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Paper Title: Comparative Performance of Empirical and Machine Learning Path Loss Models for 5G Propagation in Suburban Environments of Ibadan, Nigeria

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Abstract - The deployment of fifth-generation (5G) mobile networks in Nigeria has intensified the need for accurate path loss prediction to support efficient network planning and coverage optimisation. However, conventional empirical propagation models, developed largely for temperate environments and lower frequency bands, remain insufficiently validated for the 3.5 GHz band in Nigerian suburban terrains, where local clutter, vegetation, and building density introduce site-specific attenuation. This study characterised 5G path loss along three suburban routes in Ibadan, Oyo State—Akinolu Town, Olodo Town, and Irisom Gas Axis—using G-Net Track Pro walk-test measurements over distances of 1–525 m at 3.5 GHz. Measured data were compared against the Free Space Model (FSM), Stanford University Interim (SUI), COST 231 Hata, and 3GPP TR 38.901 models, and further benchmarked against Random Forest and XGBoost machine learning regressors using root mean square error (RMSE). Results showed that no single empirical model performed consistently across all routes: TR 38.901 yielded the lowest RMSE at Akinolu (17.35 dB) and Irisom Gas Axis (19.37 dB), while COST 231 performed best at Olodo (14.36 dB). All empirical models exceeded the desirable 6 dB RMSE threshold, whereas Random Forest achieved RMSE values of 4.92 dB, 6.76 dB, and 4.97 dB across the three routes, consistently outperforming XGBoost and all empirical counterparts. The study concludes that data-driven models better capture complex, site-specific propagation characteristics in suburban 5G environments. It recommends that operators prioritise Random Forest and XGBoost for path loss prediction, and that the Nigerian Communications Commission encourage the development of localised 5G propagation models for spectrum planning and infrastructure deployment.

Keywords: 5G path loss; propagation modelling; machine learning; Random Forest; suburban environment; 3.5 GHz band

INTRODUCTION

The fifth generation (5G) mobile network represents the latest global wireless standard, succeeding its predecessors—1G, 2G, 3G, and 4G—and is engineered to deliver unprecedented levels of connectivity [1]. This milestone in mobile communications constitutes a significant departure from existing networks, with the overarching objective of providing consistently high-speed connections and a seamless user experience.

In Nigeria, the Nigerian Communications Commission (NCC) has allocated the 3.4–3.8 GHz frequency band for MTN's deployment of 5G communication networks. Since the introduction of 5G services in the country, spearheaded by MTN, the operator has deployed over 190 sites, delivering a median download throughput of

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235 Mbps in urban areas [2]. Nevertheless, there remains a pressing need to enhance the performance of 5G technology, which is inherently more susceptible to attenuation than its 4G counterpart [3]

Path loss denotes the attenuation of an electromagnetic wave's power density as it propagates through a medium or across free space [4]. This attenuation arises primarily because the energy conveyed by the wave disperses as it radiates outward from its source. As a foundational concept in wireless communications, path loss is governed by multiple factors, including the distance between transmitter and receiver, the operating frequency, and the physical properties of the propagation medium [5].

In light of these considerations, a growing body of research has sought to characterise path loss behaviour within the specific context of 5G deployments in Nigeria. Abdullahi and his team for instance, assessed 5G radio attenuation at 3.5–3.6 GHz using drive tests in Lagos, Ibadan, Abuja, and Kano, Nigeria [6]. A locally calibrated log-distance model was compared with Okumura-Hata, COST-231 Hata, Egli, and ITU-R P.833-9. Results show significant divergence between models and city/operator panels, indicating model choice and local calibration strongly affect predicted attenuation. The study finds no universal north-south loss ranking, instead emphasizing site-, route-, and configuration-dependent behaviour, supporting cautious, measurement-informed 5G model calibration in Nigerian cities.

Shaibu and his team developed a hybrid model combining optimized COST-231 Hata with random forest for 3.5 GHz path loss prediction. Recursive feature elimination identified eleven key features from eighteen parameters [4]. Validation achieved low errors (MAE ≤ 1.82 dB, RMSE ≤ 2.05 dB, MAPE ≤ 2.4%). Cross-band validation at 1.6 GHz confirmed robustness, though retraining is recommended.

