Improved Path Loss Prediction Using Deep Learning Models

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***Abstract* - This study proposes a Deep Learning (DL) approach to improved path loss prediction, using the rural areas of Southern Plateau State, Nigeria, as case study. The DL-based models were created on bases of the Generalized Regression Neural network (GRNN) and the Multi-Layer Perceptron Neural Network (MLP-NN). These network models were created, trained, validated and tested for path loss prediction using path loss data recorded at 900MHz from multiple Base Transceiver Stations (BTSs) distributed across the rural areas. Results indicate that the GRNN and MLP-NN based models with Root Mean Squared Error (RMSE) values of 5.05dB and 5.3dB respectively, proffer slight improvement over the empirical COST 231 Hata, but significantly outperform the Hata-Okumura model.**

Keywords—Path Loss; Generalized Regression Neural Network; Multi-Layer Perceptron Neural Network; Hata-Okumura; COST 231 Hata

I. INRODUCTION

Deep Learning (DL) is a computational intelligence method that mimics the processing ability of the human brain. Due to their remarkable ability to learn unsupervised from a set of unstructured data, DL networks can efficiently solve a variety of problems. A typical example of a DL network is the Artificial Neural Network (ANN). An Artificial Neural Network (ANN) is a mathematical model that mimics the structure and functionalities of biological neural networks [1]. The Artificial neural network is a system of interconnected artificial neurons that mimic the human brain to form a complex programming structure for neural processing. Each neuron interconnects to, and receives signals from multiples of other neurons. The neuron is structured such that if the resulting sum of the signals surpasses a certain threshold, a response is sent through the axon. ANNs are widely used in areas such as data mining fields, classification, forecasting, functional approximation, rule extraction, pattern recognition and medical applications [2]. As described in [3], neural networks can learn to approximate any function to a given accuracy and behave like associative memories by using just example data that is representative of the desired task. Given sufficient amounts of training data, ANNs are capable of solving complex problems.

One of the crucial considerations in wireless network planning is path loss prediction. Path loss essentially is the reduction of signal strength as it propagates from a transmitting device to a receiver. As described in [4], path loss usually results from phenomena which include reflections, diffraction, refractions, scattering, free space loss, etc. Path loss is dependent on operating frequency, transmitter height and transmitter-receiver separation, nature of the terrain, etc. Empirical models are some of the most widely used means of predicting path loss in a given terrain. Unfortunately, existing empirical models though easier to implement, are less sensitive to the environment's physical and geometrical structures and not so accurate while the deterministic models which though are more accurate are computationally inefficient and require more detailed site-specific information which is often difficult to come by [5]. Recent approaches to path loss modelling such as [4][6][7] and [8] are based on the DL techniques.

Hence, this study is aimed at using DL-based techniques to predict path loss across the rural areas of southern Plateau State, Nigeria. The area comprises of mountains, scattered houses and trees mostly below 10 meters. The DL networks considered namely, the Generalized Regression Neural Network (GRNN) and the Multi-Layer Perceptron Neural Network (MLP-NN) are compared for performance with the empirical Hata-Okumura and the COST 231 Hata.

II. GENERALIZED REGRESSION NEURAL NETWORK

The Generalized Regression Neural Network (GRNN) is classified under Probabilistic Neural Networks. As described in [9], the GRNN, proposed by [10], is a type of Artificial Neural Network (ANN) that is capable solving a variety of problems such as function approximation, prediction, control, plant process modeling or general mapping problems [11].

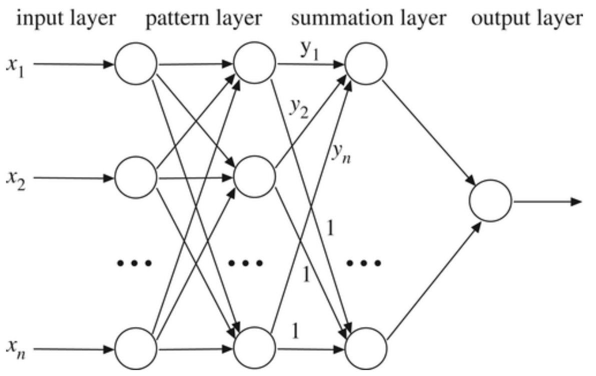

Fig. 1: Generalized Regression Neural Network Architecture [11]

Unlike back-propagation neural networks, which may require a large number iterations to converge to the desired output, the GR-NN does not require iterative training, and usually requires a fraction of the training samples a back-propagation neural network would need [10]. As shown in Fig. 1, the GRNN comprises of four layers [11]:

Input layer: This is the first layer and it is responsible for capturing and sending inputs to the next layer called the pattern layer

Pattern layer: This layer computes the Euclidean distance between input and training data, and also the activation function.

