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A Generalized Regression Neural Network Model for Path Loss Prediction at 900 MHz for Jos City, Nigeria

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ABSTRACT: *This study considers the application of a Generalized Regression Neural Network (GR-NN) based model for path loss prediction across the city of Jos, Nigeria. The GR-NN model was created and used to analyze path loss data obtained from Base Transceiver Stations situated across the city. Results indicate that the GR-NN based model with a Root Mean Squared Error (RMSE) value of 4.52B, offers a significant improvement in path loss prediction accuracy of more than 6dB in RMSE, over widely used empirical propagation models.*
Keywords: *COST 231 Hata Model, COST 231 Walfisch-Ikegami Model, , Okumura Model, Generalized Regression Neural Network, Path loss.*

I. INTRODUCTION

The determination of radio propagation characteristics of given terrain is highly crucial in mobile network planning. As such, numerous techniques have been implemented in radio propagating modeling. Due to their simplicity, empirical models are some of the most widely used. Empirical models are those models that are formulated based on observations and measurements alone [1]. They are mathematical formulations used in radio propagation modeling of a given terrain. Although empirical models are quite straight forward in implementation, they are usually not very accurate in path loss prediction when used outside the terrain for which they were formulated.

In recent times, computational intelligent techniques have been used to model radio propagation as demonstrated by [2], [3], [4], [5]. Artificial neural networks (ANNs) are some of the most widely used computational intelligent techniques in handling complex non-linear function approximation. They have been proven to handle complex non-linear function approximation with a greater accuracy than those techniques which are based on linear regression. Hence, radio propagation models created on the bases of non-linear function approximation have been proven to predict path loss with greater accuracy than those that are based on linear regression. This can be attributed to the fact that path loss across a given terrain is best modeled using non-linear function approximation since path loss is dependent on heterogeneity of terrain clutter resulting from varying obstacles that perturb radio propagation.

In this study, a Generalized Regression Neural Network (GRNN) Model is created and compared for path loss prediction accuracy across the city of Jos, Nigeria, with the following widely used empirical propagation models: the Okumura Model, the COST 231 Hata and the COST 231 Walfisch-Ikegami. The choice of these empirical models is based on their suitability for path loss prediction in built-up environments.

II. THE GENERALIZED REGRESSION NEURAL NETWORK

The Generalized Regression Neural Network (GRNN) is a type of Radial Basis Function Neural Network (RBF-NN), classified under Probabilistic Neural Networks (PNN). Given sufficient input data, the GRNN can approximate virtually any function. In contrast to 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 [6]. The GRNN is used to solve a variety of problems such as prediction, control, plant process modeling or general mapping problems [7]. As shown in Figure 1, the GRNN comprises of four layers: input layer, a hidden layer (pattern layer), a summation layer, and an output layer. According to [6], the GRNN can approximate any arbitrary function between input vector and output vector directly from the training data.

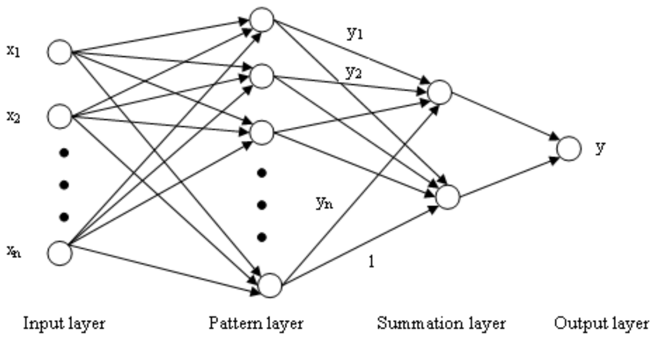

Figure 1: Generalized Regression Neural Network Architecture [8]

The general regression as described by [6] 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

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

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 equation (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.

