Performance of Empirical Models for Path Loss Prediction in Hilly Terrain and the Potential of GB Model

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***Abstract*—This study investigated the potential of machine learning model for path loss prediction in Long-Term Evolution (LTE) radio environment in Idanre. In this study, field measurements were collected from 337 locations across three operational LTE base stations at 1800 MHz, covering hilly, mixed, and urban terrain classes. The data obtained from these measurements were used to train a Gradient Boosting (GB) model for path loss prediction in this area. In addition, four other empirical models namely free-space path loss, log-distance, Hata and COST-231 Extended Hata models were investigated. The performance of these models was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 and compared to that of the GB model. The results obtained show that the GB model has good performance for path loss prediction in hilly terrain with an RMSE and R^2 value of 0.4453 dB and 0.9961, respectively. GB model recorded a 98.87% improvement over the Hata model, 98.99% improvement over the COST-231 Extended Hata and 94.53% over the log-distance model in terms of the RMSE. The results reveal that Hata and COST-231 models perform worse than a mean predictor on this terrain and are unsuitable for LTE planning in Idanre without a substantial local correction.**

Keywords—empiriacl models; gradient boosting; hilly terrain; node localisation; path loss

I. Introduction

Accurate prediction of how radio signals propagate through various and frequently complex physical environments has been a persistent challenge for network operators and telecommunications engineers, from the early deployments of second-generation (2G) cellular networks to the ongoing rollout of fifth-generation (5G) New Radio (NR) infrastructure. Although free-space or simplified ground-reflection models can reasonably represent signal propagation in open, flat terrain, real-world deployments often take place in settings with less than perfect terrain [1-3]. Mobile network infrastructure must function in some of the most geographically difficult locations, such as mountainous and hilly areas. In such terrains, a variety of propagation phenomena, such as diffraction over terrain obstacles, multipath scattering from slopes and vegetation, shadowing behind hills, and terrain-guided ducting are introduced by the presence of elevated landforms, valleys, ridgelines, and irregular ground surfaces. These phenomena interact in highly non-linear and spatially variable ways. Because a sizable portion of the world's population lives in hilly and mountainous areas that need dependable wireless coverage [4, 5], these effects make accurate path loss prediction significantly more difficult than in flat or semi-open environments. In radio frequency (RF) planning, path loss prediction models are fundamental tools. They are used in every phase of network design, from spectrum management and interference analysis to site selection and antenna height optimisation. The precision of coverage forecasts, the effectiveness of infrastructure capital expenditures, and ultimately the end-user experience are all directly impacted by the dependability of these models. While an overestimation of path loss may result in needless densification of base station deployments and excessive use of capital resources [6-8], an underestimation may lead to overly optimistic coverage assumptions, which can cause service gaps and customer dissatisfaction.

Over the past few decades, many empirical path loss models have been developed and standardised for use in network planning tools [8-15]. The telecommunications industry has embraced models like the Hata model [9], the Okumura model [10], the COST 231-Hata model, the Ericsson model, the ECC-33 model, the Stanford University Interim (SUI) model, and the International Telecommunication Union Radio communication Sector (ITU-R) model because of their comparatively wide applicability and ease of computation. These models, which contain the correlations between path loss, frequency, transmitter-receiver spacing, and antenna heights are obtained from extensive measurement campaigns. These empirical models, however, are intrinsically limited by the circumstances surrounding the underlying measurements. The majority of empirical models were calibrated using data gathered in particular geographical areas, primarily in Western Europe and Japan, and under propagation settings that might not fully reflect the variety of terrain morphologies found throughout the world. In hilly terrains, the shortcomings of traditional empirical models become very noticeable. The basic presumptions included in the majority of empirical propagation models are challenged by the terrain irregularity factor, the effective antenna height, the degree of obstruction produced by intervening ridgelines, and the complex diffraction geometry in mountainous situations [2]. For instance, the Hata model uses a terrain adjustment factor based on the effective antenna height calculated from topographic contour data within a comparatively small radius [16]. However, this correction is only a rough approximation of the complex three-dimensional geometry of hilly terrains. As a result, these models may not be useful for precision network design when applied to mountainous areas without thorough local calibration.

