



ANN-based model for multiband path loss prediction in built-up environments

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ABSTRACT

Path loss propagation models are critically needed for optimum planning and deployment of wireless communication networks. However, the complexity exhibited by the propagated signals makes the prediction of the received losses difficult in built-up environments. There is however a new paradigm shift towards the application of computational methodologies, such as the Artificial Neural Networks (ANN), for multi-band path loss prediction. In this paper, we have developed a new ANN-based model for path loss prediction. The model was developed using large scale path loss data collected across 485 base stations in 6 urban cities of Nigeria, West Africa. The data collection, which spanned a period of 9 years, were taken over open areas, sub urban and urban environments, and the bands considered were 89.3 MHz, 103.5 MHz, 203.25MHz, 429.25 MHz, 529.25MHz, 615.25MHz, 629.25MHz, 900MHz, 1800 MHz and 2100MHz. The developed model was validated using independent path loss data across different frequencies, environments; and, distances and

Abbreviations: 5G, Fifth-generation; ANFIS, Adaptive neuro-fuzzy inference system; ARFCN, Absolute Radio Frequency Channel Numbers; BPNN, Backward propagation neural network; BTS, Base transceiver station; COST, Co-operative for Scientific and Technical Research Technical Committee; COVID-19, Coronavirus Disease; DANL, Displayed Average Noise Level; dB, Decibel; DTC, Digitally Tuned Capacitor; DTDNN, Distributed time delay Neural Network; FFNN, Feed-Forward Neural Network; FSPL, Free-Space Path Loss model; FTDBB, Focused Time-Delay Neural Network; GHz, Gigahertz; GPS, Global Positioning System; GSM, Global System for Mobile Communications; IP, Internet Protocol; ITU, International Telecommunications Union; L-BFGS, Limited Memory Broyden-Fletcher-Goldfarb-Shanno; LMA, Levenberg Marquardt Algorithm; LOS, Line-of-Sight; LRNN, Layer recurrent neural network; LTE, Long Term Evolution; MATLAB, MATrix LABoratory; ME, Mean Error; MHz, Megahertz; MLP, Multilayer Perceptron; MSE, Mean Square Error; MWMF, Multi Wall Multi Floor; NDTV, New Dawn Television; NLOS, Non Line-of-Sight; NTA, Nigerian Television Authority; QoE, Quality of Experience; QoS, Quality of Service; RBF, Radial Basis Function; RBW, Resolution bandwidth; RF, Random Forest; RMSE, Root Mean Square Error; RSSI, Received Signal Strength Indicator; SC, Scale Conjugate; SCG, Scale Conjugate Gradient; SDE, Standard Deviation Error; SHF, Super high frequency; SVR, Support Vector Regression; UHF, Ultra high frequency; UMTS, Universal Mobile Telecommunications Service; UNILORIN, University of Ilorin; VHF, Very high frequency; WCDMA, Wideband Code Division Multiple Access; WiFi, Wireless Fidelity.

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the results were compared with the popular empirical models such as Hata, COST 231 and Egli models, and to previously published ANN-based multi-frequency models. The global performance of 4.81 dB was obtained in terms of RMSE value with an R-value of 0.96, thus outperforming the existing ANN-based path loss models that were developed for multiple frequencies. Based on these findings, the proposed model can be deployed across all categories since the average RMSE values are all within the acceptable thresholds. Furthermore, the model is multi-frequency, thus will be suitable for multiple and complex environments, and usable for both short- and long-range wireless communication networks

