Specific Attenuation Estimation in Perturbed Radio Wave Propagation using Artificial Neural Networks

Authors' contributions

This work was carried out in collaboration among both authors. Both authors read and approved the final manuscript.

ABSTRACT

Path loss modeling is a crucial consideration in radio engineering for wireless networks. Over the years, diverse techniques have been implemented in attempts to accurately predict path loss across a given terrain. In this study, path loss predictors created on the bases of artificial neural networks (ANN) were used to estimate path loss across a rural section of the Nigerian middle-belt grassland. The ANN structures considered were the Generalized Regression Neural network (GRNN) and the Radial Basis Function Neural Network (RBFNN), which exhibit a few differences and similarities. These ANN based predictors were trained, validated and tested for path loss prediction using path loss values computed from received power measured at 900MHz from six Base Transceiver Stations (BTSs) situated along the rural terrain. Findings show that the RBFNN predictor with a Root Mean Squared Error (RMSE) of 5.17dB and the GRNN with 4.9dB are slightly more accurate than the COST 231 Hata model with 6.64dB, while the Hata-Okumura with 25.78dB is simply not suitable for the terrain under investigation. Overall, the GRNN, which proffers a 26.21% improvement over the COST 231 Hata is recommended for the terrain in question.

Keywords: *Neural Network, Activation Function, Attenuation, Path Loss, Prediction, Empirical Model*

1. INTRODUCTION

An artificial neural network (ANN) is basically a computational structure, created by interconnecting multiple artificial neurons. They are essentially Deep Learning (DL) mathematical models that are similar in structure and functionality to biological neural networks [1]. As described in [2], Deep Learning (DL) structures are similar to the human brain in terms of processing ability. Given adequate amounts of data, they have the ability to learn complex problem solving unsupervised. Due to their amazing versatility, ANNs are applicable to a variety of problem solving areas such prediction, functional approximation, pattern recognition etc. [3]. In this study, consideration is given to two ANN architectures capable of effectively handling prediction and functional approximation problems. These include the Radial Basis Function Neural Network (RBFNN) and the Generalized Regression Neural Network (GRNN).

Although the RBFNN and the GRNN are similar, they differ in certain respects. For instance, they both use the Gaussian function as activation function to effectively handle function approximation and prediction. But while the RBFNN implements back-propagation or hybrid learning and requires large amounts of training samples, the GRNN implements single pass learning, requiring few training samples in order to converge to the underlying data function. Hence, one of the aims of this study is to determine the architecture more suited to predicting radio signal attenuation across a rural mobile communication network.

Attenuation is the loss of intensity of radio signals as they propagate from a transmitter through space. Wireless communication networks must be well planned in order to ensure quality connectivity and proper network coverage. A key issue in mobile network planning is the availability of formulations that can accurately estimate radio signal attenuation across a given terrain. A wireless network is essentially an integration of cells. A cell basically comprises of a transmitter and multiple receivers. As radio signals propagate from transmitter to receiver they undergo attenuation. Path loss is the most common measure of attenuation widely considered by network planners. Path loss refers to the difference in intensity between transmitted and received signals. According to [4], path loss occurs as a result of wave phenomena such as reflections, diffraction, refractions, scattering, free space loss, etc. Other factors that significantly impact on path loss includes terrain clutter, operating frequency, height of transceiver, distance between transmitter and receiver, etc.

For the purpose of accurately determining adequate network coverage through prediction of path loss, various formulations have been adopted by radio engineers over the decades. The most commonly used formulations are deterministic and empirical. According to [5], deterministic models implement the ray tracing technique, which can predict signal strength within short distances. Moreover, according to [6], "the accuracy of the technique is dependent on detailed environmental information". "On the other hand, empirical models, which are mathematical formulations that are dependent on in-depth field measurements [7], are preferable because of their simplicity". However, recent approaches to path loss modeling such as [2],[4],[8],[9],[10] and [11] are based on soft computing techniques.