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

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

$$D_i^2 = (X - X^i)^T (X - X^i) \tag{3}$$

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

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

It is further stated in [6] 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 OKUMURA MODEL

The Okumura model [9], [10] is one of the most widely used empirical propagation models for path loss prediction across various terrain types, classified as urban, suburban, quasi-open area and open areas. The model was developed based on empirical data collected in the city of Tokyo, Japan. The model is valid for the frequency range 150 MHz to 1920 MHz and distances up to 100 km. The path loss expression is given by

$$L = L_{FSL} - A_{MU} - H_{MG} - H_{BG} - G_{AREA} \tag{5}$$

where,
- L = Median path loss in Decibels (dB)
- L_{FSL} = Free Space Loss in Decibels (dB)

- A_{MU} = Median attenuation in Decibels (dB)
- H_{BG} = Base station antenna height gain factor given by 20log(h_b/200) for 30m<h_b<100m
- H_{MG} = Mobile station antenna height gain factor given by 10log(h_m/3) for h_m<3m
- G_{AREA}=Gain due to type of environment

IV. THE COST 231 HATA MODEL

The COST 231 Hata [11] Model was formulated from the Hata Model, to suit the European environments taking into consideration a wide range of frequencies (500MHz to 200MHz). The model is also an extension of the Okumura Model. As a result of its proven suitability path loss prediction in urban, semi-urban, suburban and rural areas, it is one of the most widely used models. The model expression is given by

$$L = 46.3 + 33.9logf - 13.82logh_B - a(h_R) + (44.9 - 6.55logh_B)logd + C \qquad (6)$$

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 Antenna effective height in Meters (30m to 100m)
- d = Link distance in Kilometers (km) (up to 20kilometers)
- h_R = Mobile Station Antenna effective height in Meters (m) (1 to 10metres)
- a(h_R) = Mobile station Antenna height correction factor as described in the Hata Model for Urban Areas.
- For urban areas, a(h_R) = 3.20(log10(11.75hr))2−4.97, for f > 400 MHz

For sub-urban and rural areas, a(h_R) = (1.1log(f) - 0.7)h_R - 1.56log(f) -0.8

V. THE COST 231 WALFISCH-IKEGAMI MODEL

As described in [12], [13] the COST-Walfisch-Ikegami Model empirical propagation model was created on the bases of the models from J. Walfisch and F. Ikegami and further developed by the COST 231 project. The model is suitable for path loss prediction in urban environments because it considers multiple diffraction losses over rooftops of buildings in the vertical plane between the Base and Mobile Stations. However, the model does not take into account path loss due to multiple reflections. The Model is valid for the following parameters:
- Frequency Range: 500 MHz to 2000 MHz
- Transmitter Height (h_b): 4m to 50 m
- Link distance: 0.02km to 5km
- Mobile Station (MS) height (h_m): 1m to 3m
- Mean height of buildings (h_{roof})
- Mean Street Width (w)
- Mean building separation (b)

The Line of Sight (LOS) path loss equation is given by

$$PL = 42.64 + 20logf + 26logd \qquad (7)$$

However, when there is No Line of Sight (NLOS) the equation is

$$PL = L_{FS} + L_{RTS} + L_{MSD} \qquad (8)$$

Where,

L_{FS} is free-space path loss and is expressed as:

$$L_{FS} = 32.45 + 20logf + 20logd \qquad (9)$$

L_{RTS} is path loss due to rooftop to street diffraction and is expressed as:

$$L_{RTS} = -16.9 - 10logw + 10logf + 20\,log(\,h_b - h_m) + L_{ori} \qquad (10)$$

L_{ori} in (9) is path loss due to orientation angle φ (in degrees), between incident wave and street, expressed as:

$$L_{ori} = \begin{cases} -10 + 0.354\varphi & for \quad 0 \le \varphi < 35 \\ 2.5 + 0.075(\varphi - 35) & for \quad 35 \le \varphi < 55 \\ 4 - 0.114(\varphi - 55) & for \quad 55 \le \varphi < 90 \end{cases} \tag{11}$$