A new area of radio propagation modelling has been made possible by the development of machine learning (ML) models. These provide the capacity to directly learn intricate, non-linear mappings between input variables and path loss values from observed data. ML models have the potential to capture the complex relationships between terrain morphology, frequency, antenna configuration, and received signal power with fidelity [17-19]. This is essentially beyond the reach of closed-form empirical expressions when trained on sufficiently large and representative datasets of field measurements collected in hilly terrains. This study examines the potential of Gradient Boosting machine learning model for path loss prediction in hilly terrains. Its effectiveness is compared with popular empirical path loss models and their prediction accuracy is assessed by a thorough comparison with field measurement data.

II. Research Methods

A. Study Area Description

Idanre is a town in Ondo State, South western Nigeria, situated at approximately 7.10^0 N, 5.10^0 E. Fig. 1 shows the Google earth location of the study area. The terrain is defined by the Idanre Hills, a cluster of prominent granite formations that rise to elevations exceeding 300 metres above the surrounding lowland areas. The transition between hill crests and valley floors occurs within distances of a few kilometres, creating a propagation environment with a mix of unobstructed Line of Sight (LOS) paths along valley routes and heavily blocked Non-Line of Sight (NLOS) paths across ridges. Vegetation on the hill slopes is secondary forest, while the valley areas contain a combination of residential settlement and farmland. Three base stations were selected as signal sources for the measurement campaign. They were chosen to provide overlapping coverage across the study area and to span different azimuths relative to the hill terrain. The first base station, operated by MTN, is sited on the Idanre Hill at coordinates 7.1044^0 N, 5.1036^0 E, with the advantage of an elevated antenna position. The second, operated by Glo, is located at Olofin Grammar School at 6.886^0 N, 5.127^0 E. The third, operated by Airtel, is at Sabo Onikulikuli at 7.0949^0 N, 4.825^0 E. All the three operate on LTE Band 3 at 1800 MHz with a transmit power of 43 dBm. The geographic spread of the stations, together with the terrain variability between them, ensures that the dataset captures both LOS and NLOS propagation at a range of distances and directions.

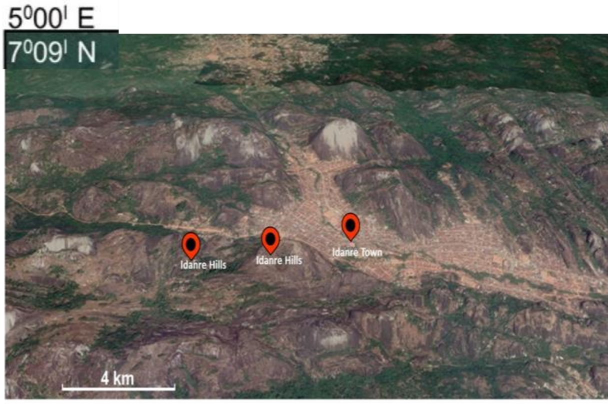

Fig. 2. *Location map of the study area.*

B. Data Collection

Signal measurements were collected using a drive test method. The primary measurement device was a Samsung Galaxy S21 Ultra smartphone, which logged LTE signal parameters including Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), Reference Signal Signal-to-Noise Ratio (RSSNR), and Channel Quality Indicator (CQI) at one-second intervals using the GENEX Probe network optimisation application. A Garmin GPS 72H handheld GPS receiver was used to record geographic coordinates, elevation above sea level, and timestamp at each measurement point. While the smartphone has an integrated GPS, the Garmin unit provided an independent coordinate record with a dedicated GPS antenna, which is more accurate under dense tree canopy and in valley terrain where satellite visibility is partially obstructed. A Dell Latitude laptop running Windows 10 was installed in the measurement vehicle to run the GENEX Probe software in real time and to capture the drive test log files during each run. A 300 W power inverter connected to the vehicle's 12 V battery socket supplied continuous power to the laptop throughout the measurement sessions.

