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A Generalized Regression Neural Network Approach to Wireless Signal Strength Prediction

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ABSTRACT

This study presents a Generalized Regression Neural network (GRNN) based approach to wireless communication network field strength prediction. As case study, the rural area between the cities of Bauchi and Gombe, Nigeria, was considered. The GRNN based predictor was created, validated and tested with field strength data recorded from multiple Base Transceiver Stations at a frequency of 1800MHz. Results indicate that the GRNN based model with Root Mean Squared Error (RMSE) value of 5.8dBm offers significant improvements over the empirical Okumura and COST 231 Hata models. While the Okumura model overestimates the field strength, the COST 231 Hata significantly underestimates it.

KEYWORDS: *Field Strength; Generalized Regression Neural Network; Okumura Model, COST 231 Hata Model*

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INTRODUCTION

In recent times, soft computing based methods (also termed computational intelligence) are used to solve a variety of problems. This is as a result of their outstanding abilities to mimic the processing power of the human brain [1]. These techniques encompass the convolutional neural network (CNN), generalized regression neural network (GRNN), multi-layer perceptron neural network (MLP-NN), adaptive neuro- fuzzy Inference system (ANFIS), radial basis function neural network (RBF-NN) etc. The aforementioned techniques are useful in areas like signal prediction, image processing, pattern recognition, voice recognition and so on. Soft computing techniques are capable of handling complex function approximation problems with greater accuracy than regression methods. In recent times, computational intelligence techniques have been applied to the field of telecommunication for radio propagation modeling.

Signal strength determination is one of the paramount requirements considered when planning wireless telecommunication systems. This is because as signals propagate through space, they tend to reduce in strength due to variable factors such as diffraction, refraction, reflection, scattering, free space losses etc. [2]. This is termed as multiple path propagation [3]. The losses in signal strength of wireless systems can also be attributed to the distance of receiving station from the transmitting station, radiated power of the transmitter, the height of the antenna, trees, nature of the terrain etc. [4], [5], [6]. The reduction in intensity of the signal from its transmitting to receiving station is known as attenuation [7]. The attenuation of signal in wireless systems prompts radio engineers to plan adequately for modeling of radio propagation for the purpose of signal prediction in view of establishing good network coverage. Radio propagation models are applicable within a specific terrain.

There are existing models that have been used widely for modeling radio propagation for accurate signal strength prediction in telecommunication systems. Some of these models were created in Japan and Europe based on empirical data. Some of the broadly used models include deterministic and empirical models. [8]

Deterministic models are based on ray tracing, which is suitable for predicting signal strength in wireless systems within short distances [9]. The accuracy of the model is due to its detailed requirements of information about the environment [10]. However, the model is time consuming in terms of computational effort. On the other hand, empirical models are preferable for radio propagation modeling as a result of their simplicity.

Empirical models are mathematical equations that are based on in-depth field measurements and observations [3], [11]. These models require less computational effort, implying greater efficiency in computation but not as accurate when compared with deterministic models. Some of the broadly used empirical models include the Okumura, Hata-Okumura and Cost 321 Hata etc.

This study is aimed at using an artificial neural network called the GRNN to predict signal strength across the rural area between the cities of Bauchi and Gombe, Nigeria. The GRNN based model is created and compared with some of the widely used empirical models such as the Hata-Okumurah and the COST 321 Hata, which are suitable for terrains like the rural, open, urban and suburban.

The Generalized Regression Neural Network (GRNN)

The GRNN was proposed by Donald F. Specht [12]. It is a type of feed-forward neural network but not a standard backward propagation network. The GRNN is related to the radial basis function neural network (RBF-NN) and are both classified under probabilistic neural networks (PNN). The GRNN is capable of approximating virtually any function when given large amounts of data. Due to its single-pass in nature, the GRNN requires a small fraction of training data of backward algorithm to give the desired output. As described in [1], the GRNN architecture consists of four layers: input layer, pattern layer, summation and output layer as shown in fig. 1.