L_{MSD} is path loss due to multi-screen diffraction, and is expressed as:

$$L_{MSD} = L_{BSH} + k_a + k_d logd + k_f logf - 9 \log b \tag{12}$$

Where,

$$L_{BSH} = \begin{cases} -18 \log\left(1 + h_b - h_{roof}\right) & for \;\; h_b > h_{roof} \\ 0 & for \quad h_b \le h_{roof} \end{cases}$$

$$k_a = \begin{cases} 54 & for \quad h_b > h_{roof} \\ 54 - 0.8\left(h_b - h_{roof}\right) & for \quad d \ge 0.5km \ and \ h_b \le h_{roof} \\ 54 - \dfrac{0.8\left(h_b - h_{roof}\right)}{0.5} & for \quad d < 0.5km \ and \ h_b \le h_{roof} \end{cases}$$

$$k_d = \begin{cases} 18 & for \;\; h_b > h_{roof} \\ 18 - 15\left(h_b - h_{roof}\right) & for \quad h_b \le h_{roof} \end{cases}$$

$$k_f = \begin{cases} -4 + 0.7\left(\dfrac{f}{925} - 1\right) & for \;\; medium \ size \ city \ and \ suburban \ area \\ -4 + 1.5\left(\dfrac{f}{925} - 1\right) & for \;\; metropolitan \ area \ (i.e. large \ city) \end{cases}$$

VI. MATERIALS AND METHODS

Received power measurements (P_R) were obtained from Base Transceiver Stations (BTS) of the mobile network service provider, Mobile Telecommunications Network (MTN), Nigeria, situated within the metropolis of the city under investigation. The instrument used was a Cellular Mobile Network Analyzer (SAGEM OT 290) capable of measuring signal strength in decibel milliwatts (dBm). Received power (P_R) readings were recorded within the radiating far field (propagation region) defined by the Fraunhofer far field radius (R_{ff}), given by $R_{ff} > \frac{2D^2}{\lambda}$, where D is the transmitting antenna length in meters and λ, the wavelength of the transmitted signal derived from $\lambda = \frac{c}{f}$, where c is the velocity of light and f, the propagation frequency. For an antenna length of 2 meters, R_{ff} at 900MHz was found to be greater than 24 meters. Hence, measurements were taken at an average mobile height of 1.5 meters within the 900MHz frequency band at intervals of 0.05km away from the BTS, starting with a reference distance of 0.05kilometer. Mobile Network Parameters obtained from the Network Provider (MTN) include the following: Mean Transmitter Height, H_T= 34 meters, Mean Effective Isotropic Radiated Power, EIRP = 47dBm. Path loss values (L_P) were computed from received power measurements using the equation

$$L_P = EIRP - P_R \tag{13}$$

The path loss prediction capability of GRNN relative to the considered empirical models was determined using two basic approaches: the first involves separately analyzing each BTS data by splitting the data into 60% training, 10% validation and 30% testing. This is to ensure that the GRNN is trained for optimum performance. The second approach involves splitting the entire data obtained from all BTSs into two sets: 50% training and 50% testing. The geometric mean of all values at each receiver-transmitter separation is obtained from the training set using equation (14), and then used to train the GRNN model. From the testing set, each BTS set of data is statistically compared with the trained GRNN model and the considered empirical models.

$$GM = \sqrt[n]{X_1 . X_2 . X_{3,} \ldots , X_n} \tag{14}$$

In performance evaluation, the geometric mean is preferred to the arithmetic mean because it is less sensitive to extreme values [14].

The statistical performance indices used in this study are based on the Root Mean Squared Error (RMSE) and the coefficient of determination (R^2). The RMSE is given by

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(M-P)^2}{N-1}} \qquad (15)$$

where, M is the Measured Path Loss, P the Predicted Path Loss and N the Number of paired values.

The coefficient of determination (R^2) is given by [3]

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \qquad (16)$$

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. R^2 can take on any value between 0 and 1, but can be negative for models without a constant, which indicates that the model is not appropriate for the data. A value closer to 1 indicates that a greater proportion of variance is accounted for by the model.

