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Path Loss Predictions in the VHF and UHF Bands Within Urban Environments: Experimental Investigation of Empirical, Heuristics and Geospatial Models

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ABSTRACT Deep knowledge of how radio waves behave in a practical wireless channel is required for effective planning and deployment of radio access networks in urban environments. Empirical propagation models are popular for their simplicity, but they are prone to introduce high prediction errors. Different heuristic methods and geospatial approaches have been developed to further reduce path loss prediction error. However, the efficacy of these new techniques in built-up areas should be experimentally verified. In this paper, the efficiencies of empirical, heuristic, and geospatial methods for signal fading predictions in the very high frequency (VHF) and ultra-high frequency (UHF) bands in typical urban environments are evaluated and analyzed. Electromagnetic field strength measurements are performed at different test locations within four selected cities in Nigeria. The data collected are used to develop path loss models based on artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and Kriging techniques. The prediction results of the developed models are compared with those of selected empirical models and field measured data. Apart from Egli and ECC-33, the root mean squared error (RMSE) produced by all other models under investigation are considered acceptable. Specifically, the ANN and ANFIS models yielded the lowest prediction errors. However, the empirical models have the lowest standard deviation errors across all the bands. The findings of this study will help radio network engineers to achieve efficient radio coverage estimation; determine the optimal base station location; make a proper frequency allocation; select the most suitable antenna; and perform interference feasibility studies.

INDEX TERMS ANFIS, artificial neural networks, backpropagation, path loss, Kriging, radio propagation.

I. INTRODUCTION

A study of the characteristics of radio waves in different propagation environments is needed for an effective network planning, and for the deployment of wireless communication systems [1], [2]. The magnitude and direction of electromagnetic waves in a practical wireless channel is usually random and highly unpredictable [3]. Meanwhile, a good understanding of this phenomenon is needed to guarantee good Quality of Service (QoS) and high data transmission rate in radio access networks.

The efficiency of a wireless communication system depends on the physical constituents of the propagation environment. The presence of buildings, mountains, bill boards, foliage, vehicles and other physical objects in a practical propagation environment usually obstructs the direct

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line-of-sight (LOS) of radio signal transmission. Hence, transmitted radio signals often reach targeted receivers through different propagation mechanisms in non-line-of-sight (NLOS) scenarios. *Refraction* occurs when the transmitted electromagnetic waves move from one medium to another medium whose refraction index is different from that of the former [4]. *Diffraction* of radio signals takes place when the transmission path is obstructed by large objects, causing the bending of the radio wave [4]. Radio signal gets *reflected* when it collides with an object whose dimension is large relative to the wavelength of the radiated signal [4]. These reflecting objects include the metallic surfaces of window frames and building rooftops. Also, a radio signal is said to have experienced *scattering* when the object's dimension is far less than the wavelength of the radio signal. In this case, radiated electromagnetic waves are reflected towards different directions. Scattering may be due to: precipitation (drizzle, rain, sleet, snow and hail); suspensions (fog and mist) and dust particles. Radio signals could also be *absorbed* when it passes through dense materials like walls or floors, trees and foliage.

The propagation of electromagnetic waves is usually influenced by the atmospheric conditions of the propagation environment [4]. Electromagnetic waves of higher frequencies, having wavelengths of just a few millimeters, get attenuated easily as the size of the transmitted wavelength tends towards the size of the atmospheric agents, which may be rain droplets, dust, snow or fogs. At Very Low Frequency (VLF), Low Frequency (LF) and Medium Frequency (MF) bands, radio waves propagate for a considerable distance close to the surface of the Earth. This mode of propagation is adopted in Amplitude Modulation (AM) broadcasting, which uses the MF band. At High Frequency (HF) bands, the ground waves tend to be absorbed by the Earth.

In practical urban propagation environment, different copies of transmitted radio wave arrive at the receiver by means of various propagation mechanisms. This phenomenon is known as *multipath* propagation and this causes signal fading at the receiver [4]. Considering a situation where the magnitude of the received signal strength changes frequently within a short duration, given that the distance remains relatively unchanged, such attenuation of signal is said to be of small-scale [5]. For large-scale fading, the mean received signal strength will significantly reduce as the distance increases [6]. This earlier concept is also referred to as *path loss*. Several propagation models have been developed for path loss estimations under different propagation scenarios. Radio network engineers depend on these models to: achieve efficient radio coverage estimation; determine the optimal base station location; make a proper frequency allocation; select the most suitable antenna and; perform interference feasibility studies.

Traditionally, each of the radio propagation models reported in the literature is regarded as either deterministic, semi-deterministic or empirical, depending on the modeling technique employed. A path loss model is said to be *deterministic* if the resulting mathematical equations are derived from the theoretical laws and principles of physics [6]. Virtual simulation tools have been developed for implementation of deterministic models towards accurate path loss predictions [7]–[9]. These tools do not require in-depth of the propagation environment and have been proven to be efficient when deployed within its constraints. Even if site-specific data about the propagation terrain is available, the use of deterministic models does not always guarantee accurate predictions [6]. One of the major challenges encountered in the use of deterministic models is the computation complexity; deterministic models require too many and well-detailed input information that may not be easily obtained. On the contrary, empirical models such as Hata model [10] and COST 231 model [11] require less computation resources during implementation. They are very easy to use but the prediction accuracy may not be as high when compared to deterministic models. Other than the effects of distance and other network parameters such as frequency of transmission and antenna heights, the impact of environmental constituents on radio wave propagation are not be adequately captured in most empirical models [12]. The effectiveness of these models was tested in a diverse set of environments and across several bands.

In some instances, some of these models were tuned to improve prediction accuracy. Hejselbæk *et al.* [13] presented electromagnetic field strength measurements at 917.5 MHz in forest terrain for device-to-device (D2D) communications. The measured loss was compared with some empirical path loss models. The dominant path of propagation was through the foliage, which resulted in high loss levels. However, it was found that, at distances exceeding 1000 m, the measured signal strength follows the fourth-power law. In [14], single-slope path loss models were found to have deficiencies in accurately capturing the effect of physical environments. For this reason, the performance of multi-slope path loss models were investigated and compared with different path loss models. García *et al.* [15] optimized the Recommendation ITU-R.P.1812-4 path loss models to improve accuracy in propagation path loss prediction for DTT systems in outdoor environments of Caracas city, Venezuela. Other works are found in [16], [17]. The common findings are inconsistencies in the performance of existing models, and high prediction errors. Therefore, it is important to explore better ways of achieving simple path loss prediction models without compromising the required efficiency in terms of accuracy.

Recently, different ANN approaches were introduced to predict signal path loss in wireless communication networks. Ayadi *et al.* [18] developed a new method for multi-band heterogeneous wireless network scenario using ANN technique. In [19], Multilayer Perceptron (MLP) neural model was developed to predict path losses when radio signals are transmitted at frequencies within Global System for Mobile communications (GSM) band. The developed neural network model predicts path loss based on three input variables namely: distance, transmit power and terrain elevation.

The three-layered neural network (input, hidden, output) was trained with field measured data based on Levenberg-Marquardt (LM) learning rules. In order to ensure best-suited network architecture, the number of hidden neurons was iterated between 31 and 39. The model proved to be more efficient than the empirical models (Hata, Egli, COST-231 and Ericsson) in terms of RMSE. Sotiroudis *et al.* [20] proposed a model for urban environment and their findings showed that ANN-based path loss model will perform efficiently, provided that the size of the neural network is correctly chosen. In [21], a three-stage approach was employed to develop an ANN model for the GSM band. The model used 33 neurons in the hidden layer and a tansig (hyperbolic tangent sigmoid) transfer activation function was also used. Similarly, Ostlin *et al.* [22] evaluated the applicability of ANN models to rural propagation environments in Australia. The training and testing datasets were obtained from a commercial Code Division Multiple Access (CDMA) network. The developed ANN model's accuracy and its ability to generalize well surpassed those of traditional path loss models. Authors in [23] adopted an ANFIS method to predict path loss within selected built-up areas in Habiye, Istanbul. The frequency of transmission covered in this study was limited to GSM 900 band. The results obtained showed an increase in prediction accuracy by 15% over Bertoni-Walfish model.