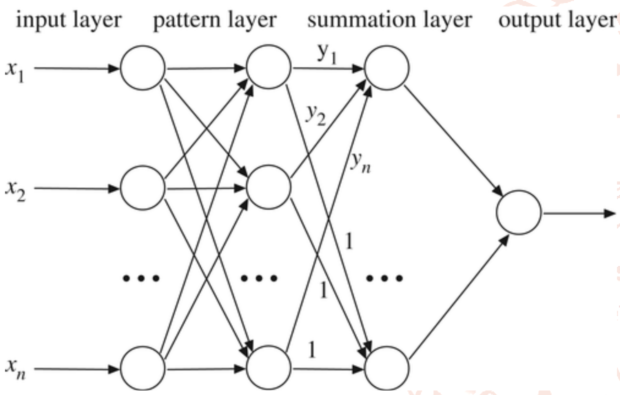

Fig. 1: The GRNN Architecture

Input layer: This is the first layer that feeds into the second layer called pattern layer.

Pattern layer: The layer that is responsible for computing the Euclidean distance and activation function and later sends to summation layer which is the third layer.

Summation layer: This layer is divided into two parts namely, numerator and denominator. The numerator has to do with the activities of summation of the multiplication of the training data and activation function. The Denominator computes the activation function.

Output layer: This generates the output by dividing the numerator part by the denominator

The general equation as described by [12] is as follows: given a vector variable, x, and a scalar variable, y, and assuming X is a particular weighted value of the random variable y, the regression of y on X is given by

$$E[y/x] = \int_{-\infty}^{\infty} yf(x,y)dy / \int_{-\infty}^{\infty} f(x,y)dy \quad (1)$$

If the probability density function $f(x,)$ is unknown, it is estimated from a sample of observations of x and y. The probability estimator $f(X,)$, 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 is the dimension of the vector variable x.

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

The scalar function D^2_i is given by (3)

$$D^2_i = (X - X)^T (X-X^i) \quad (3)$$

Combining equations (1) and (2) and interchanging the order of integration and summation yields the desired conditional mean (X).

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

It is observed by [12] that when the smoothing factor 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.

The Okumura Model

As described in [5], this is one of the widely used empirical models for signal prediction. It was formulated by Okumura based on drive test measurements in Japan at operating frequencies ranging from 150 MHz to 1920MHz, but extended to 3000MHz]. The model is created for macro-cellular networks that cover distances from 1km to 100km. The height of base station antenna is between 30m to 100m. The propagation model is good in signal prediction in terrains like urban, suburban, quasi-open area and open areas.

The model equation is given by (5)

$$L = LFSL + AMU - HMG - HBG - GAREA \quad (5)$$

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 $20\log(h_b/200)$ for $30m<h_b<100m$,
H_{MG} = Mobile station antenna height gain factor given by $10\log(h_m/3)$ for $h_m<3m$,
G_{AREA} = Gain due to type of environment

The COST 231 Hata Model

A described in [13], this model was created on the basis of the Hata-Okumura model by European cooperative of Scientific and Technical research, to suit European terrains. The model is widely used for signal prediction in wireless systems with minimum and maximum frequency from 500MHz to 2000MHz. It has correction factors for urban, sub urban, semi urban and rural areas. Due to its simplicity and availability of correction factors, it is widely used for signal strength prediction [10]. The model expression is given by (6)

$$L = 46.3 + 33.9logf - 13.82log\,h_B - a(h_m) + (44.9 - 6.55log\,h_B)logd + C \quad (6)$$

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 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) = (1.1log(f) - 0.7)h R - 1.56log(f) -0.8

Materials and Methods

A. Received Power Measurement

The terrain under investigation is the rural area between the cities of Bauchi and Gombe, North-East Nigeria. Received signal values were obtained from Base Transceiver Stations (BTSs) belonging to the mobile network service provider, popularly known as mobile telecommunication network (MTN). The device used was the Cellular Mobile Network Analyzer SAGEM OT 290. The device is capable of measuring signal strength in decibel milliwatts (dBm). Received power vaues (P_R) were recorded from the 1800 MHz frequency band at intervals of 0.15 kilometer, after initial separation of 0.1 kilometer from the BTS.

