

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

ABSTRACT

This study proposes the use of artificial neural networks (ANN) based prediction models for path loss estimation across a rural section of the Nigerian middle-belt grassland. The ANN structures considered are the Radial Basis Function Neural Network (RBF-NN) and the Generalized Regression Neural network (GRNN), which exhibit a few differences and similarities. These ANN based predictors were created, trained and tested for path loss prediction using path loss data recorded at 900MHz from multiple Base Transceiver Stations (BTSs) distributed across the rural area. Results indicate that the RBFNN and GRNN based models with Root Mean Squared Error (RMSE) values of 5.17dB and 4.9dB respectively, offer a slight improvement over the COST 231 Hata model with 6.64dB, while the Hata-Okumura with 25.78dB is simply not suitable for the terrain under investigation.

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

1. INTRODUCTION

An artificial neural network (ANN) is an interconnection of multiple artificial neurons, aimed at solving complex problems given adequate amounts of data. ANNs are essentially mathematical models that mimic the structure and functionalities of biological neural networks [1]. They are basically Deep Learning (DL) structures. As described in [2], 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. ANNs are widely used for problem solving in areas such as data mining, classification, forecasting, function approximation, rule extraction, pattern recognition and medical applications [3]. ANNs are capable of learning to approximate any function to a given accuracy. Some ANN architectures capable of effectively handling prediction and functional approximation problems 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 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. In order to ensure quality delivery of service through adequate network coverage, wireless networks must be well planned. A crucial consideration in wireless 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. As described in

[4], path loss usually results from phenomena which include reflections, diffraction, refractions, scattering, free space loss, etc. Path loss is also dependent on operating frequency, transmitter height, transmitter-receiver separation, nature of the terrain, etc.

Over the years, various formulations have been implemented by radio engineers in order to accurately determine adequate network coverage through prediction of path loss. Some of the most widely used means of predicting path loss include deterministic and empirical models. Deterministic models are based on ray tracing, which is suitable for predicting signal within short distances [5]. The accuracy of the model is due to its detailed requirements of information on environment [6]. However, empirical models are preferable for radio propagation modeling as a result of their simplicity. Empirical models are mathematical formulations that are essentially based on in-depth field measurements [7]. Recent approaches to path loss modeling such as [2],[4],[8],[9],[10] and [11] are based on computational intelligence.

In this study, the RBFNN and the GRNN are compared for path loss prediction accuracy with two widely used empirical models, namely 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 essentially a rural area with tall grasses, scattered houses and trees mostly below 15meters averagely.

2. THE RADIAL BASIS FUNCTION NEURAL NETWORK

The Radial Basis Function Neural Network (RBFNN) is a variant of ANN that uses a radial basis function (RBF) as activation function. The RBF is a function whose value depends on the distance between input and a fixed point referred to as the center. The RBFNN is capable of handling function approximation problems with high accuracy. It generalizes efficiently by using a multi-dimensional surface to interpolate the test data, hence commonly referred to as the Generalized Radial Basis Function Neural Network (RBF-NN)

As described in [12], the RBFNN network has three layers as shown in Fig. 1: the input layer for data input, the hidden layer where input data undergoes nonlinear transformation, and the output layer through which an output is produced. One neuron in the input layer corresponds to each predictor variable. With respects to categorical variables, $n-1$ neurons are used where n is the number of categories.

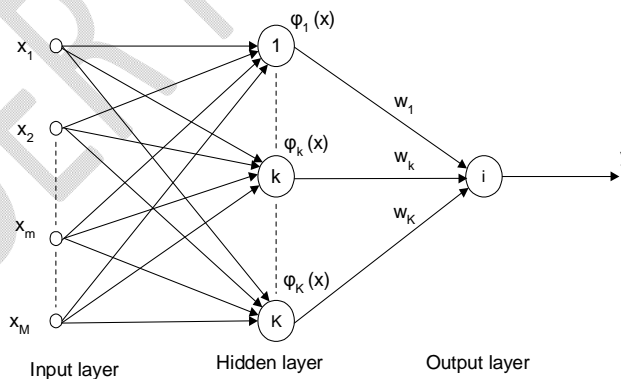


Fig. 1: The Radial Basis Function Neural Network [13].