Geostatistical approach is another useful tool for predictions of path loss in radio access networks. It can be used to correct residual errors that are inherent in deterministic models [24]. A geostatistical procedure named Kriging Interpolation Method (KIM) was introduced in [25]. In KIM, an optimal interpolation is achieved in space following the theory of 'moving average'. KIM provides a good opportunity to minimize the challenges encountered during data clustering. The concept of KIM is also popularly referred to as Wiener-Kolmogorov [26]. In [27], a spatial interpolation technique was applied to the measurement data. The Kriging method consistently provided better predictions when compared with empirical methods. In [28], an 'Energy-Efficient Map Interpolation for Sensor Fields' was produced based on Kriging technique. Furthermore, the authors in [29] investigated the ability of some propagation models to determine received signal strengths of radio signals propagated at TV frequencies, considering multiple transmitter scenario in an urban area.

Despite the inherent potential of Kriging methods in handling prediction applications, as reported in the literature, the capability of this technique for distance-based path loss predictions in VHF/UHF bands has not yet been well investigated. Moreover, the response of the heuristics and geospatial methods to diverse environments has not been established, neither have they been compared to empirical models. Furthermore, to the best of our knowledge, there is no single work found in the literature that attempted to compare the effectiveness of these approaches with the prediction accuracies of popular empirical models across different frequency bands and locations. Therefore, this present study seeks to conduct an experimental investigation that compares the efficiencies of empirical, heuristic and geospatial models for path loss predictions in VHF/UHF bands. Models that are developed accept numerical value of distance (in km) as input variable to produce a corresponding path loss value as an output. The performance of the developed models is evaluated based on Mean Error (ME), RMSE and Standard Deviation (SD) of the predicted path loss values relative to the corresponding field measured path loss values. At the end of the study, we found that the performance of the different methods varied with the performance metrics used. It was found that, in the VHF bands, across cities, the heuristic methods (i.e. ANFIS and ANN) provide the lowest mean prediction error. The overall average MPE across all bands and routes were of: −0.00000819 dB (ANFIS), 0.660 dB (ANN), 3.09 dB (KRIGING), −7.02 dB (COST 231), 0.512 dB (HATA), −11.74 dB (EGLI) and 15.54 dB (ECC-33). A similar trend was observed for the UHF transmitters. However, the Kriging method showed very high errors at some measurement points. These errors could be as high as 105.04 dB – this was due to the spacing between the path loss measurements. Kriging method uses the concept of moving averages to provide optimal interpolation across space based on spatial distance, against observed values of neighboring data points.

The rest of the paper is organized as follows: Section II explains the radio signal measurement and data collection procedures. Also, the methodology associated with the model development are presented in detail. Section III presents the performance evaluation metrics used in this work. The results and discussions are then presented in Section IV. Finally, Section V concludes the paper.

II. METHODOLOGY AND DATA COLLECTION

In this section, the radio signal measurement procedure and data collection method are presented. In addition to this, relevant theoretical background of the heuristic methods, geospatial methods and selected empirical path loss propagation models are provided. Finally, the model development process of each of the methods was well described.

A. MEASUREMENTS AND DATA COLLECTION PROCEDURE

Large-scale radio signal measurements were performed within typical urban propagation terrains in four major cities in Nigeria. The measurement campaigns were carried out within selected urban areas of Ilorin (Latitude 8.4799° N, Longitude 4.5418° E) in Kwara State, Osogbo (Latitude 7.7827° N, Longitude 4.5418° E) in Osun State, Kano (Latitude 12.0022° N, Longitude 8.5920° E) in Kano State, and Abuja (Latitude 9.0765° N, Longitude 7.3986° E) in the Federal Capital Territory of Nigeria. The measurement locations are described using geographic map of Nigeria shown in Figure 1. The locations are indicated with an arrow sign. Pictorial views of Ilorin and Abuja are shown in Figure 1(b) and Figure 1(c). The radio signal propagation terrain for both Ilorin and Abuja are shown in Figure 2. The magnitude of the strengths of radio signals received from 10 Base Transceiver

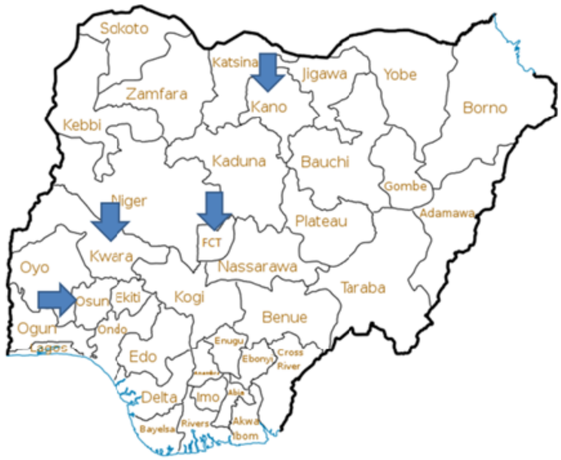

FIGURE 1. Radio signal measurement locations.

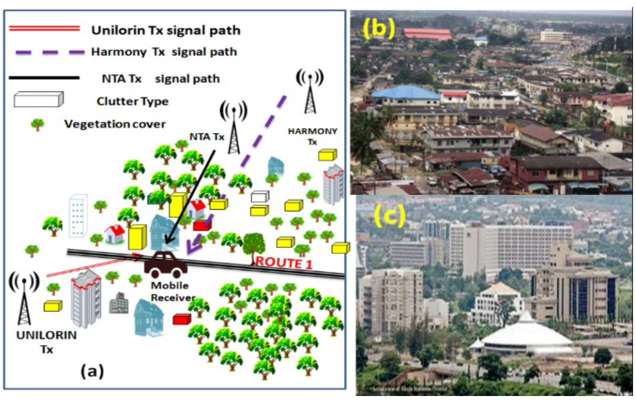

FIGURE 2. Radio signal measurement locations (a) Radio signal propagation in urban scenario. (b) Urban propagation terrain in Ilorin, Kwara State, Nigeria. (c) Urban propagation terrain in Abuja, FCT, Nigeria.

Stations (BTS) and seven TV broadcast transmitters were measured and recorded in log files. Five out of the 10 BTS transmitters operate at Global System for GSM frequencies (900 MHz and 1800 MHz) while the remaining five BTS transmitters operate at Wideband Code Division Multiple Access (WCDMA) frequency of 2100 MHz. Three of the broadcast transmitters operate at frequencies within the VHF band, while the remaining four broadcast transmitters operate at frequencies within the UHF band.

The routes considered in the four cities were characterized by a large number of diffraction scatters and the average distance between buildings range from 30 to 40 m. The buildings within the measurement locations are mostly concentrated along the road. The terrain of Kano city is relatively flat when compared with Ilorin or Osogbo. The land distance between Kano and Osogbo is 639 km.