A recent study evaluated machine learning models for 3.5 GHz path loss prediction using recursive feature elimination, identifying 11 significant features from 18 [7]. Four models (ANN, XGBoost, RF, k-NN) were trained and tested in an irregular urban environment. Random Forest performed best, achieving MAE of 0.15 dB and RMSE of 0.57 dB in LoS, and 0.62 dB and 1.42 dB in NLoS scenarios, demonstrating superior prediction accuracy.

A research work proposed deep learning methods for path loss prediction at 3.5, 3.8, and 4.2 GHz across coastal terrains and vegetation areas [8]. Using RNN and LSTM models with 240 test samples, results show coastal path loss exceeds vegetation loss by about 5 dB on average. RNN outperformed LSTM in both environments, achieving R^2 values of 0.9677 for coastal terrains and 0.9042 for vegetation areas.

Oseni and his team provided suitable transmission models for 5G deployment in Oyo and Ogbomoso, using TEMS to assess MTN, Airtel, and Glo performance [1]. Average MSE was 53.87 dB for the Ericsson model and 29.33 dB for Okumura. RMSE values exceeded the desirable 6 dB threshold across all tested models, indicating no single model effectively predicts signal strength across all scenarios, highlighting the need for localized calibration.

MATERIALS AND METHODS

Experimental Sites

Akinolu is located on Latitude 7.4441626^{O} N, Longitude 4.0020267 ^{O} E, Olodo town is located on Latitude 7.4441246 ^{O} N, Longitude 4.0021175^{O} E, and Irisom Gas Axis is located on Latitude 7.4442151^{O} N, Longitude 4.0020155^{O} E. The three locations are in Oyo state, Nigeria, and lie in close proximity to one another within the same geographical axis. This proximity makes them suitable for comparative radio propagation studies, as they share similar environmental and climatic conditions, yet slightly differ in local terrain, building density, and vegetation cover, which are critical factors in signal attenuation modelling

Walk-test Procedure

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The signal strength measurements were taken in three locations in Ibadan city, Oyo State. The maximum distance between the transmitter and the receiver in this study is 525 m while the closest distance from the transmitter is 1 m. The measurements were collected with the use of G-Net Track Pro mobile app [9]. This is an android network monitoring and drive-test app created by Gyokov Solution. The G-Net Track Pro mobile app was installed on a Tecno Pro 19 5G mobile phone. The measurements were taken at six instances across all locations. All measurements were performed using the existing operational network. The base stations were mounted at varying heights, while the mobile phone was held as the researcher walk along the specified routes. The key parameters of the measurement campaign are summarised in Table 1.

Table 1: Measurement Campaign Parameters for Path Loss Characterisation in Selected Suburban Locations

Parameter	Reported Configuration
Study Location	Akinolu Town, Olodo Town and Irisom Gas Areas
Operating Frequency	3-5 GHz
Receiver height range	1 – 1.5 m
Transmitter - antenna height	20 – 25 m
Transmitted Measurement	1 – 525 m
Reported transmitter power	23 dB
Reported antenna gain	18 dbi
Measurement platform	G-Net Track Pro

Selected Empirical Models

The empirical models used for this study are Free Space (FSM), Stanford University Interim (SUI), Cost 231 and TR38901 models. While there are several propagation for pathloss predictions, these models were the following reasons:

FSM (Free Space Model) serves as an essential baseline [10]. It assumes ideal line-of-sight propagation with no obstacles and provides a theoretical minimum path loss. By comparing your measured data against FSM, one can quantify how much additional loss is introduced by real-world suburban clutter, vegetation, and buildings—information that is critical for validating the other empirical models. The FSM path loss is expressed mathematically as:

$$PL\ (dB) = 32.5 + 20Log_{10}\,(f) + 20\ Log_{10}\,(\,d) \qquad 1$$

Where f = frequency in MHz and Distance in km.