The measurements were carried out during dry season conditions, between November and January, to avoid the signal variability introduced by wet vegetation and to ensure easy movement along the unpaved hill roads. Routes were planned in advance using Google Earth and a topographic map of the study area, targeting a mix of valley-floor paths with expected LOS conditions and elevated routes crossing the hill terrain with expected NLOS conditions. For each route, the vehicle was driven at a steady speed not exceeding 30 km/h to maintain adequate sample density along the path. On steep sections where vehicle access was not possible, the measurement equipment was carried on foot, with the laptop powered by the inverter unit and battery pack from the vehicle parked at the nearest accessible point. The GENEX Probe application was configured to log measurements at one-second intervals, and the Garmin GPS 72H was set to track mode with one-second position updates to produce a timestamp-matched coordinate log. At each measurement session, the serving cell identity was confirmed before departure to ensure the phone was locked to the intended base station where possible. After completing all measurement runs, the GENEX Probe log files and Garmin track files were exported and transferred to the laptop for post-processing. A total of 337 clean measurement samples were retained from the full dataset after preprocessing.

C. Data Preprocessing

The raw drive test log contained several categories of problematic records that required removal or correction before analysis. The preprocessing pipeline was applied in the following sequence. Stationary samples were identified as consecutive records with identical GPS coordinates and removed, since these introduced clustering artefacts at traffic stops and turnaround points. Records with missing values in any of the signal quality columns (RSRP, RSRQ, RSSNR, CQI) were dropped, as partial records cannot be reliably used for model training. GPS outliers were identified by comparing the Garmin elevation reading at each point against the 30 metre digital elevation model for the same coordinates. Points where the two elevation sources disagreed by more than 15 metres were either corrected using the SRTM value or removed if the discrepancy suggested a GPS fix error rather than a measurement offset.

Path loss at each measurement point was computed from the RSRP value using Equation (1):

$$PL(dB) = P_{TX}(dBm) - RSRP(dBm) - G_{TX}(dBi) - G_{RX}(dBi) + L_C(dB) \quad (1)$$

where P_{TX} is the base station transmit power (43 dBm), G_{TX} is the base station antenna gain (18 dBi for a standard LTE sector antenna), G_{RX} is the smartphone receive antenna gain (0 dBi), and L_C is the combined cable and connector loss estimated at 2 dB. The resulting path loss value in dB is the target variable for model training. The transmitter-receiver distance at each point was computed using the Haversine expression. The haversine formula estimates the shortest distance between two points on a sphere using their latitue and longitude. This distance was computed as shown in Equation (2) [20]:

$$d = 2r\sin^{-1}\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos\phi_1\cos\phi_2\sin^2\left(\frac{\Delta\lambda}{2}\right)}\right) \quad (2)$$

where r is the radius, ϕ is the latitude and λ is the longitude.

This was applied to the WGS-84 coordinates of the serving base station and the measurement location. Terrain class was assigned as a binary variable: 0 for LOS conditions (open valley floor, unobstructed path to the base station) and 1 for NLOS conditions (path crossing a ridge or located behind a hill feature). Assignments were made by overlaying the GPS track on the topographic map and identifying the terrain profile along each link. Bearing from the base station to each measurement point was computed as the geodetic azimuth in degrees clockwise from north. The overlap flag was set to 1 at points where the second-strongest RSRP reading from a neighbouring base station was within 6 dB of the serving cell RSRP, indicating that the measurement point was within the coverage overlap zone. These features were added as columns to the dataset, producing the final 13-column structure used for all model development.

D. Empirical Path Loss Model Implementation

Four empirical path loss models were implemented in Python as benchmark comparators. Each was evaluated on the same 67-sample test set as the ML model, using the base station parameters and measurement geometry from the dataset. The purpose was to produce a quantitative baseline for the ML improvement analysis.

1) Free-Space Path Loss

The free-space path loss model was implemented using Equation (3) where *f* is the operating frequency in GHz (1.8 GHz for LTE Band 3 at 1800 MHz).

$$PL_{FS}(dB) = 32.44 + 20\log(d) + 20\log(f) \quad (3)$$

where PL_{FS} is the free-space path loss, d is the transmitter-receiver separation distance in km, and f is the carrier frequency.