In this study, the RBFNN and the GRNN based predictors are compared for path loss prediction accuracy with two widely used empirical models: the COST 231 Hata and the Hata Okumura. The terrain under consideration is a section of the Nigerian Middle-Belt grassland, situated between the cities of Jos and Makurdi. The terrain is basically a rural area with clutter comprising of tall grasses, scattered houses mostly below 3 meters, and trees mostly below 15meters averagely.

2. THE RADIAL BASIS FUNCTION NEURAL NETWORK

According to [12], the RBFNN is a variant of ANN, suitable for solving forecasting and functional approximation problems. As the name implies, the RBFNN uses a radial basis function (RBF) as activation function, and the RBF value is dependent on the separation between input and a fixed point referred to as the center. The RBFNN has the capacity to efficiently generalize through the implementation of a multi-dimensional surface for test data interpolation.

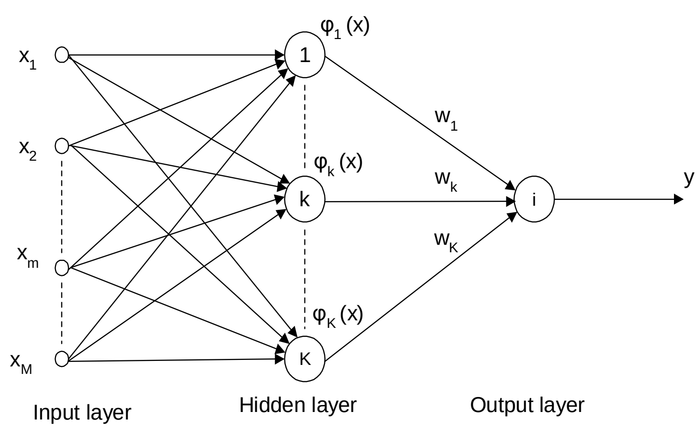

Fig. 1: The Radial Basis Function Neural Network structure [13].

As further described by [12], the RBFNN architecture comprises of three distinct layers as shown in Fig. 1: the first is the input layer, whose function is data input, the second is the hidden layer, meant for non-linear data transformation, and the third is the output layer, through which an output is produced. Each predictor variable corresponds to 1 neuron in the input layer. It is pertinent to note that where categorical variables are concerned, *n-1* neurons are used, with *n* being the number of categories. The number of neurons in the hidden layer is not fixed, with every neuron consisting of a radial basis activation function centered on a point dimensionally equal to the number of predictor variables. The output layer is responsible for producing the network output by computing the weighted sum of hidden layer outputs. According to [13], "the hidden-nodes outputs are determined by the closeness of the input vector *X* to an M-dimensional vector μ_k , which is associated with the k^{th} hidden node. It is further stated that the suitable choice for the function φ is a multivariate Gaussian function which has a corresponding suitable mean and an auto covariance matrix". The RBFNN output is expressed as (1)

$$Y_i(X) = \sum_{i=1}^{K} w_{ik} \varphi_k(X) \tag{1}$$

where,

- $\boldsymbol{X}$ represents the input vector
- $\boldsymbol{W_{ik}}$ represents the connection weight from the hidden layer to the output layer
- $\boldsymbol{k}$ is the number of hidden nodes
- $\boldsymbol{i}$ represents the ***i-th*** hidden node and
- $\boldsymbol{\varphi_k}$ is the activation function.

As further described by [14], the Gaussian function is a radial basis function variant given expressed as (2)

$$\varphi_k = \exp\left(-\frac{\left\| X - \mu_k \right\|^2}{2\sigma_k^2} \right) \tag{2}$$

Where,

- $\boldsymbol{\mu_k}$ is the center vector and
- $\boldsymbol{\sigma_k}$ represents the spread of the function

The training procedure of the RBFNN involves two phases [13]:

1. Gaussian center and spread width determination.
2. The use of supervised learning to determination the output weight.

The learning procedure involves locating a suitable surface within the multidimensional space that ensures the training data has the best fit.