Summation layer: This layer comprises of two parts: the Numerator and the Denominator. The Numerator sums up products of training data and activation function, while the Denominator sums up activation functions.

Output layer: The single neuron contained in this layer generates the output through division of the Numerator by the Denominator obtained from the previous layer.

The general regression as described by [10] is as follows: given a vector random variable, x, and a scalar random variable, y, and assuming X is a particular measured value of the random variable y, the regression of y on X is given by (1)

$$E[y|X] = \frac{\int_{-\infty}^{\infty} y f(X,y)dy}{\int_{-\infty}^{\infty} f(X,y)dy} \quad (1)$$

If the probability density function $\hat{f}(x,y)$ is unknown, it is estimated from a sample of observations of x and y. The probability estimator $\hat{f}(X,Y)$, given by (2) is based upon sample values X^i and Y^i of the random variables x and y, where n is the number of sample observations and p is the dimension of the vector variable x.

$$\hat{f}(X,Y) = \frac{1}{(2\pi)^{(p+1)/2}\sigma^{(p+1)/n}} \cdot \frac{1}{n}\sum_{i=1}^{n} \exp\left[\frac{(X-X^i)^T(X-X^i)}{2\sigma^2}\right] \cdot \exp\left[\frac{(Y-Y^i)^2}{2\sigma^2}\right] \quad (2)$$

A physical interpretation of the probability estimate $\hat{f}(X,Y)$, is that it assigns a sample probability of width σ (called the spread constant or smoothing factor) for each sample X^i and Y^i, and the probability estimate is the sum of those sample probabilities.

The scalar function D_i^2 is given by (3)

$$D_i^2 = \left(X - X^i\right)^T \left(X - X^i\right) \quad (3)$$

Combining equations (1) and (2) and interchanging the order of integration and summation yields the desired conditional mean $\acute{Y}(X)$, given by (4)

$$\acute{Y}(X) = \frac{\sum_{i=1}^{n} Y^i exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} exp\left(-\frac{D_i^2}{2\sigma^2}\right)} \quad (4)$$

It is further stated in [10] that when the smoothing parameter σ is made large, the estimated density is forced to be smooth and in the limit becomes a multivariate Gaussian with covariance σ^2. On the other hand, a smaller value of σ allows the estimated density to assume non-Gaussian shapes, but with the hazard that wild points may have too great an effect on the estimate.

III. THE MULTI-LAYER PERCEPTRON NEURAL NETWORK

As described in [12],[13] the Multi-Layer Perceptron Neural Network (MLP-NN) is a feed forward neural network trained with the standard back propagation algorithm. The MLP-NN is a supervised network so it requires a desired response to be trained. With one or two hidden layers, the MLP-NN can approximate virtually any input-output map. They have been shown to approximate the performance of optimal statistical classifiers in difficult problems.

The MLP-NN comprises of an input layer, one or more hidden layers and an output layer. Fig. 2 shows a MLP-NN architecture with 1 hidden layer. It can be observed that each neuron of the input layer is connected to each neuron of the hidden layer, and in turn, each neuron of the hidden layer is connected to the single neuron of the output layer.