VII. RESULTS AND DISCUSSION

The path loss prediction performance of the GRNN model relative the Okumura Model, the COST 231 Hata and the COST 231 Walfisch-Ikegami models, is determined using the two techniques described in the previous section. As samples, figures 2 and 3 respectively show BTS 1 and BTS 3 analyses based on the first comparative technique. It can be observed that the GRNN exhibits a closer prediction than the empirical models. This fact is buttressed by the results in Table 1, which indicate that on all Base station the GRNN outperforms the empirical models. The Geometric Mean (GM) performance across the eight BTSs shows that the GRNN is the most accurate with an RMSE value of 4.78dB and the highest R^2 value of 0.86. This can be attributed to the ability of neural networks to adapt to any environment given sufficient data. The best of the empirical models is the COST 231 Hata model with an RMSE value of 10.60dB.

Table 1: Splitting data into 60% training, 10% validation and 30% testing

MODEL	STATS.	BTS 1	BTS 2	BTS 3	BTS 4	BTS 5	BTS 6	BTS 7	BTS 8	GEOM. MEAN
GRNN	RMSE(dB)	4.58	4.32	3.70	5.83	3.77	4.71	5.20	6.90	4.78
	R^2	0.92	0.93	0.85	0.87	0.87	0.85	0.82	0.79	0.86
OKUMURA	RMSE(dB)	12.16	13.83	9.14	11.99	10.41	11.36	11.32	11.01	11.33
	R^2	0.55	0.48	0.65	0.58	0.62	0.60	0.59	0.59	0.58
COST 231 HATA	RMSE(dB)	9.55	9.61	10.60	10.73	11.12	10.78	10.35	12.29	10.60
	R^2	0.72	0.75	0.53	0.67	0.56	0.64	0.66	0.49	0.62
COST 231 WALF.	RMSE(dB)	16.97	15.56	19.85	18.95	20.16	19.27	18.61	21.39	18.76
	R^2	0.13	0.34	-0.66	-0.04	-0.43	-0.17	-0.11	-0.54	-0.10

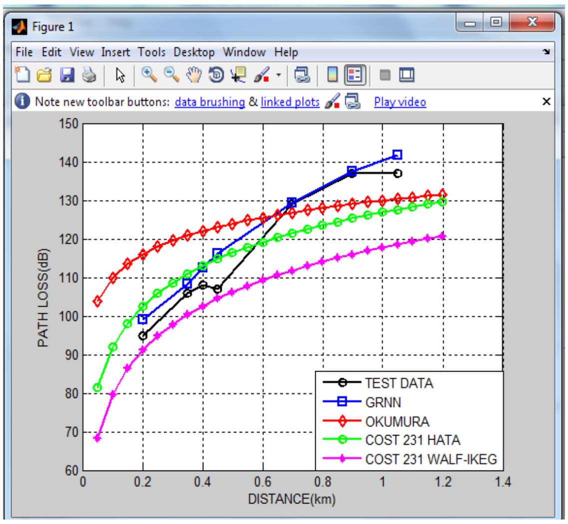

Figure 2: Analysis of BTS 1

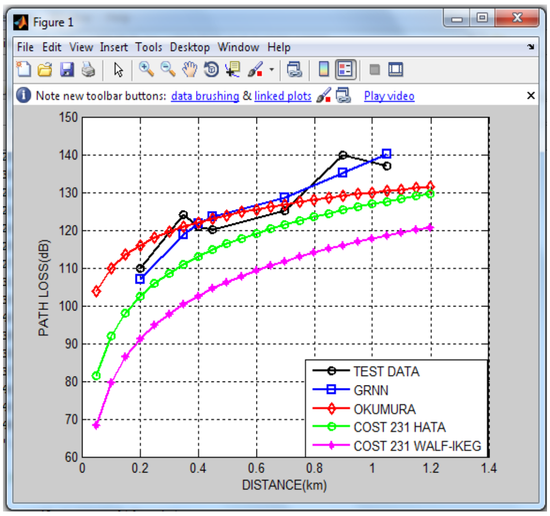

Figure 3: Analysis of BTS 3

The second approach presents a similar trend with the GRNN model outperforming the empirical models. Figure 4 presents a case of training the GRNN model with the computed GM and testing with data from BTS 7. Likewise, figure 5 shows a GM training and BTS 8 testing pairing. It can be observed from both figures 4 and 5 that GRNN plot is more convergent with the test data than the empirical models. Prediction results presented in Table 2 indicate that based on the geometric mean of performance indicators across all BTSs, the GRNN model is the most accurate with an RMSE value of 4.28dB, while the difference in performance between the Okumura and the COST 231 Hata models is negligible.

