distance of 10 meters from the transmitter, followed by further readings starting from 50 meters, with incremental steps of 50 meters, extending up to 600 meters. The use of a moving vehicle equipped with an HE200 directional antenna, mounted at a height of 1.5 meters and connected to a handheld spectrum analyzer, allowed for accurate signal reception during the campaign, as illustrated in Figure 3.

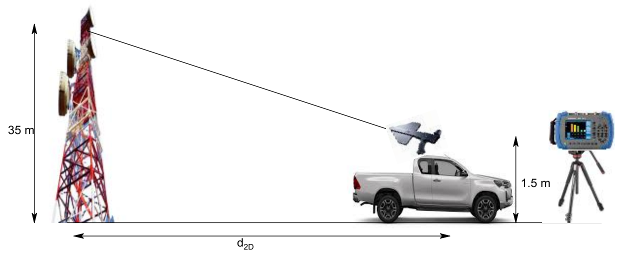

FIGURE 3: Illustration of the measurement campaign.

At each measurement point, three readings of the received signal strength were captured to ensure data accuracy and consistency. The average received signal strength for each location was calculated and recorded. The campaign was designed to capture the variations in signal behavior under two different propagation scenarios: line-of-sight (LoS) and non-line-of-sight (NLoS). These scenarios were chosen to provide a comprehensive analysis of how the 5G signal behaves in both direct and obstructed environments, reflecting typical urban conditions in Abuja.

In addition to the initial location, a second environment was selected for further validation of 5G signal propagation characteristics. This secondary site featured another live 5G network with a base transceiver station (BTS) identified as FC3112. The same measurement procedure was repeated at this location under both LoS and NLoS conditions. This repetition allowed for a comparative analysis of signal performance across different urban settings, further strengthening the reliability and applicability of the findings in understanding 5G signal propagation within Abuja's urban landscape.

4.3 Evaluation of the Path Loss Models

The measured signal strengths, along with other relevant parameters from the transmitting stations, were used to evaluate the path loss predictions of three well-established models: the Alpha-Beta-Gamma (ABG) model, the Floating Intercept (FI) model, and the Close In (CI) Free Space model.

$$PL\ (dB) = PL(d_o) + 10\eta \log_{10}\left(\frac{d}{d_o}\right) + X_\sigma, \tag{10}$$

where PL denotes the path loss in dB, d denotes the path length between the Tx and Rx, d_o denotes the reference distance from the transmitter, η is the path loss exponent, and X_σ is the random Gaussian variable with zero mean and standard deviation representing shadowing factor in the environment [15].

$$\overline{PL}(dB) = \alpha + \beta 10 \log_{10}(d), \tag{11}$$

In this context, α represents the floating intercept (FI) in dB, while β represents the path loss exponent expressed as the linear slope.

From equation 10 and 11, we can derive shadow factor as;

$$X_\sigma = PL\ (dB) - \overline{PL}(d_o) - 10\eta \log_{10}\left(\frac{d}{d_o}\right) \tag{12}$$

The linear slope value β of the path loss exponent η is derived as;

$$\beta = \frac{\sum_i^n \left(d_i - \bar{d}\right) x (PL_i - \overline{PL})}{\sum_i^n \left(d_i - \bar{d}\right)^2}, \tag{13}$$

where d_i is the separation distance between the antenna and the receiver, d is the average distance of all d_i values, PL_i is the iterated path loss value of all the measured data set as a distance-dependent variable [15]. The floating intercept α (dB) represents the tilt in the path loss model of equation 14. It is calculated by substituting 11 into 10 and making α (dB) the subject as in equation 14 [15].

$$\alpha = \overline{PL}(dB) + \beta .10 \log_{10}(d) \tag{14}$$

The standard deviation σ (dB) of the path loss model can be calculated as;

$$\sigma\ (\text{dB}) = \sqrt{\sum \frac{(PL_i - \overline{PL})^2}{N}} \tag{15}$$

where N is the total number of receiver points.

By leveraging the measured data, these models were applied to estimate the path loss experienced over various distances, ranging from 10 meters to 600 meters.

The ABG model, a widely accepted model for millimeter-wave frequency bands, takes into account three key parameters (α, β, and γ) that adjust the model to fit the measured data across different environments. This model was applied to the recorded signal strength values to evaluate how well it predicts the path loss in line-of-sight (LoS) and non-line-of-sight (NLoS) scenarios. Similarly, the Floating Intercept (FI) model, which uses a flexible intercept term to account for variations in signal behavior, was also applied to the dataset. The flexibility of the FI model allowed for more adaptability in fitting the measured data, providing insights into its performance in a real-world 5G network.

Finally, the Close In (CI) Free Space model, which is based on the fundamental principles of free space path loss, was used as a benchmark for comparison. This model typically assumes that the signal attenuates with distance according to a predictable pattern.