SUI (Stanford University Interim) model is specifically designed for frequencies up to 4 GHz, directly covering your 3.5 GHz operating band [11]. It is widely used for broadband wireless systems in suburban environments and incorporates terrain and foliage effects, making it more realistic than free space alone. The SUI model is mathematically formulated as follows:

$$PL\ (dB) = A + 10n\ log_{10}\left(\frac{d}{d_0}\right) + X_f + X_h + s \quad for\ d > d_0 \qquad 2$$

Where:

$$n = a - bh_b + \frac{C}{h_b} \qquad 2.1$$

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$$A = 20log_{10}\frac{4\pi d_0}{\lambda} \qquad 2.3$$

$$X_f = 6\ log_{10}\left(\frac{f}{2000}\right) \qquad 2.4$$

$$X_h = -10.8\ log_{10}\left(\frac{h_m}{2000}\right) \quad or \quad -20\ log_{10}\left(\frac{h_m}{2000}\right) \quad 2.5\ (which\ depends\ on\ the\ terrain\ type\ )$$

Where a,b and c are secondary constants based on environment type. S is the correction parameter for frequency above 1.5 GHz, d is the propagation distance, h_m is the height of the mobile station while h_b is the height of the transmitter antenna.

COST 231 Hata is a well-established empirical model with explicit correction factors for suburban environments. Although its standard frequency range extends to 2 GHz, numerous studies have successfully applied and optimized it for higher bands [12]. The COST 231 Hata model is expressed as:

$$PL = 46.3 + 33.9log_{10}(f) - 13.82log_{10}(h_b) - ah_m + 44.9 - 6.55log_{10}(h_b)log_{10}(d) + C_m \qquad 3$$

Where f is the transmitting frequency in MHz, h_b is the height of the transmitter's antenna in metres and C_m is the correction parameter which is a function of the environment type.

TR 38.901 is the 3GPP standard for 5G channel modelling, covering frequencies from 0.5 to 100 GHz [13]. Given that 3.5 GHz is a primary 5G band, this model is the most current and standards-compliant choice. It provides specific path loss equations for suburban scenarios (such as RMa and UMi) with both LOS and NLOS conditions. The TR 38.901 path loss models for LOS and NLOS conditions are given as:

$$PL_{LOS} = 32.4 + 17.3Log_{10}(d_{3D}) + 20\ Log_{10}(f) + \sigma_{SF}, where\ \sigma_{SF} = 3\ dB \qquad 4.1$$

$$PL_{NLOS} = \max(PL_{LOS}, PL'_{NLOS}) \qquad 4.2$$

Option 1:

$$PL'_{NLOS} = 17.3 + 38.3Log_{10}(d_{3D}) + 24.9\ Log_{10}(f) + \sigma_{SF}, where\ \sigma_{SF} = 8.03\ dB \qquad 4.3$$

Option 2:

$$PL'_{NLOS} = 32.4 + 31.9Log_{10}(d_{3D}) + 20\ Log_{10}(f) + \sigma_{SF}, where\ \sigma_{SF} = 8.29\ dB \qquad 4.4$$

RESULTS AND DISCUSSION

Akinolu Town

Pathloss Measurement

Figure 1 presents a detailed plot of pathloss propagation against distance for measured, FSM, SUI, TR38901 and COST231 models for the Akinolu town campaign. The FSM model consistently underestimates path loss, particularly at short distances where it predicts values as low as 0.8 dB compared to measured values exceeding 43 dB. This discrepancy indicates strong near-field effects and possible antenna height considerations not captured by free-space assumptions. The SUI model shows better agreement at longer

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distances, converging with measured values beyond 0.3 km. TR38901 and COST231 models demonstrate intermediate performance, with COST231 generally overestimating path loss at shorter ranges but aligning more closely at extended distances.