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Introduction

Wireless communication systems and services have become catalysts for sustainable development. With the emergence of COVID-19 pandemic, the need to have access to reliable communication systems and high-speed broadband internet services have become a necessity for learning, working and socializing. Recent statistics released by the ITU has shown that the number of internet users has increased by 800 million. This figure makes the present number of internet users to reach 4.9 billion, representing 63% of the world population [1]. This increase is driven mainly, by the broadband mobile cellular systems. Similarly, by 2023, the number of devices to be connected to the IP networks would be three times more than the global population [2]. The emerging wireless technologies such as the 5G networks have promised to provide unprecedented high data rates with extremely low latency that would support critical services such as e-health provision, equitable and inclusive education, bridging digital divide, improving social exclusiveness, public safety communication, smart transportation, smart agriculture, digital broadcasting, among others [3]. Different deployment strategies would have to be used for different use cases ranging from macro, to micro and small cell deployments [4]. Moreover, the explosive growth in demand for more data rates accruing from an increase in the number of subscribers will, no doubt, require further network expansion by the network operators. This is to ensure minimum Quality-of-Service (QoS) and Quality of Experience (QoE), in order to sustain customer loyalty and remain competitive in the global markets. Network densification with the use of small cells has been proven to be the enabler for balancing coverage footprint and capacity requirements. The need to deploy a large number of small cells to meet the capacity demands is an approach that is particularly found to be attractive due to the low carbon footprint and sustainable energy consumption of the cells [4–7]. While energy-efficient deployment is possible, there is always a need to efficiently choose appropriate base station locations and minimize interference to incumbent or protected users, thus the need for accurate and reliable radio propagation models for effective coverage estimation. The propagation of electromagnetic waves exhibits both Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) conditions. In LOS conditions, the waves are propagated in free space, and the transmitted signal experiences minimal propagation loss, which is explained by the Free-Space Path Loss model (FSPL) [8]. In the case of NLOS, the signal propagation is influenced by other environmental phenomenon such as diffraction, absorption and scattering, resulting in a further decrease of the received power beyond the free space loss [9,10].

Path loss represents the decrease in the signal power of the transmitted electromagnetic waves largely affected by fading, resulting in path losses along the communication paths. The fading could occur within a very short distance commonly, known as small scale fading, or for a large distance, i.e., large scale fading (path loss) [11]. The behavior and attenuation of the signals are characterized over a distance by several path loss models. Therefore, the path loss models to be deployed for network planning of wireless systems must be very accurate in order to avoid excessive interference and to maximise the network throughputs. Various radio propagation models are deployed for diverse set of environments and frequency bands, ranging from flat terrain to a more complex environment, thus making relative performances to be environment dependent. Most times, the general models are modified to suit peculiarities in terms of either frequency, distance or environmental types. These models are broadly categorised into three namely: the deterministic, empirical (measurement-based) and physical models [12].

Empirical models have received global attention due to their simplicity, ease of use and wider applicability, as their application requires less computational complexities, even though they are prone to high prediction errors when employed for diverse sets of environments, particularly, if they are applied in an environment other than the one the model was initially built for [13–16]. Most of the empirical models failed efficacy tests when applied in a typical Nigerian terrain due to very high coverage prediction error. This was attested to based on our previous studies conducted for over a decade [3,11,13,17–21] where most of these models consistently failed efficacy tests. Our recent findings on the efficacy of these models could be found in [22]. Therefore, there is a need to tune some of the model parameters in order to minimise prediction errors [3,23–26], and thus improve coverage prediction. However, despite a series of efforts in improving the performance of empirical radio propagation models through optimisation or tuning, they tend to have weak model generalisation ability as their performance were found to be inconsistent when tested in another environment [23,27]. The deterministic models, on

the other hand, are highly computationally expensive, as they require detailed information of the environment in which the model will be deployed. Furthermore, it was discovered in [12] and [28] that the deterministic models are not always outperforming the empirical models, even when site-specific information such as digital terrain elevation and building layers of the environment of interest are used. This raises concern as to why venturing into the complexities when the models could not consistently give better predictions.