4.5 Validation of the Models

The performances of the considered current empirical models; the Alpha-Beta-Gamma (ABG) model, the Floating Intercept (FI) model, and the Close In (CI) Free Space model were validated by comparing their predictive capability in another urban environment, using performance metrics such as the mean absolute error (MAE), root mean square error (RMSE), and the mean absolute percent error (MAPE).

These three-performance metrics—MAE, RMSE, and MAPE—work together to provide a comprehensive evaluation of how well each path loss model predicts the actual measurements in the urban environments of Abuja. While MAE gives an overall view of prediction accuracy, RMSE helps to understand the handling of large errors, and MAPE allows for easy comparison of the models in terms of percentage error. By analyzing these metrics, the study can identify which model, among the current empirical models provides the most accurate and reliable predictions for path loss in urban environments.

V. Results and Discussions

5.1 Results of the Measurement Campaigns

The results of the measurement campaigns conducted are illustrated in Figure 4**,** which clearly demonstrates that signal strength is significantly better in the line-of-sight (LoS) scenario compared to the non-line-of-sight (NLoS) scenario.

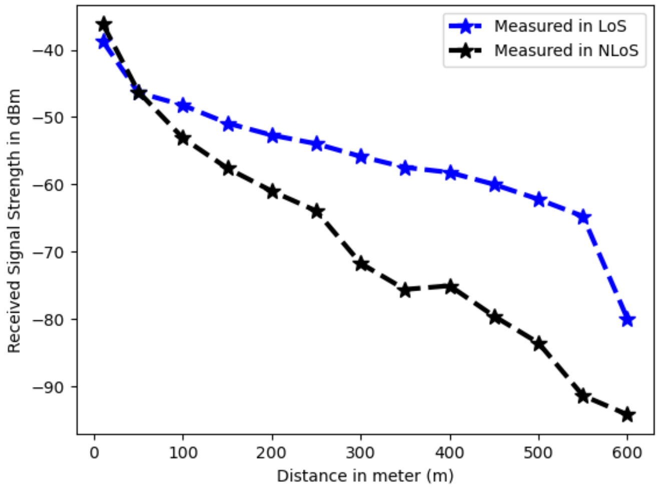

FIGURE 4: Received signal strength against the distance in LoS scenario.

The Figure 4 shows the clear fluctuations along the path, which could attributed to the multipath effect caused by obstructing buildings in the NLoS scenario, where the transmitted signals experience reflections, diffractions, and scattering. As a result, the signals do not arrive at the receiver simultaneously, leading to signal degradation and reduced strength in NLoS conditions. These findings highlight the impact of urban obstructions on 5G signal propagation and emphasize the challenges posed by complex environments.

The results of the measurement campaigns conducted in the second environment for further validation of 5G signal propagation characteristics another urban environment are presented in Figure 5**.**

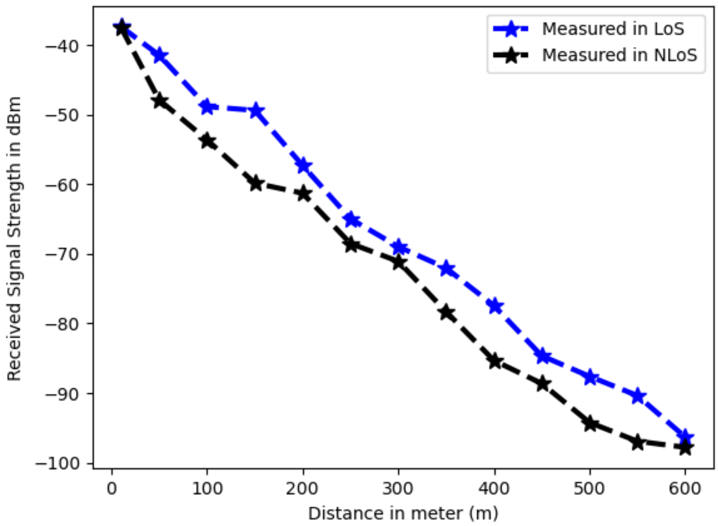

FIGURE 5: Received signal strength against the distance for the independent environment.

As seen from the Figure 5, the signal strength in the LoS scenario is better; however, the difference is not as pronounced as in the previous urban environment. This suggests that the Fresnel zone may be influencing the signal propagation along the LoS path, while multipath effects are also contributing to the overall performance of the signal strength. These factors highlight the complexities of signal propagation in urban settings, where environmental characteristics can significantly impact signal behavior.

5.2 Path Loss Prediction

The performance of the three path loss models—CI, FI, and ABG—in the line-of-sight (LoS) scenario, as presented in Figure 6, highlights important insights into their predictive capabilities for 5G networks in an urban environment like Abuja.