Path losses in radio signal transmission from five GSM transmitters located in Kano and five WCDMA transmitters located in Abuja were measured and recorded. The operating frequencies of the GSM transmitters and the WCDMA transmitters are 1800 MHz and 2112.4 MHz respectively. The measurement set-up consists of a dual band W99 Sony Ericson mobile receiver, a Global Positioning System (GPS) and a probe Dongle. These auxiliary devices were connected to a Windows operating system laptop via its Universal Serial Board (USB) ports. A Huawei Genex Probe, Genex share drive testing software v6.0 and MapInfo professional, were installed on the laptop, which was placed inside a car. The car moved at mean velocity of 40 km per hour along predefined routes. This velocity was chosen to reduce Doppler effects. All drive tests were conducted within each of the cities under investigation. While driving, the receiver was preset to establish and sustain calls to a specific telephone line. The duration of a call session was 30 seconds. At the end of a call session, the next call session is initiated after few seconds. When each drive test routine is completed, logs of field measured radio signal path loss data were retrieved from the radio network measurement software and they were stored in an external memory device for further processing. The data include the geographical information, BCCH received signal strength (RSS), Absolute Radio Frequency Channel Number (ARFCN), and scrambling codes (for 3G transmitters). The mean values of the receiver height (h_r) and the base station height (h_b) are 1.5 m and 30 m respectively. The maximum transmitter and receiver antenna separation distance was about 2 km. Radio signals that emanated from the transmitting antennas were only measured in the far field region (distances greater than 100 m).

Signal losses in radio transmission from seven TV broadcast transmitters were measured using Agilent N9342C spectrum analyzer. The radio equipment was used as a receiver and it has a Displayed Average Noise Level (DANL) of −164 dBm per Hz. An omnidirectional antenna was connected to the spectrum analyzer to facilitate radio signal reception. A GPS was used to determine the location of the receiver relative to the position of the transmitter. The GPS was placed on top of the roof of the moving vehicle to enhance line of sight with the geographic satellite. The logs of data obtained were stored in an external memory device with high storage capability.

Three of the seven broadcast transmitters were located in Ilorin, Kwara State, Nigeria. These include Unilorin FM, Harmony FM, and NTA Ilorin transmitters and their frequencies of transmission are 89.30 MHz, 103.5 MHz and 203.25 MHz respectively. The broadcast transmitters are in fixed locations with coordinates A (lat. 8° 29’ 21’’ N, long. 4° 40’ 28’’ E), B (lat. 8° 21’ 56’’ N, long. 4° 43’ 18’’ E) and C (lat. 8° 25’ 55’’ N, long. 4° 36’ 25’’ E) respectively. Three routes (i.e. routes 1 to 3) were visited. Three measurements routes (i.e. routes 4 – 6) were also visited in Osogbo, Osun State, Nigeria. The four UHF broadcast transmitters in Osogbo are: NDTV, NTA Ile-Ife, OSBC and NTA Osogbo. These transmitters radiate at frequencies of 479.25 MHz, 615.25 MHz, 559.25 MHz and 695.25 MHz respectively. Also, all the transmitters were deployed at fixed locations, being that details about their coordinates, heights and power levels can be found in Table 1. The number of measured samples was reduced to only 500 across all the routes. The RSS

TABLE 1. Radio parameters of the seven TV broadcast transmitters.

Transmitter	Location	Band	Coordinates Latitude	Coordinates Longitude	Centre Frequency (MHz)	Height (m)	Tx. Power (kW)
UNILORIN	ILORIN	VHF	8° 29' 21" N	4° 40' 28" E	89.30	100	1.0
HARMONY	ILORIN		8° 21' 56" N	4° 43' 18" E	103.5	125	7.0
NTA, ILORIN	ILORIN		8° 25' 55" N	4° 36' 25" E	203.25	185	2.4
NDTV	IBOKUN	UHF	7° 46' 32" N	4° 43' 14" E	479.25	198	2.1
OSBC	OSOGBO		7° 46' 35" N	4° 35' 19" E	559.25	340	3.5
NTA, IFE	ILE-IFE		7° 29' 59" N	4° 35' 23" E	615.25	167	3.2
NTA, OSOGBO	OSOGBO		7° 44' 01" N	4° 31' 14" E	695.25	152	4.1

levels for each route were converted to path losses. The novel measurement data obtained shall be made public and freely available in open-access data articles similar to previous works in [30]–[32].

B. ARTIFICIAL NEURAL NETWORK MODEL DEVELOPMENT

A single hidden layer and a sufficiently large number of neurons can well approximate any arbitrary continuous function [33]. Theoretical works and many experimental results have shown that a single hidden layer is sufficient for ANN to approximate any complex nonlinear function. Many researchers in the field of ANN suggest that it is usually unnecessary to use more than one hidden layer in a multilayer feedforward network. Indeed, many experimental results confirmed that one hidden layer is enough for most forecasting/regression/prediction problems [34]–[38]. A single-layered architecture was chosen for ANN path loss model development. The input layer is made up of three neurons which accept numeric values of the input variables: Tx-Rx separation distance, height of the receiver and terrain elevation. The ANN path loss model has a single output (mean path loss). With the availability of field measured data, the neural network was trained to map instances of sets of input variables to their corresponding output. The path loss predictions were modelled, trained, and simulated for the propagation environments using the MATLAB R2016a Neural Network Toolbox (MathWorks Inc). The neural network was trained using backpropagation learning algorithm. The input values were transformed to a format that is adapted to the hidden layer. Linear activation functions were used at both input and output layer of the neural network. The hyperbolic tangent sigmoid transfer function was used in the single hidden layer, while the linear transfer function was used in the output layer of the ANN as practically demonstrated across different fields in the literature [39]–[43]. The mathematical expression for the hyperbolic tangent sigmoid transfer function is given by Equation (1):

$$tansig\,(n) = \frac{2}{\left(1+e^{-2n}\right)-1} \tag{1}$$

In order to achieve faster convergence during model training, the scale conjugate gradient backpropagation algorithm was used. An optimal number of hidden neurons was obtained by performing experiments with varying incremental values. Data obtained at different measurement locations were carefully sorted, merged and divided into training, testing and validation datasets. When developing an ANN model, the available data set was randomly divided into two parts: 70% of the complete dataset was used for training of the network, while the remaining 30% was used for model validation and testing, i.e., 15% for model validation and 15% for model testing, as explained in [44], [45]. The challenge of large variations in numeric values of input data was addressed using the min-max normalization procedure given by Equation (2). The parameters of ANN were optimized using the Levenberg–Marquardt (LM) algorithm as the model training function [46], [47]. The Levenberg–Marquardt (L–M) algorithm outperformed simple gradient descent and many other conjugate gradient methods in a wide variety of problems [48]–[50]. LM is a blend of local search properties of Gauss–Newton with consistent error decrease provided by the gradient descent algorithm. The LM algorithm was implemented using its function 'trainlm' available in MATLAB 2016a. Previous research works have validated the optimization efficiency of LM algorithm in diverse practical contexts [34], [51]–[53]. The number of neurons in the single hidden layer, learning rate and epoch size were selected by means of trial and error, selecting the configuration that resulted in smaller prediction errors. In each epoch of training, each member of the train set was exposed to the network and the weights on the neuron connections changed such that the expectation of the network moves closer to the actual target (back-propagation). After the network has undergone enough epochs of training such that there is not a significant difference between the expectation of the network and the actual target values, the network is said to have been trained [54]. An epoch size of 1000 was used and the program iterated until convergence was achieved. The training process was repeated until a correlation coefficient value (R) of 0.9 or more was achieved.

$$p_i = \frac{y_i - y_{min}}{y_{max} - y_{min}}(m-n) + n \tag{2}$$

where

p_i = normalized input value, m = upper normalization limit = 0.9, n = lower normalization limit = −0.9,

y_{min} = least numeric value of the input variable and y_{max} = highest numeric value of the input variable.

C. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM MODEL DEVELOPMENT

In this work, ANFIS model is made up of five layers with fixed or adaptive nodes. First-order Sugeno-Fuzzy model was adopted as explained in [55]. The node in the first layer is adaptable and it is defined by $L_k^1 = \mu A_k(m)$; where $k = 1, 2$; m is the input to k^{-th} node, $A_k$is the alterable language related to this node and the membership function of A_k is $\mu A_k(m)$, normally taken as;

$$\mu A_k(m) = \frac{1}{1 + \left[\left(\frac{m-f_k}{d_k}\right)^2\right]^{e_k}} \tag{3}$$

$\{d_k, e_k, f_k\}$ forms a set called the antecedent parameters set. The Membership Function (MF), μ, is the degree or grade of membership of an element in a fuzzy set, which must vary between 0 and 1. Eqn. (3) represents the generalised bell membership function. This was maintained, as it is the most widely used one [55], and it has also performed quite well in our previous works [56], [57]. The second and third layers are fixed, while, the fourth layer is adaptable, details of each of these layers could be found in [56]. The output of the fifth layer is the summation of all the incoming signals based on the rule defined in [55], given by:

$$\begin{aligned} L_i^5 = z_p = \sum\nolimits_{i=1}^{2} \overline{w_i} f_i &= (\overline{w_1}x)\, p_1 + (\overline{w_1}y)\, q_1 + (\overline{w_1})\, r_1 \\ &\quad + (\overline{w_2}x)\, p_2 + (\overline{w_2}y)\, q_2 + (\overline{w_2}) r_2 \end{aligned} \tag{4}$$

where z_p is the network predicted output. The optimization method used for training the network in this work is the hybrid method, which combines both the backpropagation gradient descent algorithm and least square error estimates; these are used to establish the input and output parameters, respectively. The output (consequent) parameters p_i, q_i and r_i are adjusted first using the least squares algorithm and those of the input (antecedent) parameters d_i, e_i, and f_i by back propagating the faults from the output using the gradient descent method until the training is completed. The least squares estimate algorithm is obtained by rewriting Eqn. (5), as shown at the bottom of this page, in the matrix form [56], where n is the total number of training data (input/output) pairs and $z_p^{(n)}$ are the network predicted outputs. The errors between the desired and predicted outputs are propagated backwards from the output layer to the input layer using the backpropagation algorithm, so as to update the synaptic weights:

The weight update for the input layer is given by Eqn. (6):

$$w_i^{(k)}(M+1) = \begin{cases} w_i^{(k)}(M) + \overline{w_i}^{(k)} \\ w_i^{(k)}(M) + \overline{w_i}^{(k)} \end{cases} \tag{6}$$

where k is the input/output training pair and M represents each layer starting from the output backwards.

The structure of ANFIS models can be generated by three Fuzzy Inference Systems (FIS), namely grid partition, subtractive clustering, and fuzzy c-means (FCM). In this study, we applied the subtractive clustering method to classify the input data and to make the ANFIS model rules as the number of rules employed in this method is relatively low. This makes it convenient for using in real application problems [58].

D. KRIGING MODEL DEVELOPMENT

An ordinary Kriging interpolation algorithm was utilized in this work. The study area was divided into the desired number of meshes and the position coordinates (x, y) were computed for each of the corresponding mesh points. Let u denote a point in which the path loss is unknown and let $V(u) = \{1, \ldots, Nu\}$ denote the set of points in the surrounding point u such that value of the path loss is known at each point. A neighborhood of point u in the (x, y) plane was defined and the surveyed points in this neighborhood were mapped to the sampled path loss data based on the number of data. The predicted path loss was calculated as a linear combination of the weight (W_i) and the neighborhood (known) path loss (Z_i) using Equation (7). Equation (8) is a constraint that ensures that the set of weights minimizes the error variance and that the mean error is zero under unbiased conditions. The lag distances (h) and the semi-variogram $(\gamma_{i,j})$ were computed for a range of lags using Equations (9) and (10), respectively. The variogram model type is the only discrete parameter, and the three commonly used basic variogram models include spherical, exponential and Gaussian. The spherical variogram yielded good results in [59]. The semivariogram was fitted with the spherical model using Equation (11). This model was chosen because it is the least complex and most generally utilized variogram model [16]. A mesh grid size of 500 was used as it provides optimal interpolation across the mesh grid based on a spatial lag (distance) relationship or regression with respect to the observed path losses of the neighboring path loss points. The minimum variance method was employed in calculating the weights and the optimal weights were

$$\begin{bmatrix} z_p^{(1)} \\ z_p^{(2)} \\ \vdots \\ z_p^{(n)} \end{bmatrix} = \begin{bmatrix} \overline{w_1}^{(1)} x^{(1)} & \overline{w_1}^{(1)} y^{(1)} & \overline{w_1}^{(1)} & \overline{w_2}^{(1)} x^{(1)} & \overline{w_2}^{(1)} y^{(1)} & \overline{w_2}^{(1)} \\ \overline{w_1}^{(2)} x^{(2)} & \overline{w_1}^{(2)} y^{(2)} & \overline{w_1}^{(2)} & \overline{w_2}^{(2)} x^{(2)} & \overline{w_2}^{(2)} y^{(2)} & \overline{w_2}^{(2)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \overline{w_1}^{(n)} x^{(n)} & \overline{w_1}^{(n)} y^{(n)} & \overline{w_1}^{(n)} & \overline{w_2}^{(n)} x^{(n)} & \overline{w_2}^{(n)} y^{(n)} & \overline{w_2}^{(n)} \end{bmatrix} \begin{bmatrix} p_1 \\ q_1 \\ r_1 \\ p_2 \\ q_2 \\ r_2 \end{bmatrix} \tag{5}$$

calculated with respect to Equation (12). Finally, the Kriging variance was estimated using Equation (13):

$$\widehat{Z}_u = \sum\nolimits_{i \in V(u)} W_i Z_i \tag{7}$$

where

$$\sum\nolimits_{i \in V(u)} W_i = 1 \tag{8}$$

$$h = \left(x_j, y_j\right) - \left(x_i, y_i\right) \tag{9}$$

$$\gamma_{i,j} = \gamma\left(h_{i,j}\right) = \frac{1}{2N(h)} \sum \left(Z(x_i, y_i) - Z(x_j, y_j)\right)^2 \tag{10}$$

$$\gamma(h_{i,j}) = \begin{cases} 0, & h_{i,j} = 0 \\ C_0 + C_1\left[\frac{3h}{2R} - \frac{1}{2}\left(\frac{h}{R}\right)^3\right], & 0 < h_{i,j} < R \\ C_0 + C_1, & h_{i,j} \geq R \end{cases} \tag{11}$$

$$\begin{bmatrix} W_1 \\ W_n \\ \lambda \end{bmatrix} = \begin{bmatrix} \gamma(h_{1,1}) & \gamma(h_{1,N_u}) & 1 \\ \gamma(h_{N_u,1}) & \gamma(h_{N_u,N_u}) & 1 \\ 1 & 1 & 0 \end{bmatrix}^{-1} \begin{bmatrix} \gamma(h_{1,u}) \\ \gamma(h_{N_u,N_u}) \\ 1 \end{bmatrix} \tag{12}$$

$$\sigma^2_{\hat{Z}_u} = \sum\nolimits_{i \in V(u)} W_i \gamma\left(h_{i,u}\right) + \lambda \tag{13}$$

where h is the distance between two path loss points, C_0 represents the Nugget effect parameter, R denotes range and $C_0 + C_1$ represents the Sill parameter. Moreover, $\gamma\left(h_{i,j}\right)$ denotes a semivariogram as a function of a lag distance. The Lagrange parameter λ, λ was introduced to reduce the Kriging error. The measured path losses for each route across all the bands were used to compare with the predicted path losses obtained with ANN, ANFIS and Kriging and Empirical path loss models. The empirical path loss propagation models considered in this work are: the Okumura-Hata, COST 231, Egli and ECC-33 [30]. These models were chosen as they are the commonly and widely used empirical models today for path loss prediction in the VHF and UHF bands under study.

E. PERFORMANCE EVALUATION METRICS

Prediction Error, Mean Prediction Error, Maximum Error, Standard Deviation Error, and Root Mean Square Error are the metrics used for the performance analysis of the models relative to the measured loss. Acceptable values for RMSE are 6–7 dB for urban areas, 10–15 dB for suburban and rural areas, while the best fit for all the considered metrics are for values that are closer to 0 [4]. The Kernel Distribution Estimate (KDE), which is a non-parametric way of estimating the probability density function of a random variable, was equally used to gauge the performances of all the models. Using this metric, the model has to firstly, follow a normal distribution curve, and secondly, the error counts close to 0 dB would dominate the frequency counts.