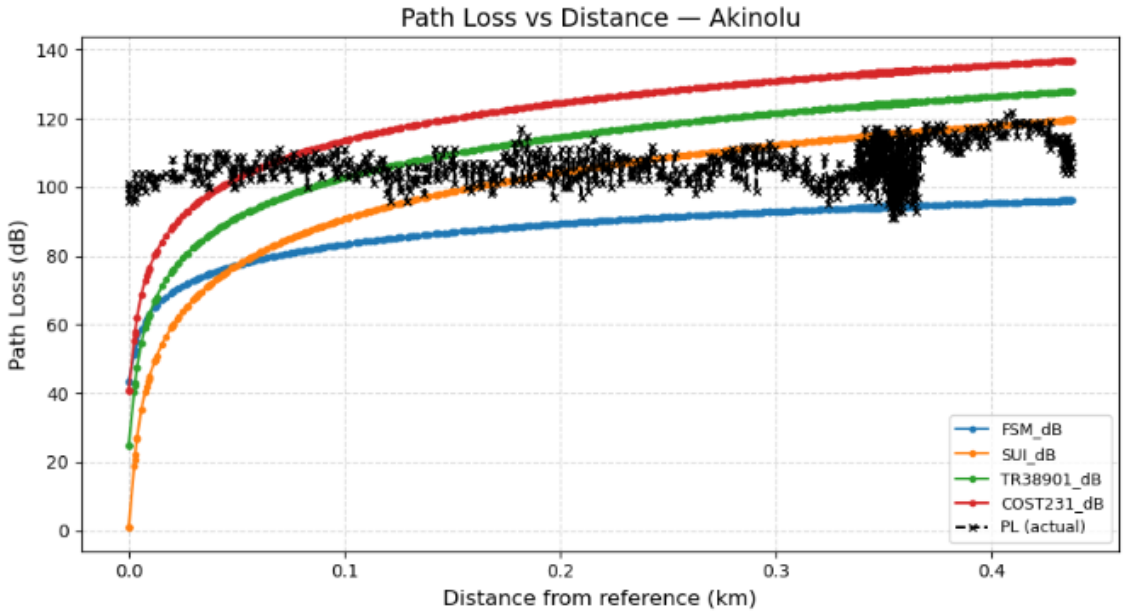


Figure 1: Path loss as a function of distance for measured data and empirical models for route 1 (Akinolu town) (COST 231, TR 38.901, SUI, and FSM)

The figure 2 presents Root Mean Square Error (RMSE) values for four propagation models evaluated at Akinolu. Among the four models, TR38901 demonstrates the best predictive accuracy with an RMSE of 17.35 dB, followed closely by SUI at 18.25 dB. The FSM model ranks third with an RMSE of 19.64 dB, while COST231 exhibits the poorest performance with an RMSE of 22.72 dB.

The strong performance of TR38901 and SUI models reflects their incorporation of empirical corrections suited to suburban and rural environments. TR38901, developed by 3GPP, includes parameters for clutter loss and height-dependent effects, making it well-suited for this measurement campaign. The Free Space Model (FSM) performs poorly because it assumes ideal propagation conditions without accounting for terrain, clutter, or atmospheric effects—factors that significantly influence signal attenuation in real-world environments. COST231, while designed for urban environments, overestimates path loss at shorter distances in this dataset, contributing to its higher RMSE.