3. THE GENERALIZED REGRESSION NEURAL NETWORK

"The GRNN, proposed by [15] is a variant of the RBFNN. The GRNN is used to solve a variety of problems such as prediction, control, plant process modeling or general mapping problems". Given few data samples, the GRNN is capable of handling functional approximation as well as prediction problems. While back-propagation neural networks may require large data samples and high numbers of iteration in order to generate the desired output, the GRNN may require just a fraction [15].

As depicted in Fig. 2, the GRNN architecture has four layers [16]: "the first is the Input layer which, captures and sends inputs to the second layer called the pattern layer". The pattern layer is responsible for computing the activation function and the Euclidean separation between the input vector *X* and the training data. The third layer is the summation layer and it has two parts: the Numerator, whose function to sum up products of training data, and the Denominator, which is responsible for summing up activation functions. And finally, the fourth layer is the output layer, whose single neuron produces the desired output by dividing the third layer Numerator by the Denominator.

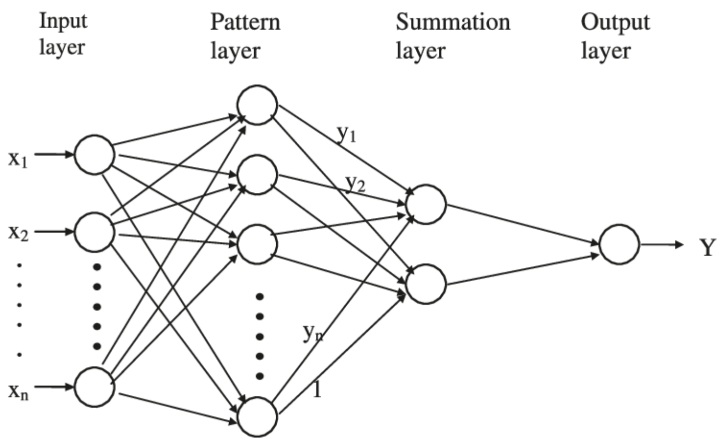

Fig. 2: Generalized Regression Neural Network Architecture [16]

"A description of the general regression proposed by [15] is as follows: consider a vector random variable, *x*, and a scalar random variable, *y*". If *X* is a particular measured value of the random variable y, then the regression of y on *X* can be expressed as (3)

$$E[y|X] = \frac{\int_{-\infty}^{\infty} y f(X,y)dy}{\int_{-\infty}^{\infty} f(X,y)dy} \tag{3}$$

The unknown probability density function $\hat{f}(x, y)$ is computed from the samples of observations *x* and *y*. The probability estimator $\hat{f}(X, Y)$, expressed as (4) is dependent on the sample values X^i and Y^i of the random variables *x* and *y*, where n represents the number of sample observations and p is the dimension of the vector variable x.

$$\hat{f}(X, Y) = \frac{1}{(2\pi)^{(p+1)/2}\sigma^{(p+1)/n}} \cdot \frac{1}{n}\sum_{i=1}^{n} \exp\left[\frac{(X-X^i)^T(X-X^i)}{2\sigma^2}\right] \cdot \exp\left[\frac{(Y-Y^i)^2}{2\sigma^2}\right] \tag{4}$$

For each sample X^i and Y^i, the probability estimator $\hat{f}(X, Y)$ assigns a sample probability of width σ (called the spread constant or smoothing factor), and the sum of those sample probabilities is the probability estimate. The scalar function D_i^2 is expressed as (5).

$$D_i^2 = (X - X^i)^T(X - X^i) \tag{5}$$

A combination of (3) and (4) and an interchange of integration and summation order generates the desired conditional mean $\acute{Y}(X)$, expressed as (6)

$$\acute{Y}(X) = \frac{\sum_{i=1}^{n} Y^i exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} exp\left(-\frac{D_i^2}{2\sigma^2}\right)} \tag{6}$$

The spread constant is the only free network parameter. During network training the optimal value of the spread for the minimal mean squared error is obtained. Unlike other feed-forward NN, the GRNN always locates the global minimum and hence, has no issues with local minima. For a large spread σ, the estimated density becomes smooth and in the limit, becomes a multivariate Gaussian with covariance σ^2. On the contrary, a small spread makes the estimated density to assume non-Gaussian shapes.