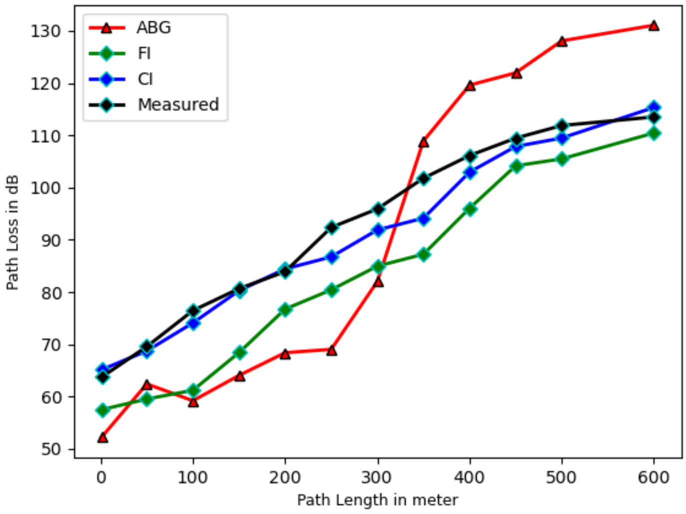

FIGURE 6: Path loss prediction in the LoS scenario.

Firstly, the CI (Close-In) model shows a remarkable alignment with the measured path loss data throughout the path length. This close fit can be attributed to the simplicity and robustness of the CI model, which uses only two parameters: the path loss exponent (PLE) and a reference path loss at a close-in distance. This allows the CI model to account for the gradual decay of signal strength as the distance increases, reflecting the real-world behavior of radio wave propagation in LoS scenarios. The CI model's simplicity minimizes overfitting, making it more adaptable to the varied urban environments and effective in predicting path loss in the relatively dense and complex urban setup of Abuja.

The FI model's slight underprediction indicates that while it captures the general trend of path loss over distance, it may not fully account for environmental factors like reflection, diffraction, and scattering that affect the urban propagation environment, particularly at shorter distances.

The ABG model, on the other hand, significantly underpredicts the path loss up to 300 meters and then begins to overpredict. This pattern suggests that the ABG model, which incorporates multiple parameters (including the frequency, path length, and slope of the environment), may struggle with fine-tuning its predictions over varying distances in a dynamic urban landscape.

In the non-line-of-sight (NLoS) scenario, both the CI and FI models exhibited noticeable deviations from the measured path loss, particularly from the reference point up to 100 meters, as presented in Figure 7.

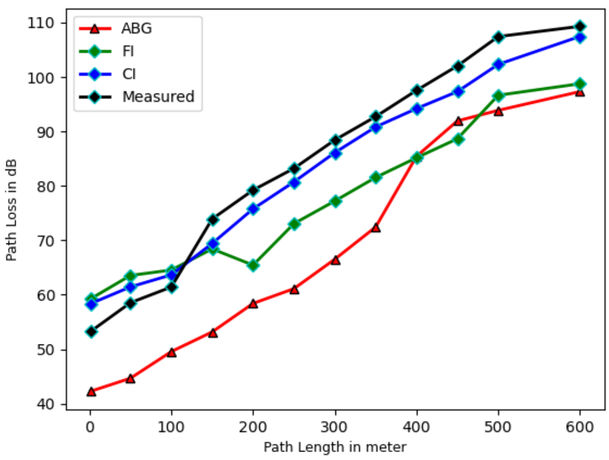

FIGURE 7: Path loss prediction in the NLoS scenario.

As shown in the Figure 7, both models underperformed, indicating that they struggled to accurately capture the signal attenuation caused by obstacles and obstructions typical of urban environments in NLoS conditions. However, after 100 meters, the CI model showed smaller variations compared to the FI model, maintaining closer proximity to the measured path loss data as the distance increased. This reveals the CI model as the best performer in the NLoS scenario, despite the initial underperformance.

The FI model, in contrast, continued to exhibit larger discrepancies throughout the path length compared to the CI model. Its flexibility in adjusting intercept and slope parameters, which may have worked reasonably well in the line-of-sight (LoS) scenario, seemed less effective in the NLoS environment. The increased number of reflections, diffractions, and scatterings in urban NLoS paths likely made it more difficult for the FI model to maintain accurate predictions, leading to larger variations as distance increased.

Unlike in the LoS scenario, where the ABG model showed a shift from underprediction to overprediction, it consistently underperformed throughout the entire path length in the NLoS scenario. This consistent underperformance suggests that the ABG model struggled to capture the complexities of signal propagation in obstructed environments, where buildings and other urban structures significantly degrade the signal strength. The model's multi-parameter structure, which might offer flexibility in other environments, appeared to introduce too much complexity for effective prediction in the NLoS scenario, failing to adapt to the additional losses encountered.