There is of recent a paradigm shift towards the application of computational methodologies such as the ANN for path loss prediction, in which quite substantial implementations have achieved promising outcomes [29–50]. Among which some authors hybridised models for path loss prediction, such as the ANFIS on the 2100 MHz in Nigeria [51], fuzzy logic for 3.35 GHz, 8.45 GHz, and 15.75 GHz in Tokyo, Japan [52], and many other works [3,4,21,30,35,53,54]. Furthermore, quite some research works have been conducted within Nigeria, where machine learning algorithms were deployed for path loss prediction. Mgbe et al [55] employed Generalized Regression Neural Network (GRNN) and smoothing factor to develop path loss model at 870.25 MHz. Results from the work were compared with FSPL, Hata and Egli models. Findings from the work revealed that the developed GRNN outperformed other models, with MSE of 1.0844 dB. Similar model was adopted by Abraham [56] for 1800 MHz band. Recently, Idogho & George [57] compared SVM, MLR and ANN models for path loss prediction for 900 MHz band. Transmission Evaluation and monitoring system (TEMS) was used for the data collection across 9 points where Levenburg- Marquardt method was employed as training algorithm. Findings from the work revealed that ANN model performed better than other models. However, Ebhota & Srivastava [58], uses MLP-NN with Bayesian regularization (BR) and Levenburg- Marquardt for training algorithms to develop predictive models for 1900 MHz band using measurement taken from a single transmitter between the distance 1m-800m. Few works hybridised different algorithms for path loss prediction. Notably, Igwe et al. [59] combined Particle Swarm Optimisation (PSO) and Artificial Neural Network (ANN) while, Isabona & Srivastava [60], combined log-distance model with ANN for path loss prediction in Ikoyi Lagos, Nigeria. However, despite these positive performances recorded from these works, it is worthy noting that the developed models have limited scope in terms of operating frequency and environment. All the models developed by the researchers such as, Mgbe et al [55] is limited to only 870.25 MHz, while, Abraham [56] and Idogho & George [57] are limited to 1800 MHz and 900 MHz bands respectively. This would invariably, pose restrictions on the applicability of the models to only the specific bands of interest, this aside, the path loss data used during the model training were few hundreds of samples, hence, not capturing peculiarities of different terrain environments, thus, affecting the model's generalisation ability.

Overall, most of these implementation approaches addressed only a single frequency band, neglecting the need to apply the models for other bands, thus making the models susceptible to high prediction error. It is, however, worthy to acknowledge the works of [33,61–67] that attempted to address the single frequency constraints and developed appropriate models for multiple frequencies. These works spanned the last 21 years (2000 to 2021) and were obtained through search from various scientific databases. One of the major limitations of these works is that they are either simulation study or measurement-based, whose data collections were limited to a few number of transmitters/locations (usually between 1 and 11). Table 1 provides a detailed summary of the works. The taxonomy of past research works from the network parameter optimisation perspectives is provided in Table 2.

The limitation in the amount of path loss data collection, viz-a-viz, a few locations and not capturing peculiarities of different terrain environments, could actually affect a model's generalisation ability since few data sets are used for training the networks. Also, the higher the data density, the closer it is to get an accurate model [50,73], hence the need to collect large scale propagation path loss measurements data in different complex environmental scenarios across many frequencies in order to improve the model generalisation ability. This work, therefore, presents a multi-frequency band ANN-based model for path loss prediction within different complex terrain environments. The model was developed using large scale data collected across 485 base stations in 6 urban cities of Nigeria, West Africa. The data collection spanned 9 years. The developed model was tested and results compared with those of the popularly known empirical models, such as Hata model [78], COST 231 model [79] and Egli model [80], and the previously published ANN-based multi-frequency models for benchmarking. The performance of the model was examined using widely accepted standard metrics such as the Root Mean Square (RMSE), Mean Error (ME), Standard Deviation Error (SDE) and the Correlation coefficient (R)-Value.

The remainder of this paper is organized as follows: Section II provides an overview of the most relevant related works. Section III summarises the attributes of some of the popular and widely used path loss models. In section IV, we describe the materials and methods adopted for the current work. Section V presents the main findings of our work, with detailed discussion. Finally, section VI concludes the paper.

Empirical propagation path loss models

This section presents the empirical propagation models considered for benchmarking in this research.

Okumura-Hata model

Hata model is the mathematical representation of the graphical path loss data model presented by Okumura [78]. This model is used to predict path losses in urban, sub-urban and open areas and is widely used in a diverse set of environments. However, the model has some limitations in terms of frequency and transmission distance. The supportive frequency range