4. THE COST 231 HATA MODEL

The COST 231 Hata as the name implies is an extension of the widely used Hata-Okumura empirical model. As described by [17], the model incorporates a wider frequency range (500MHz to 200MHz) than the Hata-Okumura model and it was formulated essentially to suit the European terrains. Taking a variety of terrain types into account, the COST 231 Hata model has appropriate correction factors for urban, semi-urban, suburban and rural terrains, and the model expression is given by (7)

$$L = 46.3 + 33.9 logf - 13.82 logh_B - a(h_{\mathrm{m}}) + (44.9 - 6.55 logh_B) logd + C \tag{7}$$

where,

- L is the Median path loss in Decibels (dB)
- C assumes the value 0 for medium cities and suburban areas, and 3 for metropolitan areas
- f is the transmission frequency in Megahertz (MHz)(500MHz to 200MHz)
- h_B is the Base Station Transmitter height in Meters (30m to 100m)
- d is the transmitter – receiver separation in Kilometers (km) (not more than 20kilometers)
- h_m is the Mobile Station height in meters (m) (1 to 10metres)
- $a(h_m)$ is the correction factor for mobile station height as described in the Hata Model for Urban Areas. $a(h_m) = 3.20(\log 10(11.75hr))^2 - 4.97$, for $f > 400$ MHz, for urban areas, while $a(h_R) = (1.1\log(f) - 0.7)h_R - 1.56\log(f) - 0.8$ for sub-urban and rural areas.

5. THE HATA-OKUMURA MODEL

The Hata-Okumura as described by [18] model incorporates graphical information from the Okumura Model. Unlike the COST 231 Hata, the Hata-Okumura Model considers a narrower frequency Range: 150 MHz to 1500 MHz. But similar to the COST 231 Hata, the Hata-Okumura model is valid for the Transmitter Height range of 30 m to 200m, link distance range of 1 km to 20 km, and Mobile Station (MS) height range of 1 to 10 meters. The model also has correction factors for urban, suburban and open/rural areas. The model expression is formulated as (8)

$$L_U = 69.55 + 26.16 logf - 13.82 logh_B - C_H + (44.9 - 6.55 logh_B) logd \tag{8}$$

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

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

and for large cities,

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

Where,

- L_U is the Urban Area Path loss
- h_B is the base station height in meters (m)

- h_M is the mobile station height in meters (m)
- f is the transmission frequency in megahertz (MHz).
- C_H is the antenna height correction factor
- d is the transmitter-receiver separation in kilometers (km).

The model expression for Suburban Areas is given by (9)

$$L_{SU} = L_U - 2(log\frac{f}{28})^2 - 5.4 \quad (9)$$

For open areas the expression is given by (10),

$$L_O = L_U - 4.78(logf\,)^2 + 18.33logf - 40.94 \quad (10)$$

6. MATERIALS AND METHODS

The data acquisition procedure involved the use of a Cellular Mobile Network Analyser (SAGEM OT 290), capable of measuring signal strength in decibel milliwatts (dBm), as measurement instrument. Received power measurements were obtained from six different Base Transceiver Stations (BTSs) scattered along the rural terrain between the middle-belt grassland cities of Makurdi and Jos, Nigeria. The Received power (P_R) values were recorded within the 900MHz frequency band at intervals of 0.2km away from the BTS, after an initial separation 0.1km. The Mobile Network Parameters obtained from the Network Provider (MTN - Nigeria) included the Mean Transmitter Height of 33 meters, and the Mean Effective Isotropic Radiated Power (EIRP) of 46dBm. Path loss values (*PL*) were computed from the received power values using (11)

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

7. RESULTS AND ANALYSIS

The ANN based model predictors were, trained, validated and tested using path loss data derived from the power readings. The simulation procedure involved analyzing each BTS data separately by randomly splitting the data into 50% training, 5% validation and 45% testing.