2) Log-Distance Model

The model takes the form described in Equation (4) [21]:

$$PL(d) = PL(d_0) + 10n \times \log\left(\frac{d}{d_0}\right) \quad (4)$$

where $PL(d)$ is the average path loss, d is the distance, d_0 is the reference distance and n is the path loss exponent, $PL(d_0)$ is the path loss at a reference close-in-distance d_0 (typically 1 m for indoor environment or 100 m for outdoor macrocell scenarios), d/d_0 is the ratio of the transmitter-receiver distance to the reference distance.

The log-distance model was fitted to the training set by estimating the path loss exponent n and the reference path loss $PL(d_0)$ at a reference distance d_0 of 100 m using ordinary least squares linear regression in the log domain. The fitted parameters were then used to generate predictions on the test set.

3) Hata Model

The Hata's urban model at 1800 MHz was implemented using Equation (5).

$$L_u(dB) = 69.55 + 26.16\log(f_c) - 13.82\log(h_{te}) - a(h_{re}) + (44.9 - 6.55\log(h_{te}))\log d \quad (5)$$

where f_c is the frequency in MHz, h_{te} is the base station antenna height in metres, h_{re} is the mobile antenna height in metres, d is the distance in kilometres, and $a(h_{re})$ is a correction factor for mobile antenna height that differs for large and small or medium cities. For a large city and f_c greater than 300 MHz, the mobile antenna height correction factor is given as shown in Equation (6) [22]:

$$a(h_{re}) = 3.2(\log(11.75h_{re}))^2 - 4.9 \tag{6}$$

In this study, the base station antenna height is 30 m, and the mobile antenna height is 1.5 m.

4) COST-231 Extended Hata Model

The COST-231 model was implemented using Equation (7).

$$PL_{COST}(dB) = 46.3 + 33.9\log(f_c) - 13.82\log(h_{te}) - a(h_{re}) + [44.9 - 6.55\log(h_{te})]\log(d) + C_M \tag{7}$$

In Equation (7), C_M denotes the city correction factor (0 dB for suburban/rural, 3 dB for urban/dense urban environments). The $a(h_{re})$ term follows the Hata definition for small and medium cities. In this study, C_M is given as 0 dB for a medium city or suburban environment. The antenna heights and correction factors followed the same as in the Hata model.

E. Gradient Boosting Machine Learning Model

GB is an ensemble model that iteratively combines several weak learners, typically decision trees to reduce classification errors. By concentrating on cases that each successive learner incorrectly categorised, the overall accuracy can be improved [19]. GB is a desirable choice for categorising discretised path loss in diverse urban or suburban settings since it is especially well-suited to structured tabular data with intricate feature interactions. The gradient boosting model was built using scikit-learn's GradientBoostingRegressor. The model was trained with 300 estimators at a learning rate of 0.05, a maximum tree depth of 5, and a subsampling fraction of 0.8 applied at each boosting stage.

C. Model Evaluation

The performance of all the models were evaluated on the held-out 67-sample test set based on the Root Mean Square Error (*RMSE*), Mean Absolute Error (*MAE*), and the coefficient of determination R^2.

The *RMSE* is the primary metric because it penalises large prediction errors more heavily than *MAE* and is directly interpretable in dB units. The *RMSE* was obtained using Equation (8):

$$RMSE = \sqrt{\sum_{i=1}^{n}\left[\frac{(PL_m(i) - PL_p(i))^2}{n}\right]} \tag{8}$$

where $PL_m(i)$ and $PL_p(i)$ are the measured and predicted path losses at sample i while n is the number of test samples.

The Mean Absolute Error was estimated using Equation (9):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|PL_m(i) - PL_p(i)\right| \tag{9}$$

The R^2 quantifies how much of the observed path loss variance the model accounts for. This was estimated using Equation (10):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(PL_m(i) - PL_p(i))}{\sum_{i=1}^{n}(PL_m(i) - \overline{PL})} \tag{10}$$

where $\overline{PL}$ is the mean path loss.