The hidden layer has a variable number of neurons. Each neuron consists of a radial basis function centered on a point with the same dimensions as the predictor variables. The output layer computes a weighted sum of outputs from the hidden layer to form the network outputs. The outputs of hidden-nodes are not calculated using the weighted-sum activation function; rather the output of each hidden-node, ϕ_k is obtained by the closeness of input X to an M -dimensional parameter vector μ_k associated with the k^{th} hidden node [13].

According to [13], the most popular choice for the function φ is a multivariate Gaussian function with an appropriate mean and auto covariance matrix. The output of a Radial Basis Function Neural Network is given by (1)

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

where,

X is the input vector

w_{ik} is the connection weight in the second layer (from hidden to output layer)

k is the number of hidden nodes

i denotes the i -th hidden node

φ_k is the radial basis activation function.

As described in [14], the radial basis function is a multi-dimensional function that describes the distance between a given input vector and a pre-defined centre vector. The Gaussian function is a type of radial basis function given by (2)

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

Where,

μ_k denotes the center vector

σ_k denotes the spread (width) of the function

The learning process is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data, with the criterion for the “best fit” being measured in some statistical sense [13]. The training of a RBFNN is in two stages:

1. Determination of radial basis function parameters, i.e., Gaussian centre and spread width
2. Determination of output weight by supervised learning.

3. THE GENERALIZED REGRESSION NEURAL NETWORK

The Generalized Regression Neural Network (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 [6]. Given sufficient data, the GRNN is capable of approximating virtually any function given a few data samples. In contrast to back-propagation neural networks, which may require a large number iterations in order to converge to the desired output, the GRNN does not require iterative training, and usually requires a fraction of the training samples a back-propagation neural network would need [15]. As shown in Fig. 2, the GRNN comprises of four layers [16]:

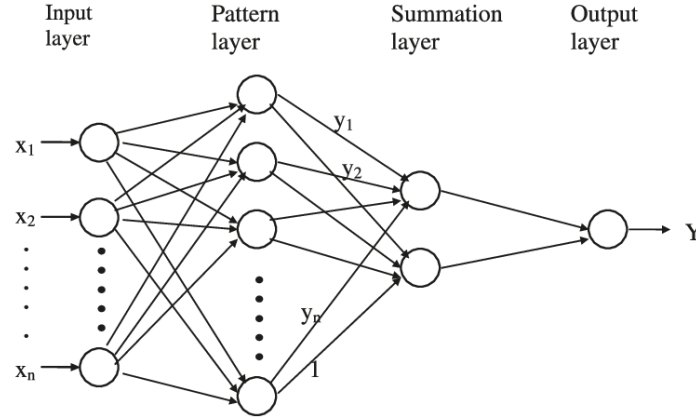


Fig. 2: Generalized Regression Neural Network Architecture [16]

Input layer: This captures and sends 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 [15] 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 (3)

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

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 (4) 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 .

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

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 (5)

$$D_i^2 = (X - X^i)^T(X - X^i) \quad (5)$$

Combining equations (3) and (4) and interchanging the order of integration and summation yields the desired conditional mean $\hat{Y}(X)$, given by (6)

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

The only free network parameter is the smoothing parameter. Neural network training involves finding the optimal value of the smoothing parameter, for which the mean squared error is minimum. As a key advantage over standard feed-forward neural nets, the GNN always converges to a global minimum and hence, has no issues with local minima. It is further stated in [15] 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.