The performance metrics considered for the evaluation of model predictors include the Root Mean Square Error (*RMSE*), expressed as (12), and the Coefficient of Determination (R^2), expressed as (13). *RMSE* is a measure of the difference between predicted and observed data. The lower the *RMSE* value, the higher the model's prediction accuracy. The R^2 is an indication of the proportion of variance and ranges between 0 and 1, but can also be negative. Values close to 1 indicate acceptable model accountability of greater variance proportion. However, if the value is negative, the model is deemed inappropriate for the data.

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

where,
- M is the observed path loss value
- P is the predicted path loss value
- N is the 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 observed path loss value
- $\hat{y}_i$ is the predicted path loss value and
- $\bar{y}_i$ is the mean of the observed path loss values.

Graphical simulation results for the six different BTSs are presented in Figs. 3 to 8. There is a clear indication that the Hata-Okumura model is divergent from other contenders by significantly undervaluing the path loss across all six BTSs. Fig.3 shows that the GRNN is convergent with the test data at distances closer to the BTS while all predictors are convergent at farther distances. Figs. 4 and 5 show that the ANN based models and the COST 231 Hata are convergent in prediction simulation. However, Figs. 6, 7 and 8 indicate that the COST 231 Hata slightly overvalues the path loss. Overall, it can be clearly observed that GRNN is most convergent with the test that across all six BTSs.