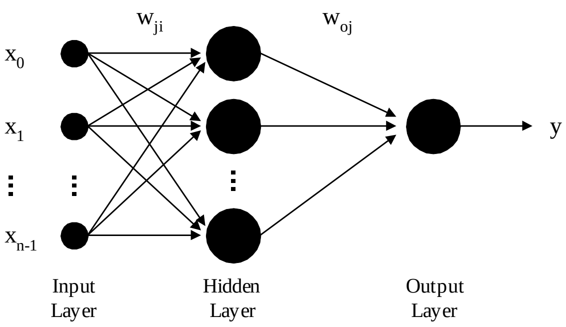

Fig. 2: Multilayer Perceptron Neural Network with one hidden layer [12]

Signal propagation across the entire network is always in the forward direction, i.e, from the input layer, through the hidden layer and eventually to the output layer. Error signals propagate in the opposite direction from the output neuron across the network. The output of the MLP-NN is given by (5)

$$y = F_0\left(\sum_{j=0}^{M} w_{0j}\left(F_h\left(\sum_{i=0}^{N} w_{ji}x_i\right)\right)\right) \quad (5)$$

where:

- $\mathbf{W_{oj}}$ represents the synaptic weights from neuron j in the hidden layer to the single output neuron,
- $\mathbf{X_i}$ represents the $\mathbf{i^{th}}$ element of the input vector,
- $\mathbf{F_h}$ and $\mathbf{F_0}$ are the activation function of the neurons from the hidden layer and output layer, respectively,
- $\mathbf{W_{ji}}$ are the connection weights between the neurons of the hidden layer and the inputs.

The learning phase involves adaptively adjusting the free parameters of the system based on the mean squared error E, between predicted and measured path loss for a set of appropriately selected training examples. The mean squared error is given by (6),

$$E = \frac{1}{2}\sum_{i=1}^{m}\left(y_i - d_i\right)^2 \quad (6)$$

where, $\mathbf{y_i}$ is the output value computed by the network and $\mathbf{d_i}$ is the desired output. When the error between network output and the desired output is minimized, the learning process is terminated and the network can be used in a testing phase with test vectors. At this stage, the neural network is described by the optimal weight configuration, which means that theoretically ensures the output error minimization.

IV. THE HATA-OKUMURA MODEL

As described in [14], the Hata-Okumura Model incorporates the graphical information from the Okumura Model. The Hata Model is a widely used propagation model for predicting path loss in urban areas, and also has formulations for predicting path loss in Suburban and Open Areas. The Hata Model for Urban Areas is valid for the following parameters:

Frequency Range: 150 MHz to 1500 MHz
Transmitter Height: 30 m to 200 m
Link distance: 1 km to 20 km
Mobile Station (MS) height: 1 m to 10 m

Hata Model for Urban Areas is formulated as (7).

$$L_U = 69.55 + 26.16logf - 13.82logh_B - C_H + (44.9 - 6.55logh_B)logd \quad (7)$$

For small or medium sized cities (where the mobile antenna height is not more than 10 meters),

$$C_H = 0.8 + (1.1logf - 0.7)h_M - 1.56logf$$

and for large cities,

$$C_H \begin{cases} 8.29(log(1.54h_M))^2 - 1.1, & for\ 150MHz \le f \le 200MHz \\ 3.2(log(11.75h_M))^2 - 4.97, & for\ 200MHz \le f \le 1500MHz \end{cases}$$

Where,

L_U - Path loss in Urban Areas
h_B - Height of base station antenna in meters (m)
h_M - Height of mobile station antenna in meters (m)
f - Frequency of Transmission in megahertz (MHz).
C_H - Antenna height correction factor
d - Distance between the base and mobile stations in kilometers (km).

The Hata Model for Suburban Areas is given by (8)

$$L_{SU} = L_U - 2(log\frac{f}{28})^2 - 5.4 \quad (8)$$

Hata model for open areas is formulated as (9)

$$L_O = L_U - 4.78(logf)^2 + 18.33logf - 40.94 \quad (9)$$

V. THE COST 231 HATA MODEL

As described in [15], the COST 231 Hata Model was derived from the Hata Model by the European Cooperative for Scientific and Technical research, to suit the European environments taking into consideration the frequency range 0.5GHz to 2GHz. This model is suitable for path loss prediction in urban, semi-urban, suburban and rural areas. The model expression is given by (10)

$$L = 46.3 + 33.9logf - 13.82logh_B - a(h_m) + (44.9 - 6.55logh_B)logd + C \quad (10)$$