Table 1

Taxonomy of Related Studies Based on Network System Parameter

S/No.	Reference	Measurement Country	No. of measurement locations	Frequency Bands	Frequencies (MHz)
1	[64]	Nigeria	11	UHF	1800
2	[68]	Germany	1	UHF	947
3	[33]	Minna, Nigeria	20	UHF	1800
4	[69]	Greece	1	UHF	1890
5	[30]	Simulation	1	UHF	900
6	[70]	Simulation	1	UHF	900
7	[45]	Simulation	1	NA	NA
8	[63]	Val d'Or, Canada	2	SHF	3000 - 10000
9	[64]	Benin, Nigeria	1	VHF	92.3 and 189.25
10	[71]	Kavala, Greece	1	UHF	1890
11	[39]	Rural Western Australia	1	UHF	881.52
12	[72]	Simulation	1	UHF	2350
13	[66]	Val d'Or Canada	9	SHF	3000 - 10000
14	[61]	Simulation	11	UHF	900 and 1800
15	[67]	Tunis, Tunisia	5	UHF	900, 1800, 2100, and 2400
16	[62]	Simulation	1	UHF	900, 1800, and 2100
17	[73]	Minna, Nigeria	1	UHF	1835 - 1850
18	[74]	Hyderabad, India	1	UHF	947.5
19	[32]	Simulation	1	UHF	600
20	[75]	Rio de Janeiro, Brazil	1	UHF	1140
21	[51]	Ibadan, Nigeria	3	UHF	2100
22	[76]	Simulation	3	UHF	877.26, 2127.6
23	[52]	Tokyo	2	SHF	3,350, 8,450 and 15,750
24	[30]	Korea	2	SHF	3000 - 6000
25	[29]	Tripoli, Libya	10	UHF	900, 1800, 2100
26	[34]	suburban area in Nonsan, Korea	2	SHF	450, 1450, and 2300
27	[37]	UK, South Korea, and Japan	4	UHF, SHF	800 - 70,000
28	[65]	Simulation	7	UHF	2,400, 3,520, and 5,800

Table 2

Taxonomy of related studies based on network parameter optimization.

S/No.	Reference	Varying input Data Variables	Varying hidden layer activation functions	Varying output layer activation function	Varying training Algorithm	Varying number of neurons in the hidden layer	Varying the optimization algorithm	Varying the Learning Rate
1	[42]	x	x	x	x	✓	x	x
2	[68]	✓	x	x	x	x	x	x
3	[33]	x	✓	x	x	✓	x	x
4	[69]	x	x	x	x	x	x	x
5	[30]	x	x	x	x	✓	x	x
6	[77]	✓	✓	x	x	✓	x	x
7	[45]	x	x	x	✓	✓	x	x
8	[63]	x	x	x	x	✓	x	✓
9	[64]	✓	✓	✓	✓	✓	x	x
10	[71]	✓	x	x	x	✓	x	x
11	[39]	x	x	x	✓	✓	x	x
12	[72]	x	x	x	x	✓	x	x
13	[66]	✓	x	x	x	x	x	x
14	[61]	x	x	x	x	x	x	x
15	[67]	x	x	x	x	✓	x	x
16	[62]	x	x	x	x	x	x	x
17	[73]	x	✓	x	✓	✓	x	x
18	[74]	x	✓	x	✓	✓	x	x
19	[32]	x	x	x	x	✓	x	x
20	[75]	✓	x	x	x	✓	x	x
21	[51]	✓	x	x	x	x	x	x
22	[76]	x	x	x	x	x	x	x
23	[76]	✓	x	x	✓	✓	x	x
24	[41]	x	x	x	✓	✓	x	x
25	[29]	x	x	x	x	x	x	x
26	[34]	x	x	✓	x	x	x	x
27	[37]	✓	x	✓	x	✓	✓	✓
28	[65]	x	x	x	x	✓	x	x

is between 150 MHz to 1500 MHz, while the transmission distance is up to 20 km. Also, the height of the transmitter ranges from 30 to 200 m and that of the receiver from 1 to 10 m. The models are represented as:

a *Urban Regions Path Loss* (PL_{Urban})

$$PL_{Urban} = 69.55 + 26.16 \times \log f - 13.82 \times \log h_t - C(h_r) + (44.9 - 6.55 \times \log h_t) \times \log d \quad (1)$$

b *Sub Urban Regions Path Loss* ($PL_{Suburban}$)

$$PL_{Suburban} = PL_{Urban} - 2 \times (\log(f/28))^2 - 5.4 \quad (2)$$

c *Open Areas Path Loss* (PL_{Open})

$$PL_{Open} = PL_{Urban} - 4.78 \times (\log f)^2 + 18.33 \times \log f - 40.94 \quad (3)$$

Where, PL is the path loss in dB, f the operating frequency (in MHz), h_t transmitter height (in meters), h_r receiver height (in meters), d the separation distance between the transmitter and receiver (in km) and $C(h_r)$ the receiver height correction factor.