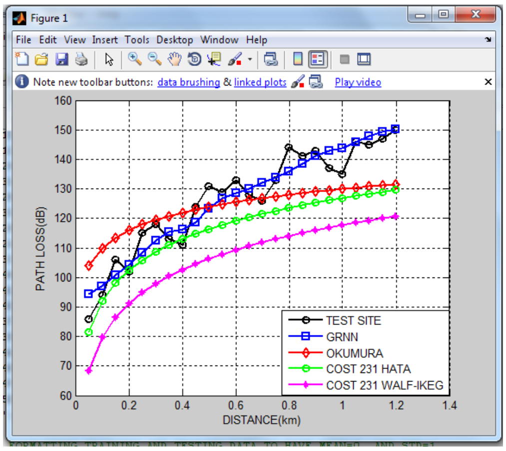

Fig.4 : Training with GM, Testing with BTS7

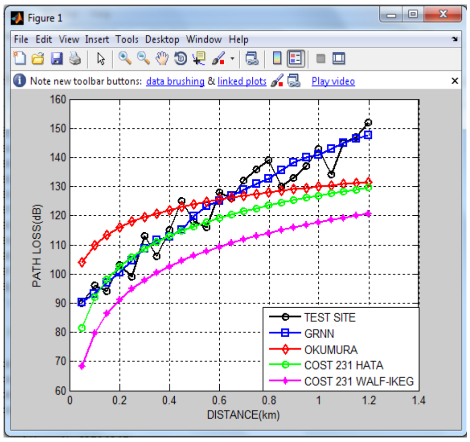

Fig.5: Training with GM, Testing with BTS8

Table 2: Training with GM of Training Set and Testing with data from Testing Set

MODEL	STATS.	GM/ BTS 5	GM/ BTS 6	GM/ BTS 7	GM/ BTS 8	GEOM. MEAN
GRNN	RMSE(dB)	3.97	3.70	4.64	4.92	4.28
	R^2	0.94	0.96	0.93	0.92	0.94
OKUMURA	RMSE(dB)	10.41	11.36	11.32	11.01	11.02
	R^2	0.62	0.60	0.59	0.59	0.60
COST 231 HATA	RMSE(dB)	11.12	10.78	10.35	12.29	11.11
	R^2	0.56	0.64	0.66	0.49	0.58
COST 231 WALF.	RMSE(dB)	20.16	19.27	18.61	21.39	19.83
	R^2	-0.43	-0.17	-0.11	-0.54	-0.26

The geometric mean performance of the two approaches shows that the GRNN is the most accurate with an RMSE value of 4.52dB and an impressive R^2 value of 0.9. The best of the empirical models is the COST 231 Hata with RMSE and R^2 values of 10.85dB and 0.6 respectively. This is a typical example of a terrain where the inadequacies of empirical modes are exposed as the results further buttress the fact that empirical models are not always accurate outside the terrains for which they were formulated. On the other hand, the much greater accuracy of the GRNN can be attributed to the ability of neural networks to adapt to any environment given sufficient data.

VIII. CONCLUSION

This study considers the application of a Generalized Regression Neural Network (GR-NN) model for radio propagation modeling of the city of Jos, Nigeria. Measurements obtained at 900 MHz from Base Transceiver Stations were analyzed for path loss prediction using two distinct approaches. Results indicate that the GRNN has a combined RMSE value of 4.52dB. This is a significant improvement on the widely used empirical models Okumura, COST 231 Hata and COST 231 Walfisch-Ikegami. The COST 231 Hata model is the most accurate of the three empirical models with an RMSE value of 10.85dB.

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