4. THE COST 231 HATA MODEL

This is one of the most widely used empirical path loss models. As described in [17], the model was formulated on the basis the Hata-Okumura model, to suit the European environments taking into consideration a wider range of frequencies (500MHz to 200MHz). The Hata-Okumura model in turn is an extension of the Okumura Model. With suitable correction factors the COST 231 Hata model is suitable for path loss prediction in urban, semi-urban, suburban and rural areas, and the model expression is given by (7)

$$L = 46.3 + 33.9 \log f - 13.82 \log h_B - a(h_m) + (44.9 - 6.55 \log h_B) \log d + C \quad (7)$$

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, $a(h_m) = 3.20(\log_{10}(11.75h_m))^2 - 4.97$, for $f > 400$ MHz
- For sub-urban and rural areas, $a(h_m) = (1.1 \log(f) - 0.7)h_m - 1.56 \log(f) - 0.8$

5. THE HATA-OKUMURA MODEL

This model incorporates graphical information from the Okumura Model. As described in [18], the Hata-Okumura Model is a widely used for predicting path loss in urban areas, and also has formulations for predicting path loss in Suburban and Open Areas. The Hata-Okumura 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 to 10 meters. The Hata Model for Urban Areas is formulated as (8)

$$L_U = 69.55 + 26.16 \log f - 13.82 \log h_B - C_H + (44.9 - 6.55 \log h_B) \log d \quad (8)$$

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

$$C_H = 0.8 + (1.1 \log f - 0.7) h_M - 1.56 \log f$$

and for large cities,

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

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 kilometres (km).

The Hata Model for Suburban Areas is given by (9)

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

The Hata model for open areas is formulated as (10),

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

6. MATERIALS AND METHODS

Received power readings were recorded from six (6) Base Transceiver Stations (BTSs) situated within the rural terrain between the middle-belt grassland cities of Makurdi and Jos, Nigeria. The measurement instrument used was a Cellular Mobile Network Analyser (SAGEM OT 290) capable of measuring signal strength in decibel milliwatts (dBm). Received power (P_R) readings 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 Mean Effective Isotropic Radiated Power (EIRP) of 46dBm. Path loss values (PL) were computed from the received power readings using (11)

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

7. RESULTS AND ANALYSIS

The performance comparison of predictors in this study is based on the Root Mean Square Error ($RMSE$), given by (12), and the Coefficient of Determination (R^2), given by (13). $RMSE$ is essentially a measure of the differences between predicted and observed values. The smaller the $RMSE$ value, the higher the prediction accuracy of the model. As for the R^2 a value closer to 1 indicates that a greater proportion of variance is accounted for by the model and ranges between 0 and 1. 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 – 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.

The path loss prediction procedure involved analyzing each BTS data separately. During network training, validation and testing, path loss data recorded from a given BTS was randomly split as follows: 50% training, 5% validation and 45% testing.

Figs. 3 to 8 depict graphical performance comparisons of the four predictors across the six different BTSs. The figures show that across the six BTSs, the ANN based predictors are convergent with the test data in terms of performance. It can also be observed that the COST 231 Hata model on the other hand slightly overestimates the path loss across all but BTS3. However, the Hata-Okumura model significantly underestimates the path loss across all six BTSs. The wide disparity could stem from the fact that the terrain for which the Hata-Okumura model was formulated could have had lesser clutter congestion than the one under investigation.