The parameters obtained from mobile network service provider include: Mean Transmitter Height (H_T) of 40m Mean Effective Isotropic Radiated Power (EIRP) of 46dBm.

B. Statistical Comparison Criteria

As described in [1], performance testing comparison of model was based on two indecies,, namely, the Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). The RMSE is a measure of the differences between predicted and observed values. The RMSE expression is given by (7)

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(M-P)^2}{N}} \qquad (7)$$

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

R^2 ranges between 0 and 1, but can be negative without a constant, which indicates the model is inappropriate for the data. A value closer to 1 indicates that a greater correlation of the model with test data. The R^2 is given by (8)

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \qquad (8)$$

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.

Results and Analysis

It can be observed from Figures 2 to 7 that on the average, the empirical Okumura model overestimates the signal strength across all Base Transceiver Stations. On the contrary, it can be observed that the COST 231 Hata significantly underestimates the signal strength. Furthermore, the figures indicate that, of the three predictors, the GRNN based model depicts the greatest prediction accuracy 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 5.8dBm and an R^2 value of 0.71. It can be further observed that the Okumura model with an RMSE value of 10.21dBm and R^2 value of 0.168 outperforms the COST 231 Hata.

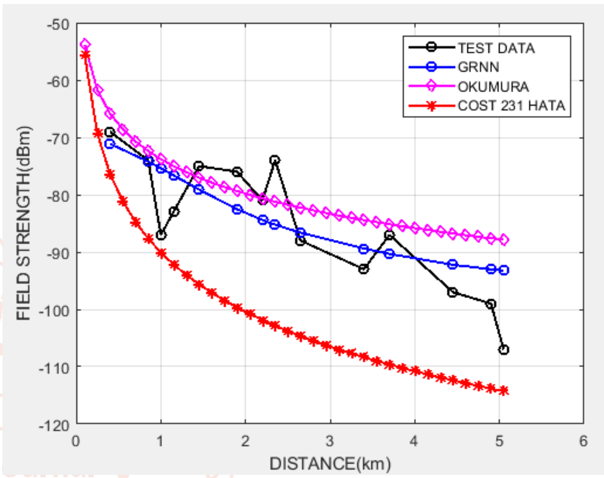

Fig. 2: Model Comparison for BTS 1

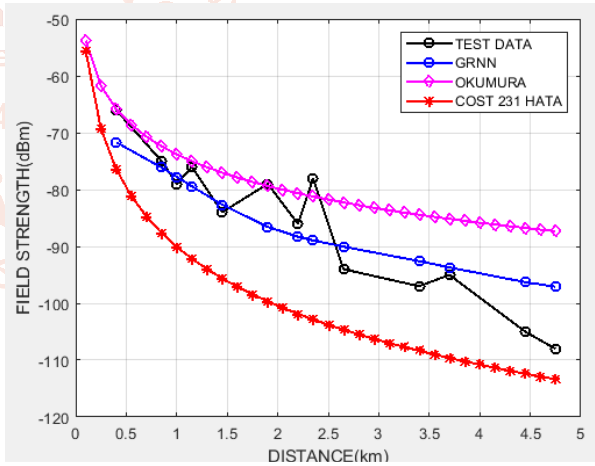

Fig. 3: Model Comparison for BTS 2

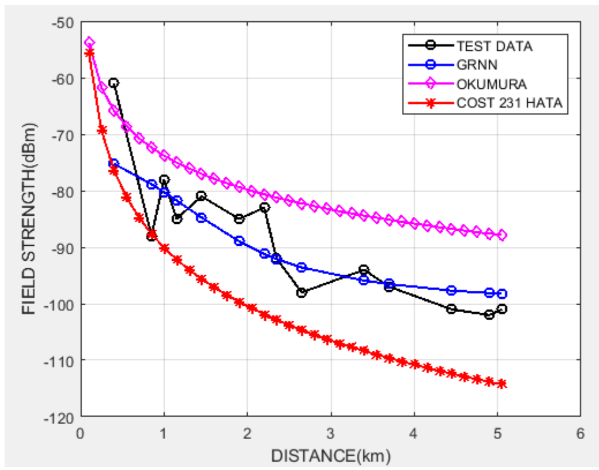

Fig. 4: Model Comparison for BTS 3

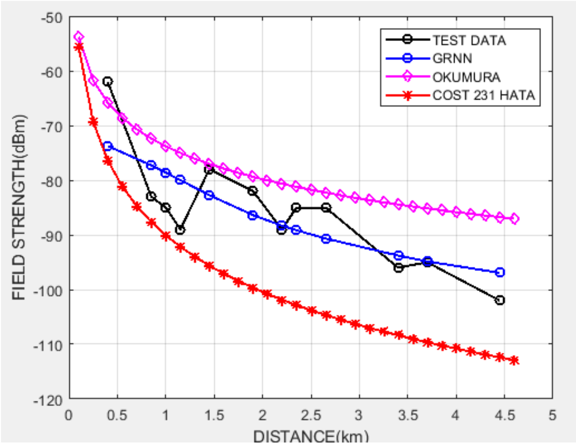

Fig. 5: Model Comparison for BTS 4

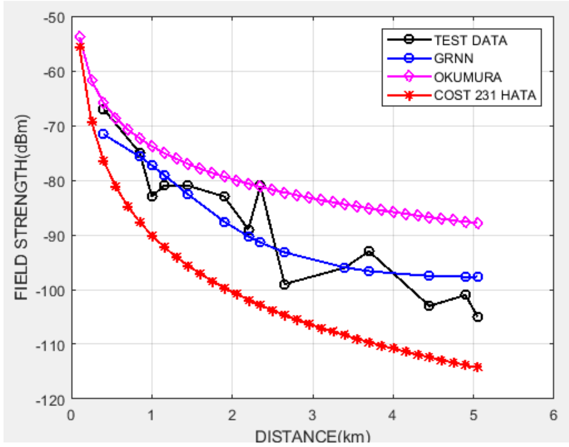

Fig. 6: Model Comparison for BTS 5

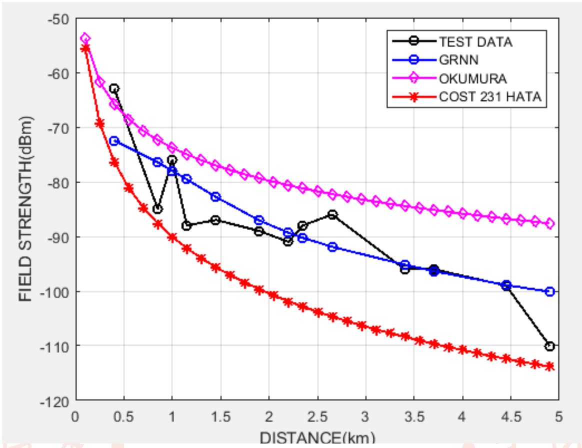

Fig. 7: Model Comparison for BTS 6

TABLE1. Statistical Performance Comparison of Predictors

MODEL	STATS.	BST 1	BST 2	BST 3	BST 4	BST 5	BST 6	MEAN
GRNN	RMSE (dBm)	6.83	5.97	5.71	5.88	4.88	5.55	5.80
	R^2	0.59	0.76	0.73	0.63	0.80	0.74	0.71
Okumura	RMSE (dBm)	7.68	9.71	11.40	9.92	11.20	11.37	10.21
	R^2	0.51	0.40	1.01	0.18	0.18	0.16	0.16
COST 231 Hata	RMSE (dBm)	16.75	13.76	11.69	12.90	12.17	11.50	13.13
	R^2	-1.33	-0.20	-0.04	-0.40	0.03	0.14	-0.30

Conclusion

This study considers the use of an artificial intelligence based method, namely the GRNN, in mobile communication network field strength prediction. The GRNN based predictor was created, validated and tested with field strength data obtained from the terrain under investigation. Performance comparisons indicate that GRNN based model proffers greater prediction accuracy over the widely used empirical Okumura and COST 231 Hata models.

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