Where,

- L = Median path loss in Decibels (dB)
- C=0 for medium cities and suburban areas
- C=3 for metropolitan areas
- f = Frequency of Transmission in Megahertz (MHz)(500MHz to 200MHz)
- h_B = Base Station Transmitter height in Meters (30m to 100m)
- d = Distance between transmitter and receiver in Kilometers (km) (up to 20kilometers)
- h_m = Mobile Station Antenna effective height in Meters (m) (1 to 10metres)
- $a(h_m)$ = Mobile station Antenna height correction factor as described in the Hata Model for Urban Areas.
- For urban areas, $a(h_m)$ = $3.20(\log10(11.75hr))^2-4.97$, for f > 400 MHz
  For sub-urban and rural areas, $a(h_R)$ = $(1.1\log(f) - 0.7)h_R - 1.56\log(f) -0.8$

VI. MATERIALS AND METHODS

A. Received Power Measurement and Path Loss Computation

Received power measurements (P_R) were recorded from multiple Base Transceiver Stations (BTSs) situated within the Southern Plateau rural areas. The BTSs belong to the mobile network service provider, Mobile Telecommunications Network (MTN), Nigeria. The instrument used was a Cellular Mobile Network Analyser (SAGEM OT 290) capable of measuring signal strength in decibel milliwatts (dBm). Received power (PR) readings were recorded within the 900MHz frequency band at intervals of 0.15km, after an initial separation of 0.1km. Mobile Network Parameters obtained from the Network Provider (MTN) include Mean Transmitter Height of 33 meters and Mean Effective Isotropic Radiated Power (EIRP) of 46dBm.

Corresponding path loss (PL) values were computed using (11)

$$PL = EIRP - P_R \quad (11)$$

B. Statistical Indices for Performance Comparison

Similar to [16], the performance comparison indices adopted in this study are based on the Root Mean Square Error (RMSE), given by (12), and the Coefficient of Determination (R^2), given by (13). The RMSE is a measure of the differences between predicted and observed values. The smaller the RMSE value, the higher the prediction accuracy of the model. R^2 ranges from 0 to 1, but can be negative, which indicates the model is inappropriate for the data. A value closer to 1 indicates a greater correlation of the model with the test data, and hence, greater fit.

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(M-P)^2}{N}} \quad (12)$$

Where,

M – Measured Path Loss
P – Predicted Path Loss
N- Number of paired values

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{N}(y_i-\bar{y}_i)^2} \quad (13)$$

Where

y_i is the measured path loss,
$\hat{y}_i$ is the predicted path loss and
$\bar{y}_i$ is the mean of the measured path loss values.

VII. RESULTS AND ANALYSIS

It can be observed from Figures 3 to 10 that on the average, the empirical COST 231 Hata model slightly overestimates the path loss across all Base Transceiver Stations. On the other hand, it can also be clearly observed that the Hata-Okumura model significantly underestimates the path loss. Furthermore, the figures clearly depict a greater prediction accuracy of the DL-based predictors relative to the test data. The statistical performance indices in Table 1 further buttress the fact that on the average, the GRNN-based predictor is the most accurate with a RMSE value of 5.05dB and an R^2 value of 0.74. This is closely followed by the MLPNN based predictor with a RMSE value of 5.3dB and an R^2 value of 0.75. On the average, the DL-based predictors proffer a slight improvement over the COST 231 Hata, but significantly outperform the Hata-Okumura model.

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Table 1: Statistical Performance Comparison of Predictors

MODEL	STATS.	BST 1	BST 2	BST 3	BST 4	BST 5	BST 6	BST 7	BST 8	MEAN
GRNN	RMSE(dB)	6.24	4.32	4.98	4.66	4.96	6.07	4.01	5.19	**5.05**
	R^2	0.70	0.89	0.81	0.82	0.79	0.21	0.86	0.81	**0.74**
MLPNN	RMSE(dB)	5.96	4.57	5.81	4.78	4.29	3.79	6.64	6.56	**5.30**
	R^2	0.73	0.87	0.75	0.81	0.85	0.69	0.63	0.70	**0.75**
Hata-Okumura	RMSE(dB)	26.40	25.24	25.76	26.09	25.57	24.86	27.79	28.06	**26.22**
	R^2	-3.10	-2.21	-3.23	-2.53	-2.74	-4.25	-4.51	-4.04	**-3.33**
COST 231 Hata	RMSE(dB)	7.36	8.04	6.90	7.27	6.95	8.80	5.38	6.11	**7.10**
	R^2	0.68	0.67	0.70	0.73	0.72	0.34	0.79	0.76	**0.67**