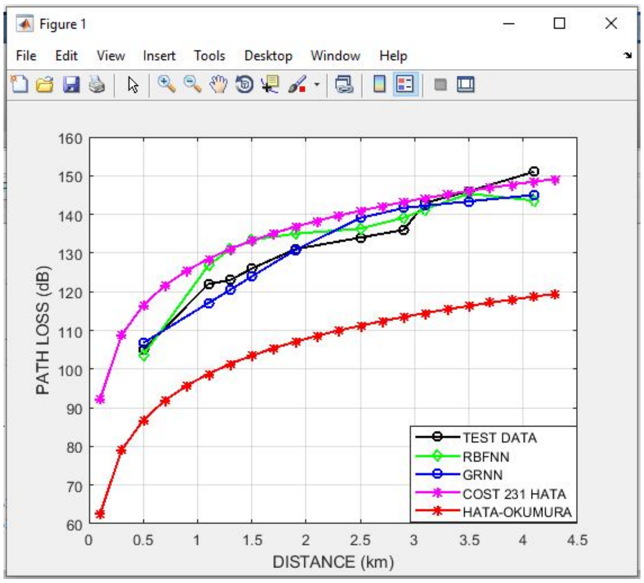

Fig.3 : BTS1 Comparison of Predictors

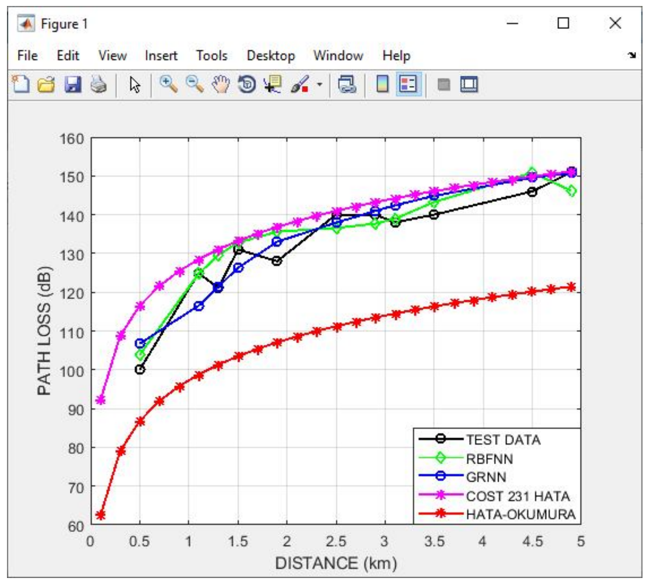

Fig.4 : BTS2 Comparison of Predictors

Table 1 presents the statistical evaluation metrics for all the Predictors. The table indicates that on the average, the ANN based predictors with *RMSE* values of 5.17dB and 4.9dB for the RBFNN and the GRNN respectively, are more accurate than their empirical counterparts. It can as well be noticed that the COST 231 Hata with an *RMSE* value of 6.64dB is slightly less accurate than the ANN based models, while the Hata-Okumura model significantly undervalues the path loss by an *RMSE* value of 25.78 dB. Interestingly, the table clearly shows that the ANN based predictors and the COST 231 Hata exhibit high correlation with the test data, with R^2 values above 0.8. On the other hand, the negative R^2 value of the Hata-Okumura indicates that it is just not suitable for the terrain under consideration. Overall, the most accurate of all the predictors is the GRNN, which proffers a 26.21% improvement over the COST 231 Hata. Hence, the GRNN based predictor is recommended for the terrain in question.