All the metrics were computed independently for each model, permitting direct comparison on identical evaluation data.

III. Results and Discusion

Table 1 presents the RMSE, MAE, and R^2 values for the four empirical path loss models and the GB machine learning model on the 68-sample test set. As shown in Table 1, the free-space path loss model produced an RMSE of 6.92 dB and an R^2 value of 0.226. The log-distance model, fitted to the training data using linear regression with a resulting exponent of n = 1.49, produced an RMSE of 11.62 dB and an R^2 value of 0.239. The fitted exponent of 1.49 is below the free-space value of 2.0, reflecting the compression of the path loss range in this dataset, and the mean positive residual of 10.62 dB indicates systematic under-prediction across the test set.

Table 1: Model performance on the test set (n=68)

Model	RMSE (dB)	MAE (dB)	R²
Free-Space Path Loss	6.92	5.25	0.2260
Log-distance	11.62	9.87	0.2389
Hata	39.40	38.71	-0.0991
COST-231 Extended Hata	44.27	43.65	-0.0991
Gradient Boosting	0.4453	0.0706	0.9960

The Hata model produced an RMSE of 39.40 dB with a negative R^2 of -0.0991. The COST-231 Extended Hata model returned an RMSE of 44.27 dB with the same negative R^2. A negative R^2 means each model's predictions are less accurate than simply predicting the mean path loss for every test point. Both models place their predictions 20 to 50 dB above most measured values, generating large mean residuals of -37.25 dB (Hata) and -42.20 dB (COST-231 Extended Hata), which reflect systematic and severe overestimation of path loss across the measurement range. As shown in Table 1, the ML model achieved

Journal of Multidisciplinary Engineering Science Studies (JMESS)
ISSN: 2458-925X
Vol. 12 Issue 5, May - 2026

substantially better prediction accuracy than all empirical models. The gradient boosting produced an RMSE of 0.4453 dB with an R^2 of 0.9960. Also, the gradient boosting achieved the lower MAE of 0.0706 dB compared to the other models.

Fig. 2 shows the predicted path loss curves from all the four empirical and ML model overlaid on the full measured dataset. As shown in Fig. 2, the Hata and COST-231 Extended Hata curves sit far above the data across all distances. The free-space and log-distance curves are closer to the measured values but diverge from the observed trend at both ends of the distance range. The gradient boosting prediction curve, computed on all 337 samples, tracks the measurements closely throughout. From Fig. 2, it can be observed that empirical model curves diverge substantially from measured values. The gradient boosting prediction tracks the measurements across the full distance range.

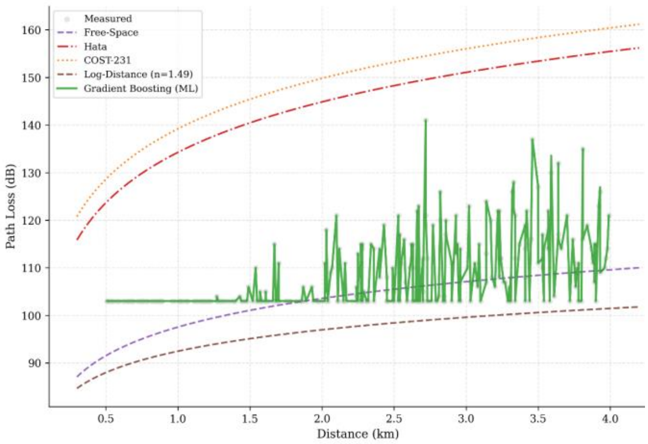

Fig. 2. *Predicted path loss from all the models overlaid on the full 337-sample dataset.*