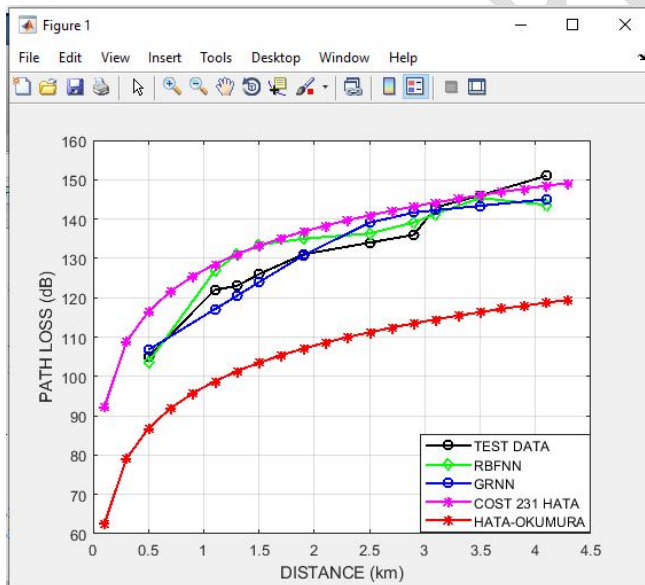


Fig.3 : BTS1 Comparison of Predictors

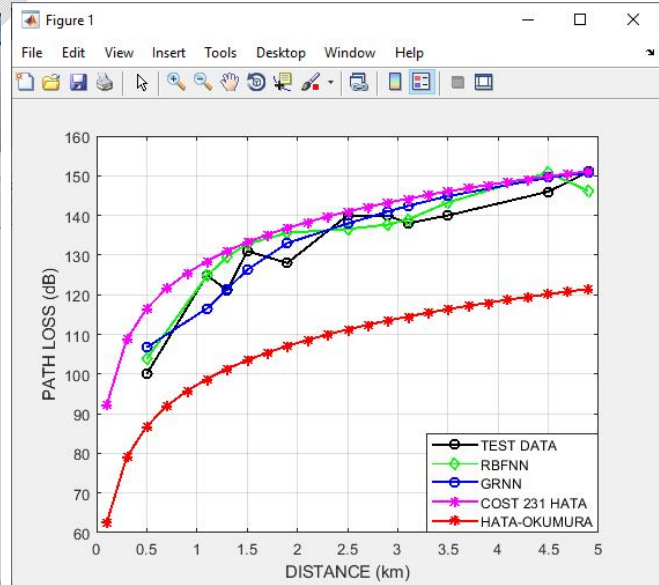


Fig.4 : BTS2 Comparison of Predictors

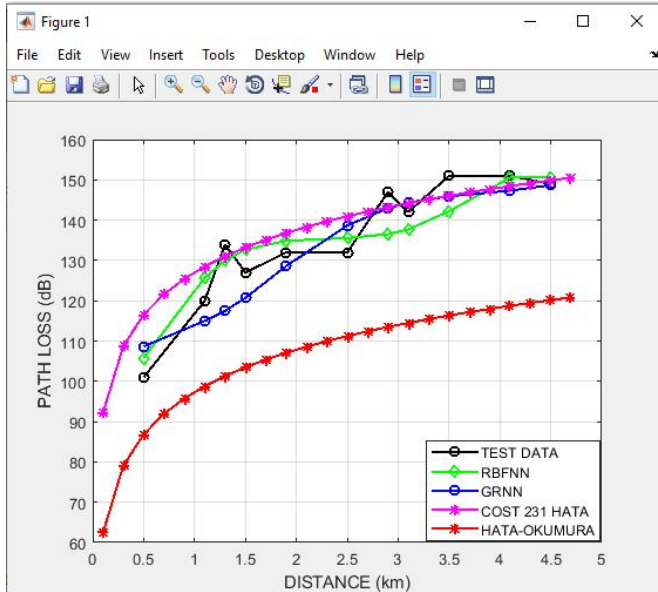


Fig.5 : BTS3 Comparison of Predictors

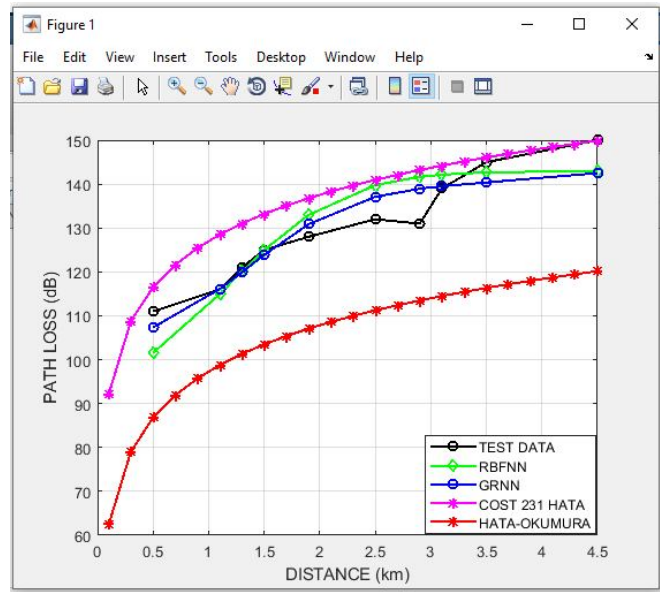


Fig.6 : BTS4 Comparison of Predictors

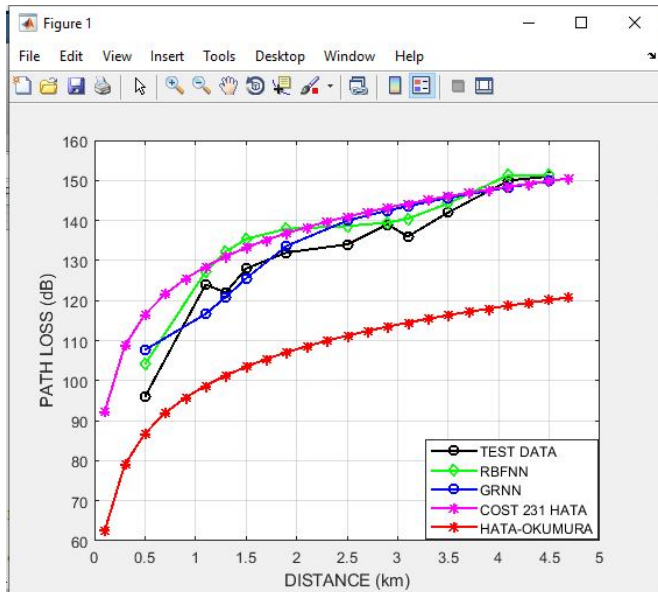


Fig.7 : BTS5 Comparison of Predictors

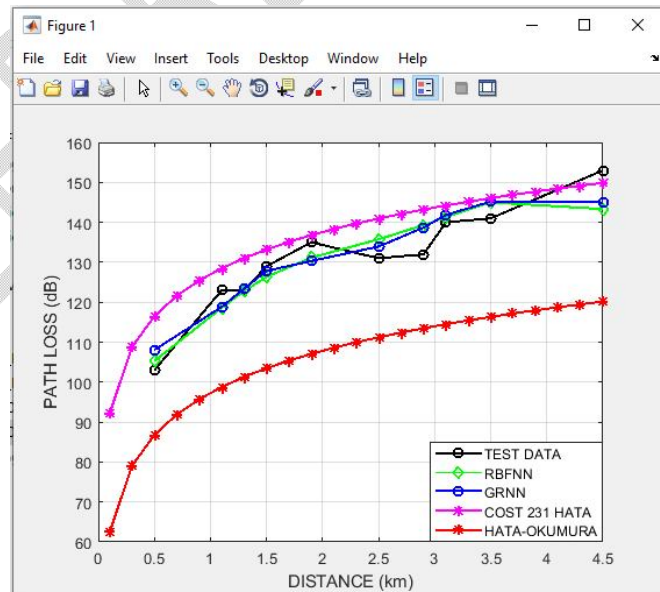


Fig.8 : BTS6 Comparison of Predictors

Table 1 shows the statistical performance indices of all the Predictors. The table shows that on the average, the most accurate of the predictors are the ANN based predictors with $RMSE$ values of 5.17dB and 4.9dB for the RBFNN and the GRNN respectively. The table also shows the COST 231 counterpart is slightly less accurate than the ANN based models with an $RMSE$ value of 6.64dB, while the Hata-Okumura model significantly underestimates the path loss by an $RMSE$ value of 25.78 dB. Interestingly, the ANN based predictors and the COST 231 Hata model 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 investigation. Overall, the most accurate of all the predictors is the GRNN. Hence, the ANN based predictors are recommended for path loss estimation across the terrain in question.

Table 1. Statistical Performance Indices of Predictors across all Base Transceiver Stations

MODEL	STATS.	BTS 1	BTS 2	BTS 3	BTS 4	BTS 5	BTS 6	MEAN
RBF-NN	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 two widely used existing empirical models, namely the COST 231 Hata and the Hata-Okumura. Findings show that although ANN based models are convergent in terms of performance, the GNN is slightly more accurate than the RBFNN. But overall, the ANN based models offer a slight improvement over the COST 231 Hata model, while the Hata-Okumura is simply not suitable for the terrain under investigation. Hence, the ANN based techniques are recommended for path loss prediction across similar terrains.

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