III. RESULTS AND DISCUSSIONS

In this section we present the performance evaluation results of the three methods used in predicting path losses. For each route visited, we compared the measured loss with the predictions of the ANN, ANFIS, Kriging, Hata, COST 231, Egli and ECC-33 models.

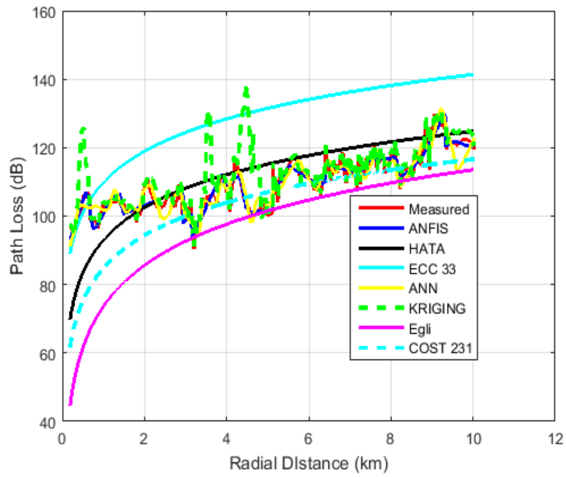

FIGURE 3. Path loss with distance for Unilorin Route 1.

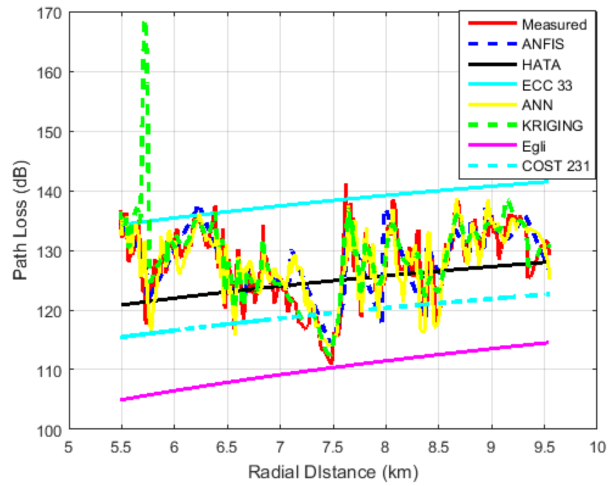

FIGURE 4. Path loss with distance for NTA_Ilorin Route 1.

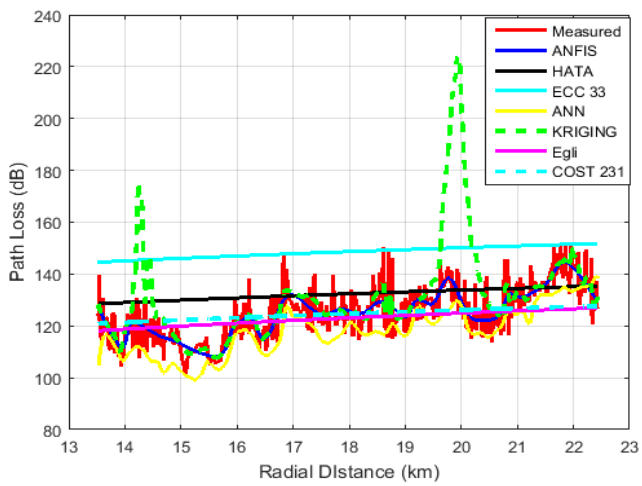

FIGURE 5. Path loss with distance for Hamony Route 1.

Figs. 3 to 5 show the graphical depiction of the measured and predicted path losses as a function of distance for the Unilorin, NTA, and Harmony transmitters along route 1.

In Fig. 3, large scale fading was observed due to shadowing and multipath as a result of different diffracting objects within the transmission path. This route is considered to be urban, being characterized as a mixed path with hills, valleys and thick vegetation within the area. We also observed that the ANN, ANFIS and Kriging methods mimic the measured path loss with predictions close to that of the measured path loss. The prediction of the Kriging model was found to have followed a smoothed variation of the measured path loss with minimal prediction error across the measurement route, except at some coordinates (distances) from the reference base station (i.e., 0.431-0.539 km, 2.21 km, 4.61 km, and 4.85 km) where the method overshot the path loss. We have also employed the ANN and ANFIS, which are the two widely, used heuristic methods, in the path loss prediction process.

The ANN prediction closely aligns with the measured loss. However, the ANFIS method maps inputs to outputs. Overall, it was observed that the ANFIS predictions contend with those of ANN. The empirical path loss models, i.e., COST 231 and Hata provided optimum predictions for distances greater than 2 km, while Egli underestimated and ECC-33 overestimated the loss. The average losses at a distance of 1 km are: 94.11 dB (measured), 97.24 dB (Kriging), 94.17 dB (ANFIS), 94.86 dB (ANN), 92.93 dB (Hata), 84.77 dB (COST 231), 73.53 dB (Egli) and 109.78 dB (ECC-33).

In Figs. 4 and 5, similar trends were observed for the NTA and Harmony transmitters. The fading observed on this scenario was quite higher than that of Unilorin, although the terrain profile along the specific measurement route (e.g. route 1) is the same; the terrain elevation (i.e. Rx height) is also the same. However, the clutter cover along each of the communication paths between the transmitters and the receiver were different. The average loss along this path is 128.9 dB, while 109 dB were measured for the Unilorin-Rx path, all within the span of 5 - 10 km. This high measured loss for the NTA transmitter was attributed to the presence of thick vegetation covering the entire communications path, which causes scattering and absorption of the measured far field signal. For the predicting models, a sharp spike was observed at $d = 5.56$ km in Fig. 5, and at $d = 14.3$ and 20 km in Fig. 5 for the Kriging method. These spikes resulted in a high prediction error and this severely affects the RMSE performance of the model. Surprisingly, the physical objects (clutters) along the communication paths for each of the transmitters do not have any effect on the predictions of the empirical models. The prediction of these models solely depends on the system parameters of the propagation environment (i.e. frequency, height and distance). In Fig. 5, all the empirical path loss models provide good predictions, except for the ECC-33 model, that overestimated the path loss. From this scenario, the geospatial (i.e. Kriging) method is purely dependent on the path loss data, while the heuristic approaches (i.e., ANFIS and ANN) partly depend on the clutter types.

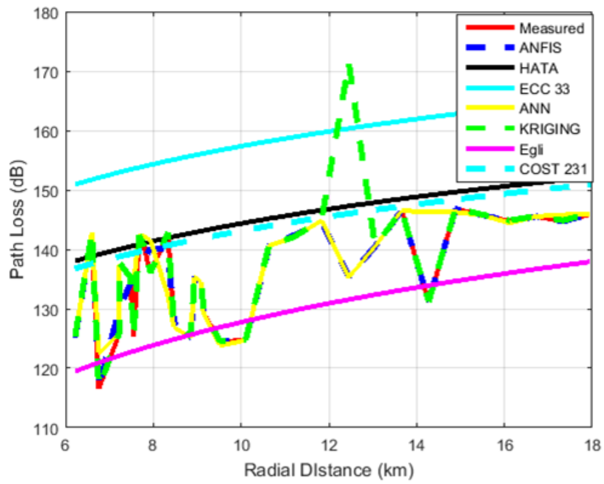

FIGURE 6. Path loss with distance for NTA_Osogbo Route 1.