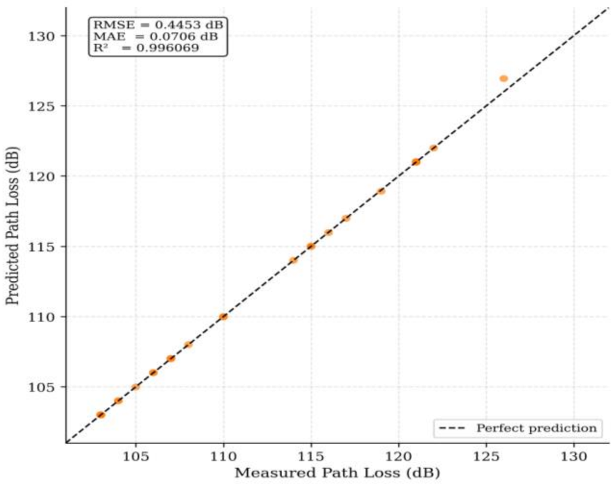

Fig. 3. *Actual vs predicted path loss for the GB model on the 68-sample test set.*

Fig. 3 shows the actual versus predicted path loss scatter plot for gradient boosting. The model produce points clustered tightly along the 45-degree identity line across the full measured path loss range of 103 to 141 dB, with no visible systematic offset or curvature in either direction.

Fig. 4 to Fig. 8 show the residual distributions for each of the models. As shown in Fig. 4, the empirical model residuals reveal large systematic biases. The free-space model has a mean residual of +4.03 dB with a standard deviation of 6.25 dB (Fig. 4), indicating a slight under-prediction on average. The Hata model carries a mean residual of −37.25 dB and a standard deviation of 7.79 dB (Fig. 5), while the COST-231 model produces a mean residual of −42.20 dB with the same standard deviation of 7.79 dB (Fig. 6). These large negative mean residuals confirm that both models consistently and severely overestimate path loss, placing their predictions 37 to 42 dB above the measured values on average. The log-distance model produces a mean residual of +10.62 dB and a standard deviation of 6.14 dB (Fig. 7), confirming consistent under-prediction across the test set.