5.3 Validation Result

The validation of the results using three widely accepted performance metrics—Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE)—as presented in Figure 8, provides a quantitative assessment of the predictive accuracy of the CI, FI, and ABG models.

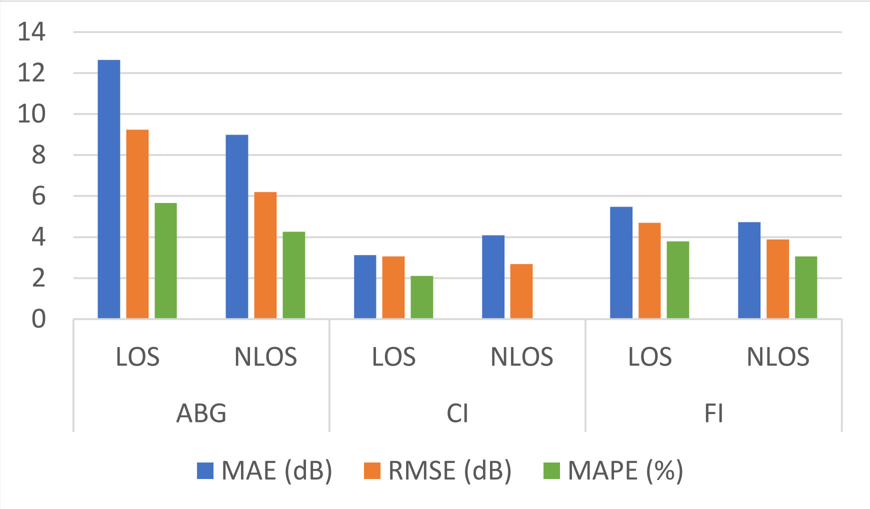

FIGURE 8: Models' prediction performances.

In both the line-of-sight (LoS) and non-line-of-sight (NLoS) scenarios, the CI model consistently outperformed the FI and ABG models, demonstrating its robustness and reliability across different urban environments.

In the LoS scenario, the CI model achieved the lowest MAE of 3.12 dB, RMSE of 3.05 dB, and MAPE of 2.11%. These low error values indicate that the CI model closely matched the measured path loss, with minimal deviation across the entire path length. The RMSE value, which penalizes larger errors more heavily, confirms that the CI model was able to maintain accurate predictions without significant outliers or large deviations. The MAPE value, which expresses the prediction error as a percentage of the actual values, further highlights the model's strong performance, reflecting its ability to adapt to variations in the environment while keeping the error rate relatively low. These metrics validate the earlier qualitative assessment that the CI model's simplicity and the use of a single path loss exponent make it well-suited for LoS environments.

In the NLoS scenario, the CI model continued to outperform the other two models, with an MAE of 4.08 dB, RMSE of 2.68 dB, and MAPE of 0.79%. While the MAE increased slightly due to the more complex signal propagation in the NLoS environment, the RMSE and MAPE values remained impressively low. The lower RMSE in the NLoS scenario compared to the LoS scenario suggests that the CI model was able to handle the increased variability in the propagation conditions without significant degradation in accuracy. The MAPE of 0.79% is particularly noteworthy, as it indicates that the CI model maintained a highly accurate prediction even in challenging NLoS conditions, where obstacles like buildings and other structures introduce significant signal loss.

VI. Conclusion

This paper has demonstrated a comprehensive evaluation of three widely-used empirical path loss models—CI, FI, and ABG—in both line-of-sight (LoS) and non-line-of-sight (NLoS) scenarios. Through detailed analysis and validation using performance metrics such as MAE, RMSE, and MAPE, it is evident that the CI model consistently outperformed the FI and ABG models. In the LoS scenario, the CI model exhibited the closest alignment with the measured path loss, achieving low error values, MAE of 3.12 dB, RMSE of 3.05 dB, and MAPE of 2.11%, that confirm its robustness and accuracy. Similarly, in the NLoS scenario, despite the increased complexity of signal propagation, the CI model remained the most reliable predictor, with minimal variation and error compared to the other models with MAE of 4.08 dB, RMSE of 2.68 dB, and MAPE of 0.79%.

The FI model, while showing reasonable performance, underpredicted the path loss more significantly, particularly in the NLoS environment. The ABG model, however, underperformed across the entire path length, especially in NLoS conditions, underscoring its limitations in urban 5G environments. Overall, the CI model's simplicity and adaptability make it the most suitable model for predicting path loss in Abuja's complex urban landscape. Although the FI and ABG models demonstrated limitations, particularly in underpredicting path loss, there is potential for improving their predictive accuracy. Further research should focus on refining these models by incorporating additional environmental parameters specific to urban areas, such as building density, height, and material properties, to enhance their adaptability and precision.

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