Furthermore, in the Hata model, some set of correction factors $C(h_r)$ are provided that would cater for environmental differences such as small, medium and large cities, these are given as:

i For small and medium city

$$C(h_r) = (1.1 \times \log f - 0.7)h_r - (1.56 \times \log f - 0.8) \quad (4)$$

ii For large city

$$C(h_r) = \begin{cases} 8.29 \times (\log 1.54 \times h_r)^2 - 1.1 & f \leq 200\text{MHz} \\ 3.2 \times (\log 11.75 \times h_r)^2 - 4.97 & f \geq 200\text{MHz} \end{cases} \quad (5)$$

COST 231 model

The COST 231 model was developed to extend the model's applicability from 1500 MHz to 2000 MHz (2 GHz) at the same distance of 20 km [79]. COST 231 model is mathematically expressed as:

$$PL_{COST} = 46.3 + 33.9 \times \log f - 13.82 \times \log h_t - C(h_r) + (44.9 - 6.55 \times \log h_t) \times \log d + D_m \quad (6)$$

Where; $D_m = 3$ dB for metropolitan regions and 0 dB for medium-sized and sub urban regions. h_t , h_r , $C(h_r)$, and d , are as earlier defined for the Hata model above.

Egli Model

This model was developed in 1957 [80] for an outdoor path loss prediction in the VHF and UHF bands over an irregular terrain based on extensive path loss measurements in several European cities. The frequency validity range of the model is 90 - 1000 MHz for a distance of less than 60 km. The Egli path loss could be obtained as follows:

$$PL_{Egli}(\text{dB}) = \begin{cases} 76.3 + 20 \times \log f + 40 \times \log d - 20 \times \log h_t - 10 \times \log h_r & \text{for } h_r \leq 10\text{m} \\ 85.9 + 20 \times \log f + 40 \times \log d - 20 \times \log h_t - 10 \times \log h_r & \text{for } h_r \geq 10\text{m} \end{cases} \quad (7)$$

Materials and methods

Method of Data Collection and Sample size

In this research work, large scale data, consisting of Received Signal Strength (RSS), Frequency (f), Elevation (e), longitude ($\log$) and latitude (lat), height of transmitter (h_t) and the height of receiver (h_r), were collected. Two measurement categories were considered: measurement data from (i) the Mobile cellular transmitters and (ii) broadcasting frequencies. The mobile cellular technologies consisted of bands within the GSM, WCDMA and LTE technologies. The GSM band measurements were carried out in two Urban cities, i.e., Kano State (Latitude 12.0022° N, Longitude 8.5920° E) and Lagos State (Latitude 6°35'N, Longitude 3°45'E). For the WCDMA band, the measurements were conducted in Kano State, FCT Abuja (Latitude 9.0765° N, Longitude 7.3986° E) and Ogun State (Latitude 7°00'N, Longitude 3°35'E) while, for the LTE, the measurements were conducted in Lagos and Ogun States. These cities (i.e., Lagos, Abuja, Kano, Kwara, Ogun, and Osun) are states located in