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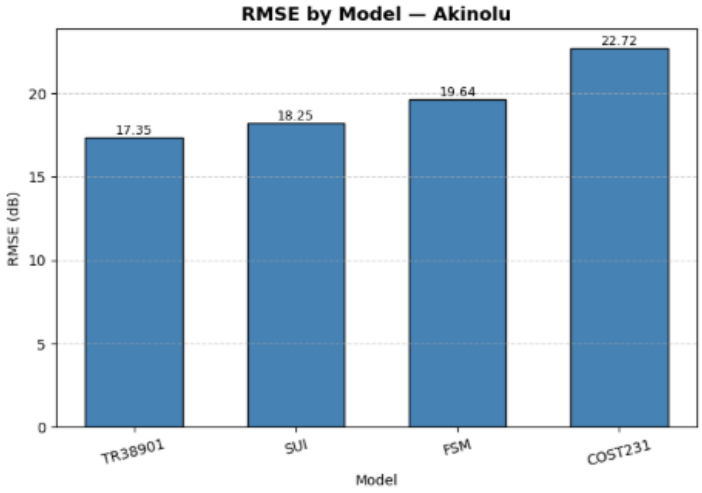
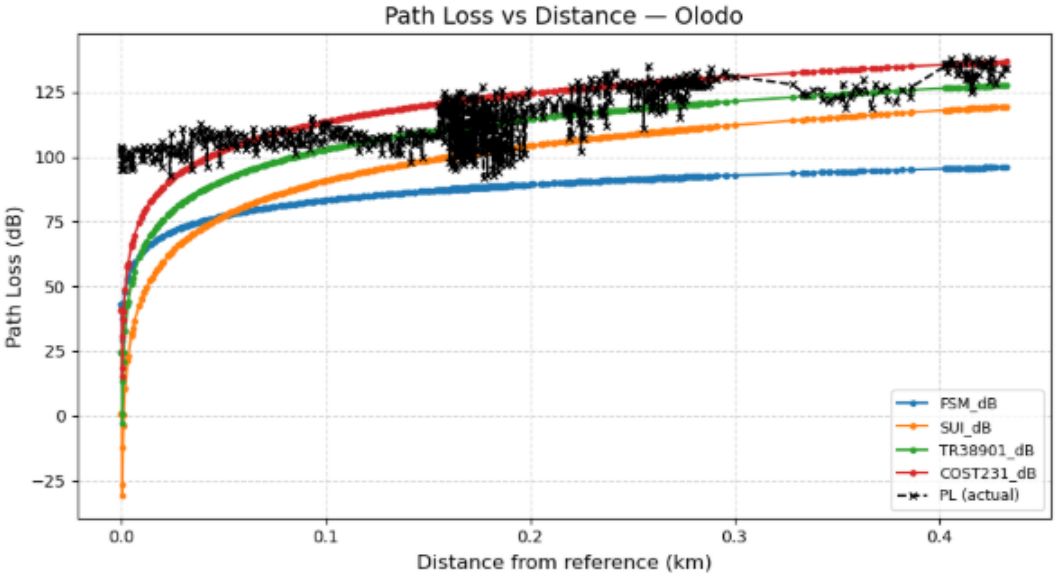


Figure 2: Comparative RMSE performance of empirical path loss models for 5G propagation in Akinolu Town

Olodo Town

Pathloss Measurement

This figure 3 presents pathloss propagation measurements for Olodo Town. For each distance, the file records the measured pathloss values and the corresponding pathloss values when computed with FSM, SUI, TR3890,, and COST231 models. Comparing the models, at all values of the propagration distance, the FSM consistently underestimated the signal loss which indicates that the model doesn't fit the terrain for pathloss prediction. At distance of 0.1 km, the value of the measured PL is 111 dB while the value of the FSM, SUI, TR38901 and COST231 are 83 dB, 91 dB, 103 dB and 114 dB respectively. COST231_dB gives the highest path loss values, followed by TR38901, then SUI, while FSM gives the lowest values. For example, at 0.434 km, COST231_dB is about 128 dB, while FSM is much lower. This means COST231 is the most conservative model for Olodo Town, and SUI may underestimate signal loss.



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Figure 3: Comparison of measured path loss with empirical model predictions (COST 231, TR 38.901, SUI, and FSM) as a function of distance in route B (Olodo town).

For Location B, the Root Mean Square Error (RMSE) values reveal clear differences in model performance. COST231_dB achieves the lowest RMSE at 14.36 dB, followed closely by TR38901_dB at 15.87 dB. SUI_dB performs moderately with an RMSE of 24.24 dB, while FSM_dB shows the highest error at 29.67 dB as shown in figure 4. These results indicate that COST231 and TR38901 are the most accurate models for predicting path loss in Olodo Town, as they produce the smallest prediction errors. In contrast, FSM_dB is the least reliable for this location, with an RMSE nearly double that of COST231. For practical network planning in Olodo Town, COST231_dB is recommended based on its superior RMSE performance.