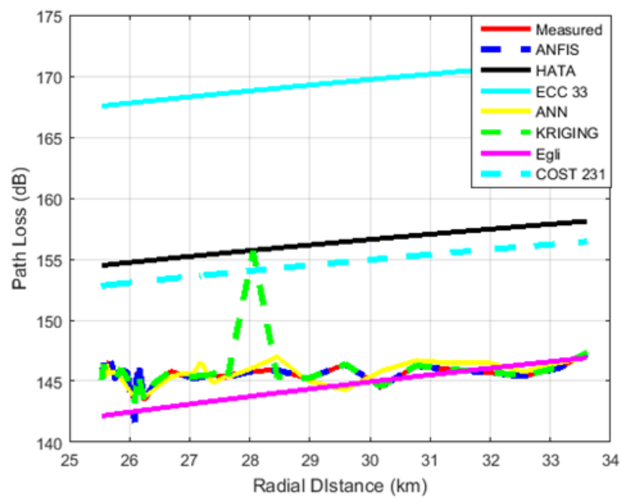

FIGURE 7. Path loss with distance for NTA_IFE Route 1.

In Figs. 6 to 9, the path loss of the measured and the models' predicted losses for the UHF transmitters along route 1 were presented. Similarly, the results obtained with the ANFIS, ANN and Kriging methods mimicked the measured path loss, providing an almost perfect prediction due to the density of the data set, as 100 data sets were used for these routes. For the empirical path loss models, the trend is also similar to that of Figs. 3 and 5, where the ECC-33 and Egli models overestimated and underestimated the losses, respectively. In Fig. 7, the Egli model provides an optimum prediction over all other empirical models, while, in Fig. 8, none of the models provides a good fitting. These deviations are results of the models' validity and the different clutter effects along the communications path.

Although the terrain elevation along the route is the same (measurements were conducted simultaneously) and the receiver height (h_t) is also the same, they nonetheless experience varying clutter types along the transmission path (TX-RX). Figs. 10 and 11 depict the measured and predicted path losses for the cellular bands. Multipath fading and clutter

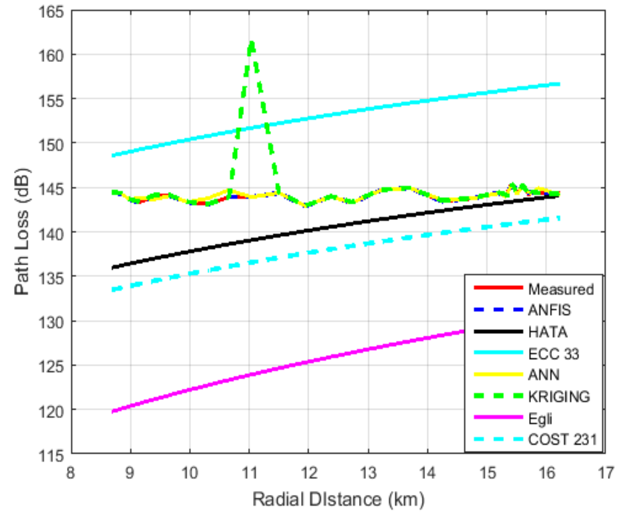

FIGURE 8. Path loss with distance for NTA_Ibukun Route 1.

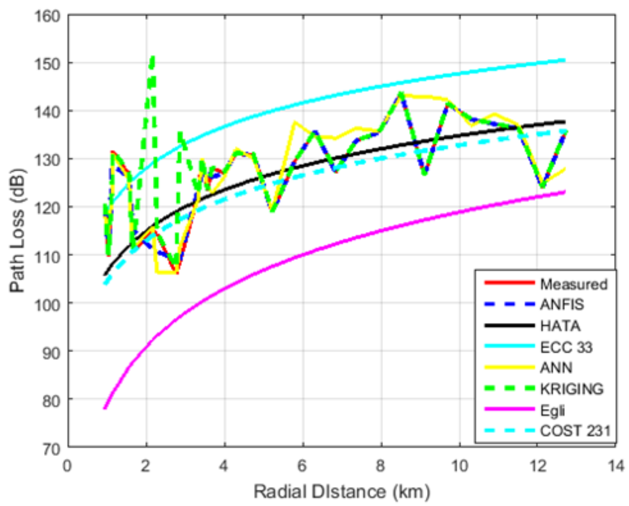

FIGURE 9. Path loss with distance for OSBC Route 1.

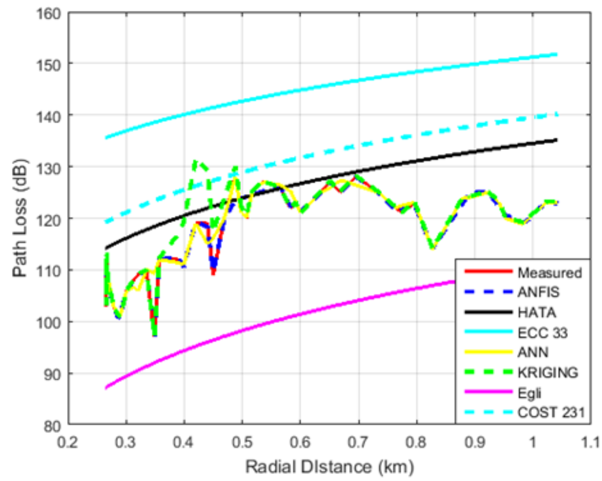

FIGURE 10. Path loss with distance for 2G BTS 2.

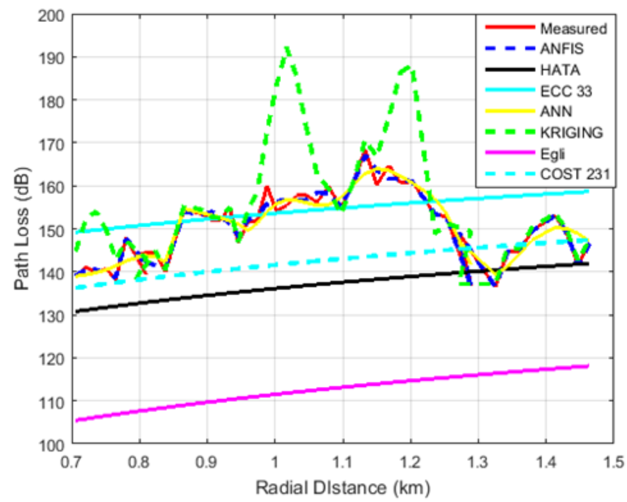

FIGURE 11. Path loss with distance for Node B 5.

effects were noticeable on the two curves with significant impacts on the NodeB 5 due to its operating frequency. Furthermore, we computed the MPE along all the three routes for the VHF and UHF transmitters. The MPE is the average value of the predicted error (i.e., the difference between the model's predicted path loss (P_i^p) at distance i and the measured path loss (P_i^m) of sample (n) along route j.

For the VHF transmitters, the overall average MPE across all the bands and routes are: −0.00000819 dB (ANFIS), 0.660 dB (ANN), 3.09 dB (KRIGING), −7.02 dB (COST 231), 0.512 dB (HATA), −11.74 dB (EGLI) and 15.54 dB (ECC-33). Nevertheless, some methods show very high errors at some measurement points. For example, the Kriging method's maximum error was 82.04 dB along route 1 for the Unilorin transmitter. For the UHF transmitters, the Hata model overestimated loss in all routes, except for route 1 for the Unilorin scenario. COST 231 also has an anomaly, as it now overestimated the loss when compared to VHF bands. For the cellular bands, the average MPE across 2G BTS 1-5 is: 0.00000426 dB (ANFIS), 1.152 dB (ANN), 3.6985 dB (KRIGING), 12.5505 dB (COST 231), 10.5361dB (HATA), −4.784 dB (EGLI), and 28.7304 dB (ECC-33); for 3G BTS, Node Bs 1-5 are: 0.00000303 dB (ANFIS), 1.99 dB (ANN), 0.7592 dB (KRIGING), 5.6860 dB (COST 231), 3.2023 dB (HATA), −4.4656 dB (EGLI), and 21.6166 dB (ECC-31).