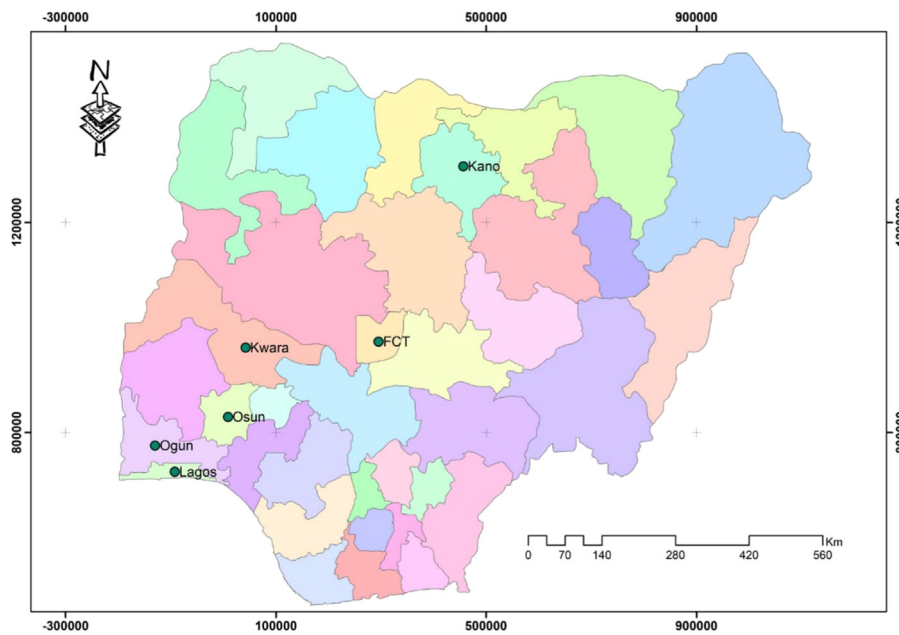


Fig 1. Measurement Locations

Nigeria. For the broadcasting band, the measurements were carried out in Kwara State (Latitude 8.4799° N, Longitude 4.5418° E) and Osun State (Latitude 7.7827° N, Longitude 4.5418° E), Nigeria. Fig. 1 shows the locations of the measurements. The overall number of transmitters considered during the measurements were 485, among which 478 were cellular base stations comprising 147 in the GSM band, 299 in the WCDMA bands and 32 in the LTE frequencies and 7 broadcasting stations.

For the broadcasting frequencies, seven (7) broadcast transmitters (i.e., 3 in the VHF, and 4 in the UHF bands) were considered and, for each BTS, three measurement routes were used, with an overall total of 145.5 km distance and 71,871 samples. The VHF transmitters were named Harmony (8° 21' 56"N, 4° 43' 18"E), UNILORIN (8° 29' 21"N, 4° 40' 28"E), and NTA Ilorin (8° 25' 55"N, 4° 36' 25"E) with respective frequency, antenna height and peak power of: 103.50 MHz, 125m and 1.0 kW; 89.30 MHz, 100m and 7.0kW, and 203.25 MHz, 185m and 2.4 kW. The UHF transmitters consisted of NDTV, Ibokun (7° 46' 32"N, 4° 43' 14"E), OSBC, Osogbo (7° 46' 35', 4° 35' 19"E), NTA, Ile- Ife (7° 29' 59"N, 4° 35' 23"E) and NTA Osogbo (7° 44' 01"N, 4° 31' 14"E) with respective frequency, antenna height and peak power of: 479.25 MHz, 198m and 2.1 kW; 559.25 MHz, 340m and 3.5kW; 615.25 MHz, 167m and 3.2kW, and 695.25 MHz; 152m and 4.1kW. At the receiving end, an Agilent spectrum analyser N9342C (100 Hz- 7.0 GHz) was used.

The path loss data collection for the cellular band was also achieved through a drive test with Huawei Genex Probe v 6.0 drive test software. The software was installed on a laptop, with a multi-band handset and a Probe Dongle attached to the laptop. For this experiment, the system was configured where the handset initiates an automatic call to a constant number for a hold period of 30 seconds; thereafter, the call would drop. The mobile phone would be inactive for a period of 5 seconds, afterwards, the call will be reinitiated. The software log the signalling files which contain other system parameters such as the Received Signal Strength Indicator (RSSI), operating frequencies in the case of 2G system and the scrambling codes in the case of 3G networks. Furthermore, coordinates information were logged, these include the longitude, latitude and elevation. The GSM 900 MHz and 1800 MHz were used and the corresponding Absolute Radio Frequency Channel Numbers (ARFCN) were all noted. Since the WCDMA uses the same operating frequency, the NodeBs were separated using scrambling codes, among which were: 132, 188, 484, 485, 486, and 155. For all the measurement routes, the height of the transmitter varied according to its application.

Ann Model Development for Multi-Frequency Path Loss Prediction

In this work, a multilayered neural network architecture was chosen for the development of the model due to its high degree of connectivity, which is determined by the synaptic weights used on the network. The input layer is made up of five neurons, and the variables are height of the transmitter (h_t), height of the receiver (h_r), operating frequency (f), elevation (e), and separation distance (d) as shown in Fig 2. The number of neurons in the hidden layer was varied from 5 to 30 in order to choose the optimum network configuration. The complete dataset that was used for the model development has 5 attributes (i.e. f , e , d , h_t , and h_r), each represented in a column having 200,000 rows corresponding to one million (1,000,000) data entries.