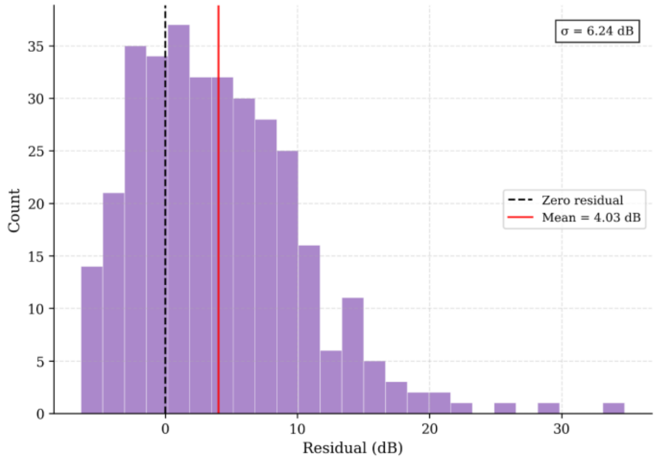

Fig. 4. *Residual distribution for the free-space path loss model.*

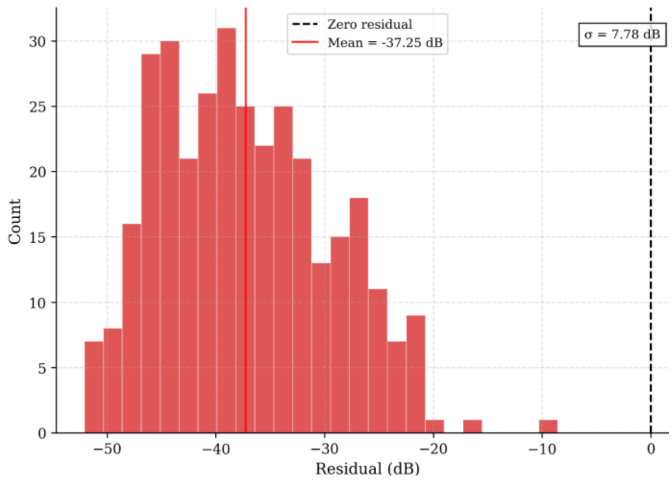

Fig. 5. *Residual distribution for the Hata model.*

ISSN: 2458-925X
Vol. 12 Issue 5, May - 2026

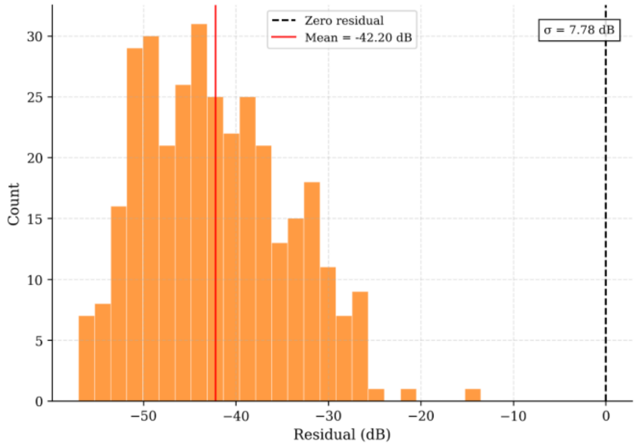

Fig. 6. *Residual distribution for the COST-231 Extended Hata model.*

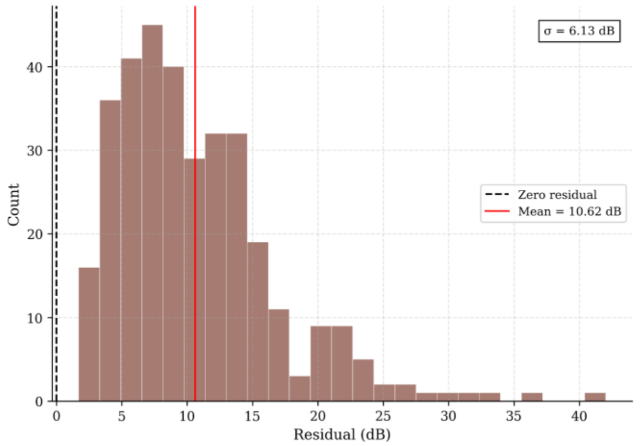

Fig. 7. *Residual distribution for the fitted log-distance model*

The gradient boosting residual (Fig. 8) is centred close to zero, with mean residuals of −0.06 dB and standard deviation of 0.44 dB respectively. This distribution does not show any meaningful directional bias. The absence of systematic error in the ML model residuals stands in sharp contrast to all four empirical models, which carry directional errors large enough to render their predictions unreliable for link budget or distance estimation purposes.

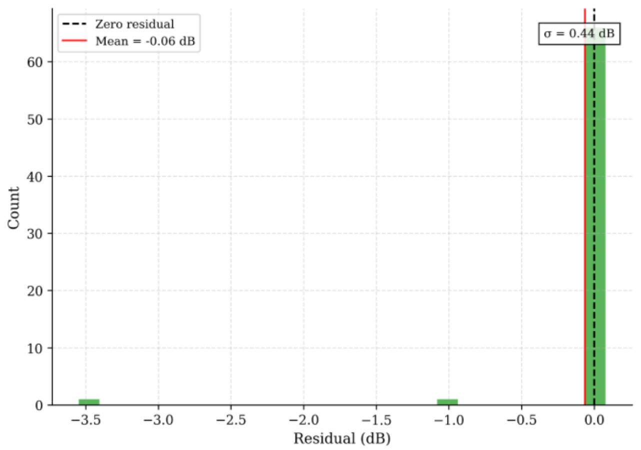

Fig. 8. *Residual distribution for the gradient boosting model.*

IV. Conclusion

In this study, the performance of the Gradient Boosting model was compared to four empirical models for path loss prediction in hilly terrains. The results obtained show that the Gradient Boosting model performed better than the four empirical models with a reduced RMSE of 0.4453 dB. The GB model produce a perfect prediction of path loss as it clustered around the measured path loss with less significant differences. The low MAE recorded by the GB model revealed that the GB model can be used for path loss prediction in hilly terrains with minimal prediction errors.

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