In Fig. 12 the variation of the errors as a function of the distance from the transmitter is given. In this scenario, the Unilorin Tx was used, and it was discovered that, for distances of less than 1 km from the transmitter, all the models underestimated the path loss. Above 1 km, the Hata, COST 231, and Egli models underestimated loss and converged towards 0 dB after 3 km, while the ECC model overestimated the path losses, showing a high PE across the entire distance range. The high errors were due to the initial offset parameters defined by the models. Moreover, at $d < 1$ km from the transmitter, LOS clearance between the Tx and the Rx and the free space loss was $71.46 + 20 \times \log d$, while

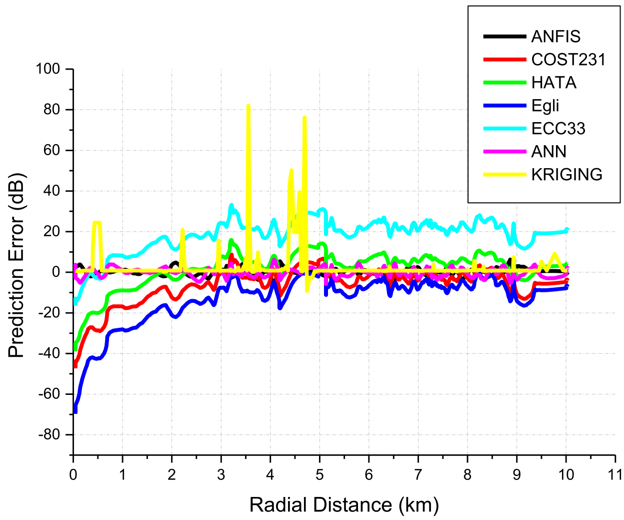

FIGURE 12. Error and radial distance for Unilorin TX along route 1.

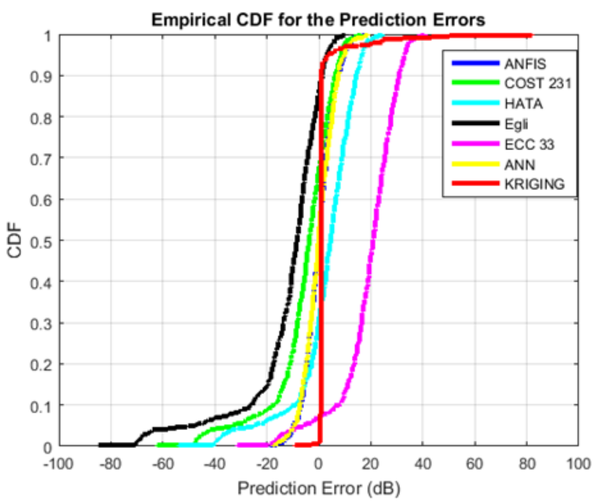

FIGURE 13. Empirical cumulative distribution of the prediction error for Unilorin R1.

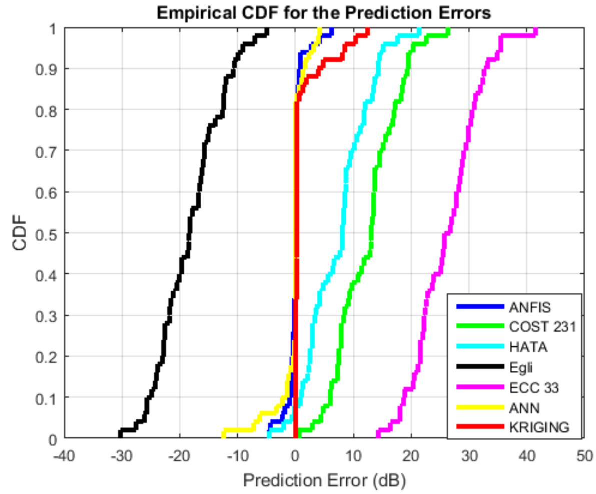

FIGURE 14. Empirical cumulative distribution of the prediction error for GSM BTS 2.

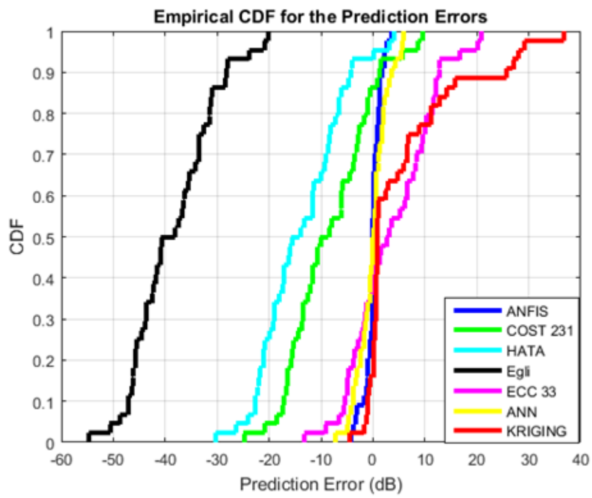

FIGURE 15. Empirical cumulative distribution of the prediction error for Node B5.

the loss computed with the HATA model was $92.94 + 31.8 \times \log d$. This resulted in an excess loss of 21 dB for the HATA model, while for the other models it was 40 dB (COST 231), 44 dB (Egli), and 62 dB (ECC-33).

However, these do not affect the ANFIS, ANN and Kriging methods, except for the spikes, which accounted for path loss overestimation, as illustrated in Fig. 3. All these errors were normalized and as an illustration, in Figs. 13-15 we present the empirical cumulative distribution of the prediction errors for all the methods for the Unilorin Tx route 1, 2G BTS 2 and NodeB 5. These figures show how the errors were distributed across the bands. In all the cases, it was observed that the heuristic and the geospatial methods skewed towards a 0dB error margin, while the empirical models yielded a high cumulative error distribution. In Fig. 13, the error distribution for the Kriging method was quite high for the CDF 0.6-1, which was due to the overshoot in path loss predictions, as observed in Fig. 11.

In Tables 2 and 3, the statistical analysis of the error for each method/model across all the routes for the VHF and UHF transmitters are provided. Table 2 shows the RMSE for each of the models and for each of the VHF transmitters. The RMSE between 0-7 dB is considered acceptable for urban areas [36], although for typical suburban and rural areas, up to 10-15 dB can still be acceptable [37]. For the Unilorin transmitter, the average RMSE values are 4.82 dB, 5.3 dB, 12.03 dB, 12.48 dB, 9.11 dB, 16.51 dB and 18.63 dB for the ANFIS, ANN, KRIGING, COST 231, HATA, EGLI and ECC-33 models, respectively. Based on these findings, the ANFIS method is shown to provide the lowest RMSE across all routes, followed by ANN, Hata, Kriging, COST 231, Egli and finally ECC-33. However, for the NTA transmitter, ANN has the least RMSE (4.28), followed by Kriging with 4.33, and ANFIS with 4.95. The COST 231 and Hata are still within the range that could be considered acceptable for path loss prediction. Finally, for

TABLE 2. RMSE performance metrics for the VHF transmitter models.

Models/Routes	UNILORIN			NTA			HARMONY		
	R1	R2	R3	R1	R2	R3	R1	R2	R3
ANFIS (dB)	5.71	4.16	4.60	7.10	3.82	3.94	5.87	5.46	6.21
ANN (dB)	5.94	3.82	6.14	4.90	3.96	3.98	6.11	4.32	3.21
KRIGING (dB)	7.00	10.63	18.48	7.580	1.11	4.32	22.04	2.79	12.58
COST 231 (dB)	13.39	12.54	11.51	13.14	9.56	7.49	8.85	9.68	10.19
HATA (dB)	12.39	7.07	7.87	9.79	6.41	8.24	10.66	8.24	7.99
EGLI (dB)	19.74	16.22	13.58	21.21	16.22	11.24	9.04	10.17	10.68
ECC-33 (dB)	22.24	15.45	18.2	12.53	13.01	18.77	24.02	20.2	19.34

TABLE 3. RMSE performance metrics for the UHF transmitter models.