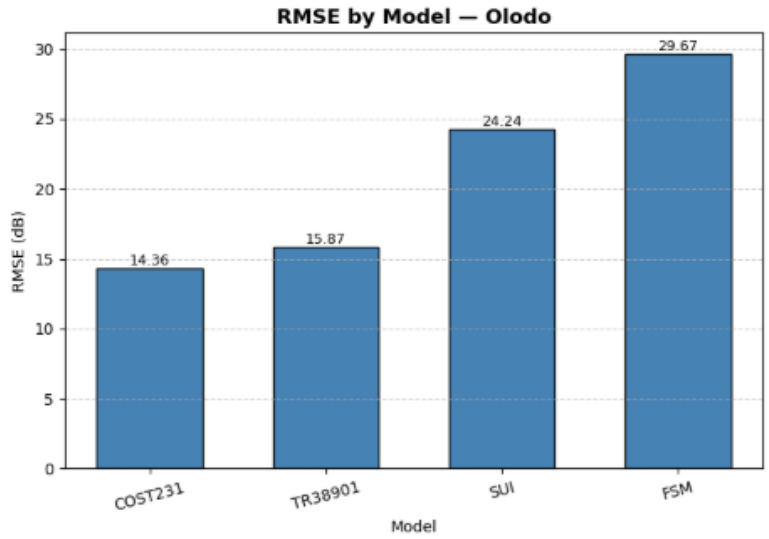


Figure 4: RMSE Comparison across Empirical Path Loss Models for Olodo Town

Irisom Gas Axis

Measured Received Signal Strength

Figure 5 presents path loss measurements across multiple models—PLFSM, SUI, TR38901, and COST231—as a function of distance from a reference point for Irisom Gas Axis. The data spans distances from 0 km to approximately 0.525 km, capturing signal behaviour in a dense urban or suburban environment. At the reference point (0 km), all models converge at a path loss of 43.33 dB, reflecting the free-space condition. As distance increases, path loss rises sharply, particularly within the first 50 metres, before gradually tapering. The FSM consistently reports values 10–15 dB lower than empirical models like COST231, which reaches 139.8 dB at 525 m. The SUI and TR38901 models exhibit intermediate behaviour, with TR38901 closely tracking COST231.

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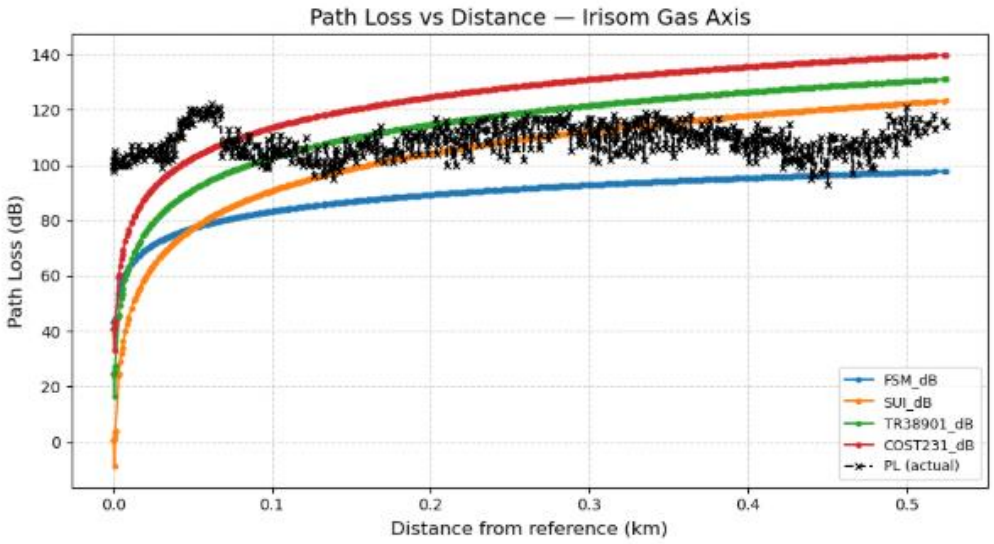


Figure 5: Distance-Dependent Path Loss Characteristics of 5G Suburban Propagation: Measured versus Empirical Models.