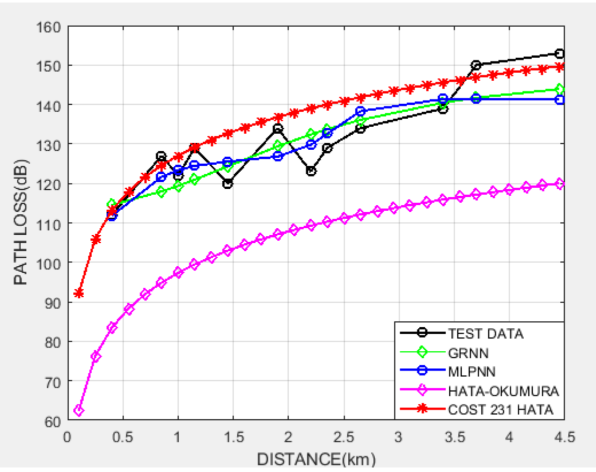

Fig. 3: *Model Comparison for BTS 1*

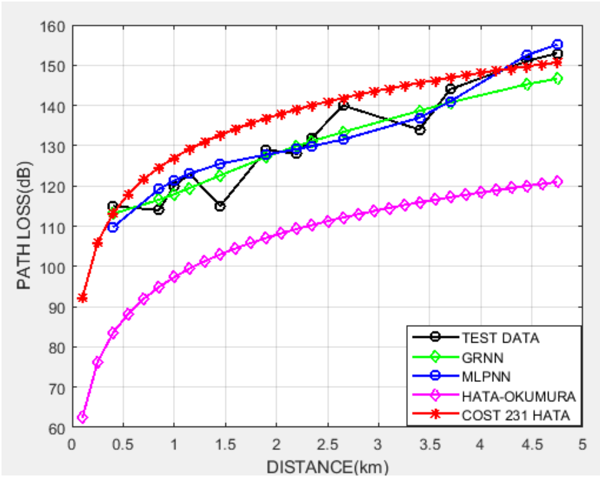

Fig. 4: *Model Comparison for BTS 2*

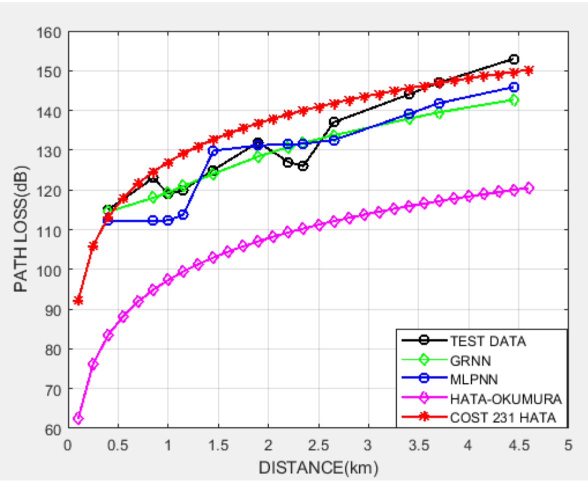

Fig. 5: *Model Comparison for BTS* 3

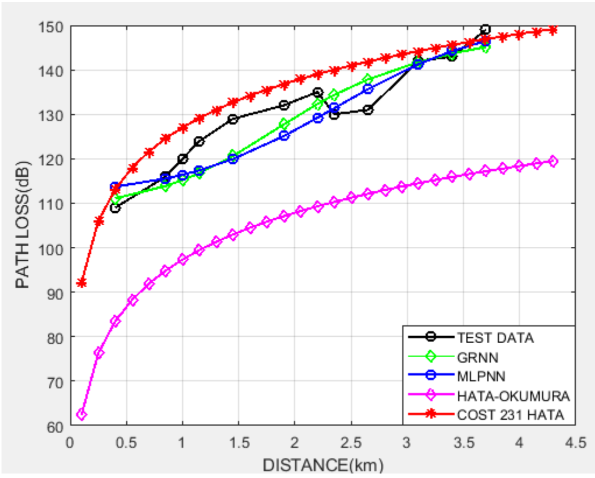

Fig. 6: *Model Comparison for BTS 4*

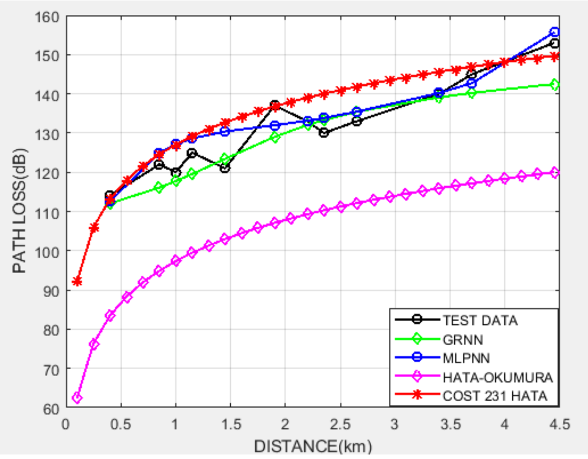

Fig. 7: *Model Comparison for BTS 5*

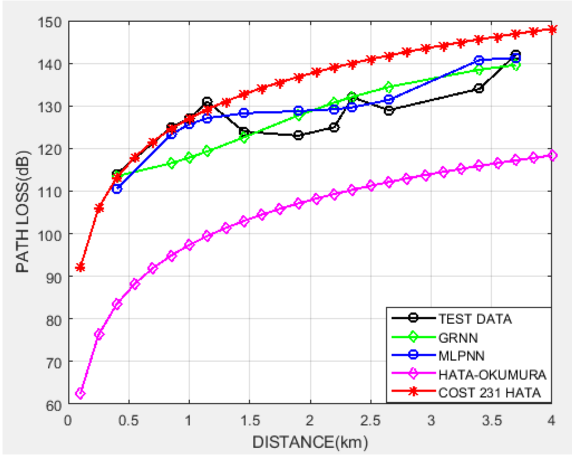

Fig. 8: *Model Comparison for BTS 6*

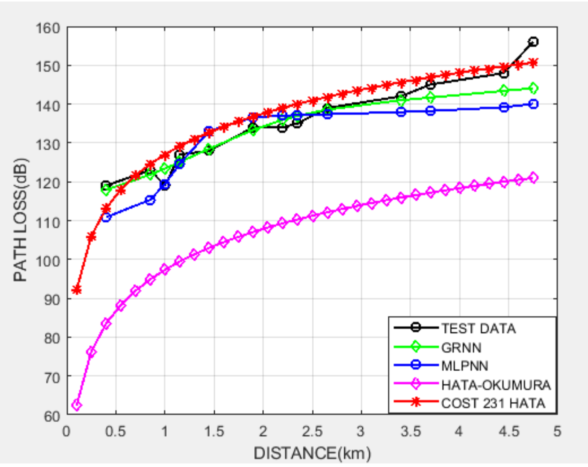

Fig. 9: *Model Comparison for BTS 7*

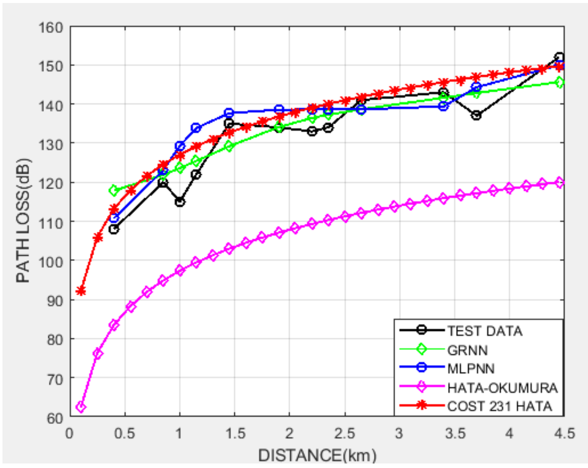

Fig. 10: *Model Comparison for BTS 8*

VIII. CONCLUSION

This study considers a Deep Learning (DL) approach to the path loss modeling of the rural areas of Southern Plateau State, Nigeria. The deep learning models were based on the Generalized Regression Neural Network (GRNN) and the Multi-Layer Perceptron Neural Network (MLP-NN). Performance comparisons indicate that DL-based models proffer slight prediction accuracy over the widely used COST 231 Hata model, but significantly outperform the Hata-Okumura model.

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