Models/ Routes	NDTV			NTA IFE			OSBC			NTA Osogbo		
	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
ANFIS (dB)	0.19	0.49	0.39	4.02E-01	3.01	1.05	1.84	2.41	4.78	2.75	0.69	4.476
ANN (dB)	0.25	0.59	0.04	0.74	5.57	0.810	4.42	2.10	5.23	3.97	2.34	5.48
KRIGING (dB)	3.19	1.07	4.14	1.77	3.94	0.23	8.24	10.31	7.91	6.46	12.55	7.583
COST 231 (dB)	6.24	8.39	5.50	8.45	6.47	10.08	9.43	5.31	8.54	9.77	8.33	9.43
HATA (dB)	4.09	10.88	7.95	10.10	7.42	11.72	8.66	6.62	9.79	10.70	9.49	10.23
EGLI (dB)	18.03	1.59	3.56	2.43	13.85	1.67	25.17	7.34	10.29	10.76	6.57	14.64
ECC-33 (dB)	9.79	23.4	20.52	23.15	18.60	24.78	13.3	17.62	20.67	22.31	22.39	21.20

the Harmony transmitter, ANN still maintained the best performance with an RMSE of 4.54 dB, followed by ANFIS with 5.84 dB and then the COST 231, Hata and Egli models. For Kriging and ECC-33, the RMSE values were quite high. The Standard Deviation Error (SDE) across all the models, transmitters and routes were computed and it was found to be quite high for the Unilorin Tx when compared to other transmitters. This was due to the high prediction errors recorded across the models for $d < 1$ km. Along this route, the SDE for ANN was 3.71 dB and this was the lowest one when compared to 8.27 dB (ANFIS), 11.79 dB (KRIGING), 16.09 dB (COST 231), 16.09 dB (HATA), 20.24 dB (EGLI) and 14.98 dB (ECC-33).

The Route-on-Route average SDE for the methods across all the bands are: 6.03 dB (ANN), 4.31 dB (ANFIS), 12.55 dB (KRIGING), 2.8 dB (COST 231), 2.82 dB (HATA), 5.16 dB (EGLI), and 4.30 dB (ECC-33). From this analysis, the Kriging method has the highest SDE, which was due to sudden spikes on the PE observed. However, the SDE for the UHF transmitters is higher than that of VHF, although NDTV introduces fewer errors. For the cellular bands, the average RMSE across 2G BTS 1-5 are: 6.19 dB (ANFIS), 2.17 dB (ANN), 12.22 dB (KRIGING), 4.21 dB (COST 231), 4.21 dB (HATA), 4.784 dB (EGLI) and 3.293 dB (ECC-33); for 3G BTS, Node Bs 1-5 are: 5.64 dB (ANFIS), 1.96 dB (ANN), 9.4930 dB (KRIGING), 3.93 dB (COST 231), 3.93 dB (HATA), 4.46 dB (EGLI) and 3.15 dB (ECC-33). Using this metric, for the broadcast frequencies, the empirical path loss models (i.e., Hata and COST 231) provide less error, followed by ECC-33.

For the cellular frequencies, ANN has the best overall performance, followed by the empirical models. It is worth noting that the fitness of the ANN model for these frequencies was possible, as a result of the high data density. The path loss data obtained was small, which is due to the coverage distance of the base stations, mostly being less than 1.5 km and, as such, the ANN model tends to learn fast and provides fewer errors. The Kriging method consistently yielded a high SDE, and ANFIS was found to be a solution in-between the two methods. Therefore, the three methods can be ranked in order of performance as follows: empirical models, heuristic methods and geospatial methods. The empirical models yielded the best results using this metric, as these models are independent of the underlying physical objects (clutters) along the communication paths, which resulted in a lower loss deviation from the local mean. Regarding the heuristic and geospatial methods, these are dependent on the measured path losses, which are mostly affected by fading and shadowing due to the presence of clutters.

IV. CONCLUSION

In this paper, heuristic methods, geospatial and empirical models in predicting path loss in the VHF and UHF bands were presented for specified routes. Electromagnetic field strength measurements were conducted using drive tests at four different urban environments across cellular and broadcasting bands to test their effectiveness and also to evaluate the prediction ability of the Artificial Neural Network, Adaptive Neural Fuzzy Inference Systems, Kriging, COST-231, HATA, Egli and ECC-33 models.

The performance of the different methods varied with the performance metrics used. It was found that, in the VHF bands, across cities, the heuristic methods (i.e. ANFIS and ANN) provide the lowest mean prediction error. The overall average MPE across all bands and routes were of: −0.00000819 dB (ANFIS), 0.660 dB (ANN), 3.09 dB (KRIGING), −7.02 dB (COST 231), 0.512 dB (HATA), −11.74 dB (EGLI) and 15.54 dB (ECC-33). A similar trend was observed for the UHF transmitters. However, the Kriging method showed very high errors at some measurement points. These errors could be as high as 105.04 dB - this was due to the inter space between the path loss measurements. As the method uses the concept of moving averages to provide optimal interpolation across space based on spatial distance, against observed values of neighboring data points.

In terms of the RMSE, the heuristic methods still provided the least RMSE across the bands for the broadcasting and cellular approaches, followed by the geospatial and empirical methods, in that order. Nonetheless, it was discovered that, for some instances, the empirical models performed better than the geospatial ones; in all cases, though, heuristic methods-maintained consistency in their performance. The Route-on Route average standard SDE for the methods showed that the empirical models have lower error deviations from the mean when compared with the other methods. This occurred because empirical models do not account for the dynamic variation of the path loss due to physical objects such as the terrain and clutter effects along the communication paths, while the heuristic and geospatial methods depend on the actual measured path loss, which is mostly affected by fading and shadowing. The Kriging method has the highest SDE. This was due to sudden spikes on the PE observed as a result of data density and neighborhood distance of the path loss data.

This work has discovered that the three methods performed quite well, depending on the performance metrics used in gauging them. The RMSE for all the methods falls within acceptable values, except for the Egli and ECC-33 models. However, all the empirical models provided the least standard deviation errors when compared to the two other methods. It should be noted that the geospatial method required sample measurements to be taken before predictions can be done within the neighborhoods. This approach, standalone, cannot be used to make predictions. The heuristic approach can be used to make predictions based on the trained network, while the empirical methods do not require training measurements to make predictions; in fact, only the required propagation parameters are needed. Therefore, this indicates that empirical models are still the simplest and the most widely applicable among the three methods. In terms of prediction accuracy, heuristic methods are the best. Therefore, a trade-off is needed to balance between simplicity, ease of application, and accuracy. This paper thereby emphasizes that the empirical path loss propagation models can still be improved upon to provide an optimum prediction that is comparable to other methods. In particular, we consider that there is further scope for refinement in order to reduce the prediction error by incorporating other ambient parameters into the existing propagation models. A hybrid of the two methods, i.e., heuristic and empirical, can improve the application of heuristic methods and may possibly decrease the high prediction errors associated with empirical models. This matter will be addressed in future works.

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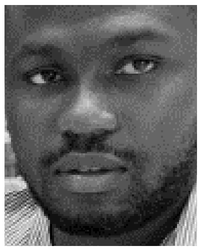

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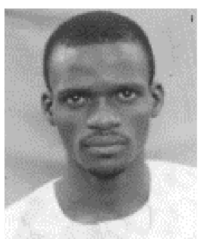

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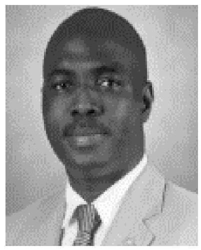

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