For Irisom Gas Axis, the Root Mean Square Error (RMSE) values across the four path loss models are as follows: FSM (22.93 dB), SUI (23.01 dB), TR38901 (19.37 dB), and COST231 (22.41 dB) as provided in figure . Among these, TR38901 yields the lowest RMSE, indicating it provides the closest agreement with measured path loss values at Location C. In contrast, SUI produces the highest RMSE (23.01 dB), suggesting it performs least accurately in this environment. The differences between models are modest, ranging from approximately 19 to 23 dB, which implies that no single model dramatically outperforms the others. Nonetheless, TR38901_dB demonstrates the best predictive accuracy for Irisom Gas Axis as shown in figure 6.

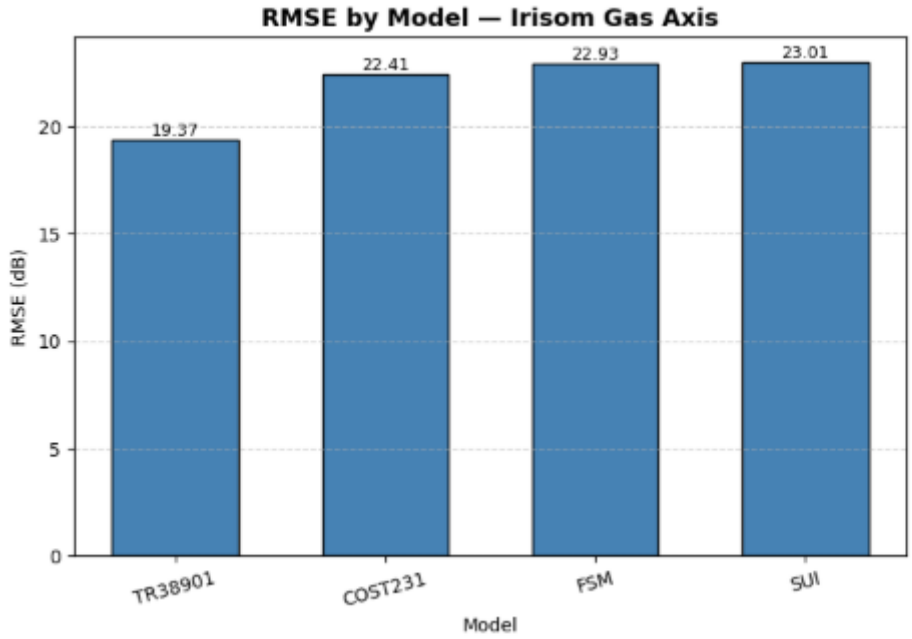


Figure 6: RMSE-Based Performance Comparison of Empirical Path Loss Models for Irisom Gas Axis

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Comparative Performance of Machine Learning Models

To benchmark the empirical models against data-driven approaches, XGBoost and Random Forest regressors were trained on the measured path loss dataset [14]. Model performance was evaluated using RMSE. Based on the presented data, the machine learning models consistently and substantially outperform the conventional empirical path loss models across all three routes. In Akinolu Town (Route 1), Irisom Gas Axis (Route 3), and Olodo Town (Route 2), Random Forest and XGBoost demonstrate superior predictive accuracy with RMSE values ranging from 4.92 dB to 7.38 dB. In contrast, the conventional models exhibit significantly higher error margins, with TR38.901, SUI, FSM, and COST231 producing RMSE values between 14.36 dB and 29.67 dB as presented in figure 7.

The ensemble learning approach proves particularly robust given the varied environmental characteristics of each route. Random Forest consistently achieves the lowest RMSE, marginally edging out XGBoost in every scenario. Notably, Route 2 (Olodo Town) presents the greatest prediction challenge for all models, as evidenced by the comparatively elevated errors for both machine learning and empirical techniques. Overall, the findings strongly suggest that data-driven machine learning models offer a more reliable and precise means of path loss prediction in these environments than traditional deterministic and empirical formulations.