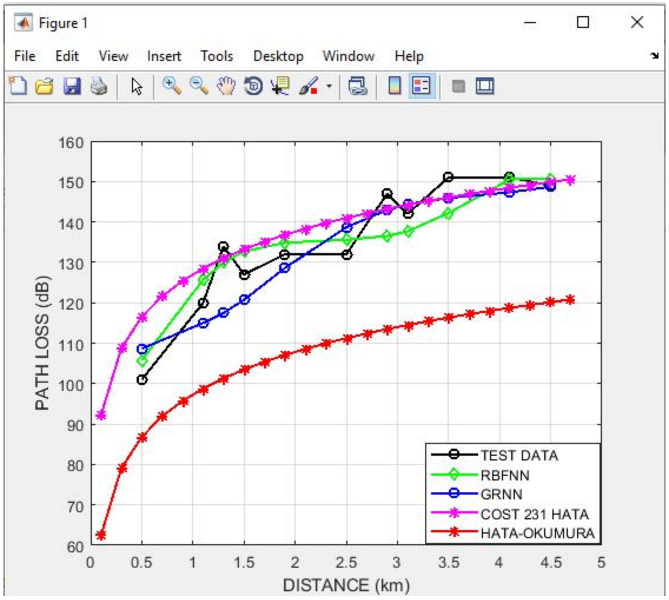

Fig.5 : BTS3 Comparison of Predictors

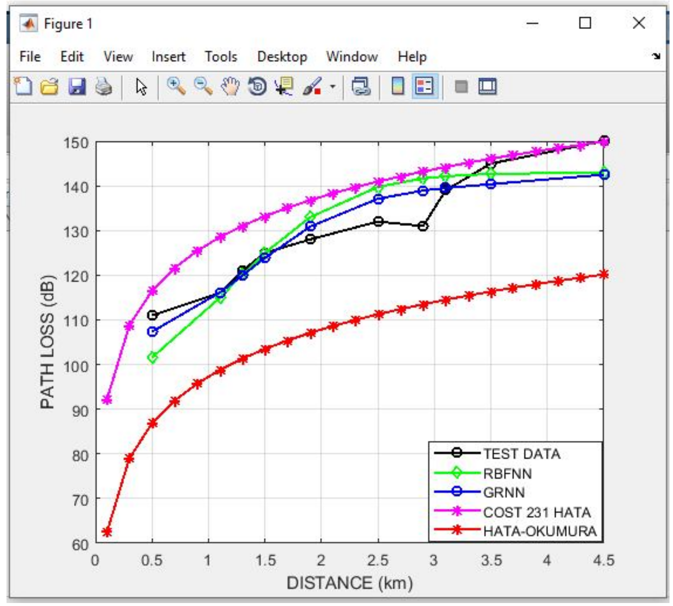

Fig.6 : BTS4 Comparison of Predictors

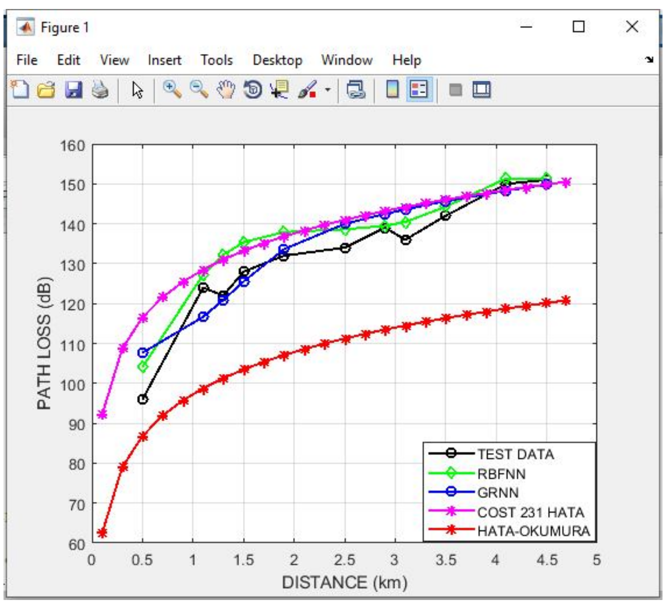

Fig.7 : BTS5 Comparison of Predictors

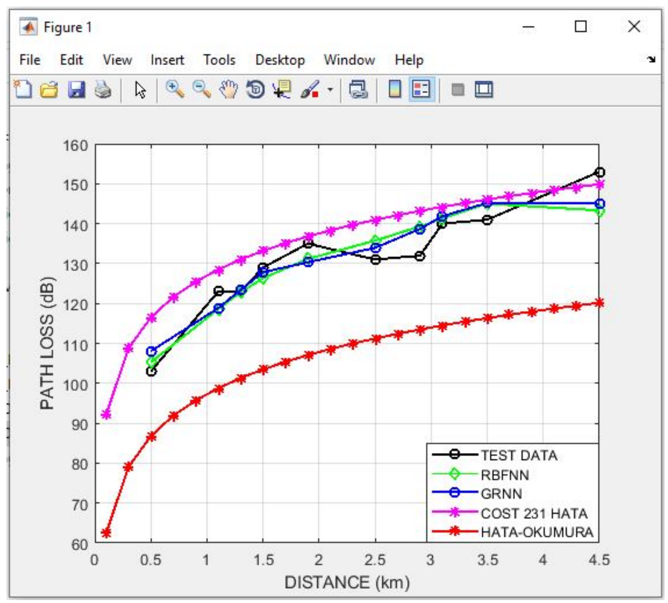

Fig.8 : BTS6 Comparison of Predictors

Table 1. Statistical Evaluation Metrics of Predictors across all Base Transceiver Stations

MODEL	STATISTICS	BTS 1	BTS 2	BTS 3	BTS 4	BTS 5	BTS 6	MEAN
RBFNN	RMSE(dB)	4.83	4.53	5.50	5.95	5.38	4.84	5.17
	R^2	0.86	0.89	0.86	0.74	0.86	0.85	0.84
GRNN	RMSE(dB)	3.73	4.53	6.83	4.37	5.42	4.53	4.90
	R^2	0.92	0.89	0.78	0.86	0.86	0.87	0.86
COST 231 Hata	RMSE(dB)	6.22	5.98	6.38	8.07	6.70	6.47	6.64
	R^2	0.85	0.87	0.86	0.74	0.84	0.82	0.83
Hata – Okumura	RMSE(dB)	25.15	26.25	27.56	24.33	26.20	25.16	25.78
	R^2	-1.51	-1.57	-1.67	-1.35	-1.41	-1.73	-1.54

8. CONCLUSION

In this study, two similar, but yet different ANN architectures, namely the RBFNN and the GRNN, were compared for prediction accuracy with the widely used empirical COST 231 Hata and Hata-Okumura models. Findings show that although ANN based models are convergent in terms of performance, the GNN is slightly more accurate than the RBFNN. But on the average, the ANN based models proffer a slight improvement over the COST 231 Hata model, while the Hata-Okumura is simply not suitable for the terrain under investigation. Overall, the most accurate of all the predictors is the GRNN, which proffers a 26.21% improvement over the COST 231 Hata. Hence, the GRNN based predictor is recommended for the terrain in question.

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