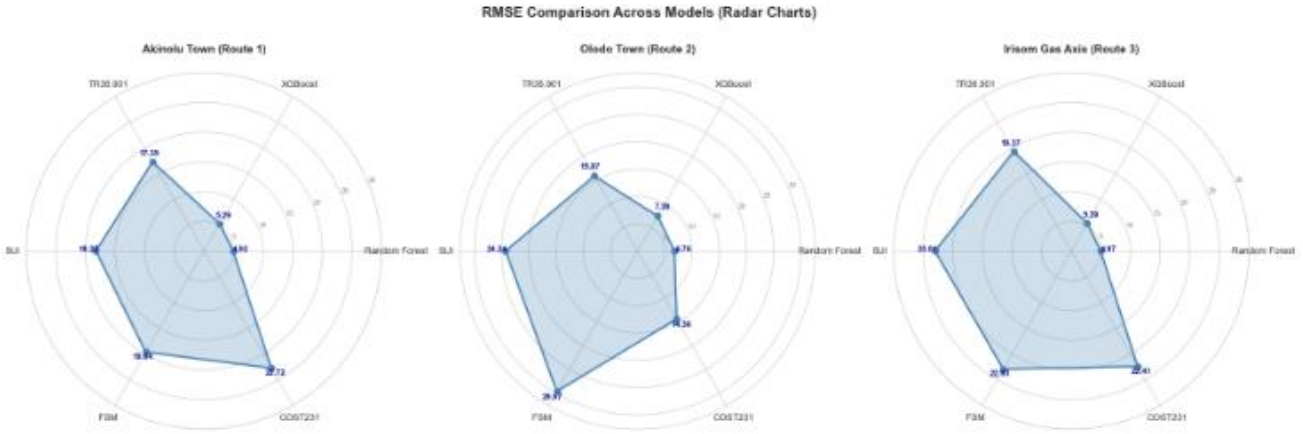


Figure 7: Comparative RMSE Performance of Machine Learning and Empirical Path Loss Models across All Three Routes

CONCLUSION

This study evaluated the performance of conventional empirical path loss models (FSM, SUI, COST231, and TR38.901) alongside machine learning approaches (Random Forest and XGBoost) for 5G path loss prediction across three suburban routes in Ibadan, Oyo State. The measured data reveal that no single empirical model consistently excels across all locations. TR38.901 produced the lowest RMSE in Akinolu Town (17.35 dB) and Irisom Gas Axis (19.37 dB), while COST231 performed best in Olodo Town (14.36 dB). However, all empirical models exceeded the desirable 6 dB RMSE threshold, underscoring their limited predictive accuracy in these environments. In contrast, the machine learning models demonstrated markedly superior performance, with Random Forest achieving RMSE values of 4.92 dB, 6.76 dB, and 4.97 dB for Routes 1, 2, and 3 respectively—consistently outperforming XGBoost and all empirical counterparts. These findings confirm that data-driven models are better suited to capturing the complex, site-specific propagation characteristics of suburban 5G environments, and that localized calibration is essential for reliable path loss prediction.

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RECOMMENDATION

Based on the findings of this study, it is recommended that telecom operators and network planners in similar suburban environments prioritize Random Forest and XGBoost models for path loss prediction, given their consistently low RMSE values and robustness across varied routes. Where empirical models must be used, TR38.901 and COST231 should be locally calibrated with measurement data to improve accuracy, as their performance varied significantly across routes. Future studies should extend data collection to more locations, frequency bands, and seasonal conditions to improve the generalizability of the machine learning models, while incorporating terrain, building density, vegetation, and meteorological parameters could further enhance prediction accuracy. A hybrid approach combining empirical models with machine learning corrections may offer a balanced solution for operators seeking both physical interpretability and predictive precision. Finally, the Nigerian Communications Commission (NCC) should encourage the development of localized 5G propagation models to support efficient spectrum planning and infrastructure deployment.

Acknowledgement

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