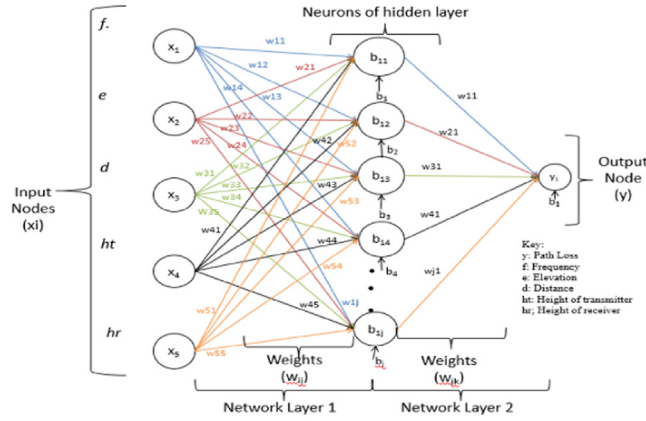


Fig 2. Model design and development architecture.

The path loss data from diverse set of environments were trained, simulated and modelled using MATLAB R2019a Neural Network Toolbox (MathWorks Inc., 2019). Three different environmental classifications were considered (i.e. open areas, sub-urban and dense urban areas). All the measurements were conducted outdoor; hence, indoor scenarios were not considered. The path loss data generated from the measurements have been partitioned into training, testing, and validation sets. The dataset was first divided into two segments. One segment was used for training and testing, while the second segment was used for validation and was never used for the model development. The first segment was further partitioned into 70% for training, 15% for testing, and 15% for validation. The second segment, which consisted of data set from the two main categories (i. broadcasting and cellular bands), were reserved for validation. This dataset (from second segment) was carefully chosen to have enough sample space that would aid validation across frequency bands, environmental categories (i.e. open, sub-urban and dense urban) and distances. In this work, a back-propagation learning algorithm was used to train the neural network [64]. For data adaptivity to the hidden layer, the input path loss values were transmuted and a linear activation (*logsig*) function used at the input of the hidden layer, while a hyperbolic tangent sigmoid transfer function (*tansig*) was used from the hidden to the output layer. The ANN model development considers two training algorithms: Scale Conjugate Gradient (SCG) and the Levenberg Marquardt (LM) training algorithms. The SCG and LM algorithms were implemented using functions 'trainscg' and 'trainlm', respectively, available in MATLAB 2019a. The number of neurons used in the hidden layer for the ANN model development, learning rate, and epoch size was varied to obtain the smallest prediction error possible. The neuron is the fundamental element of ANN. Given N number of inputs with k neurons and a single output y is given as:

$$v_k = \sum_{i=1}^m x_i W_{ki} + b_i \quad (8)$$

$$y_k = \varphi \left(\sum_{i=1}^m x_i W + b_i \right) \quad (9)$$

$$\varphi = \frac{1}{1 + e^{-aV_k}} \quad (10)$$

Where: N, v_k , φ , b, y_k and is the number of inputs, input layer neuron, activation function, bias and Output layer.

The values used as input data for the input nodes in the artificial neural network architecture were approximated by the neurons using the *logsig* activation function through the synaptic weights to the hidden neurons. Then, it was further approximated from the hidden neurons to the output neuron using the *tansig* activation function as represented in Equation (11) to give the determined path loss values.

$$f(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \quad (11)$$

The determination of the ability of the model and its prediction accuracy were generalised by the evaluation based on different statistical metrics, which include MAE, SDE, ME and RMSE relative to the measured datasets reserved for testing and validation. Eqs. (12)–(16) give the mathematical models of these statistical performance metrics.

$$e_i = z_d^k - z_p^k \quad (12)$$

$$MAE = \frac{1}{n} \sum_{k=1}^n (e_i) \quad (13)$$

$$SDE = \sigma = \sqrt{\frac{1}{n} \sum_{k=1}^n (z_d^k - \bar{z}_p^k)^2} \quad (14)$$

$$ME = \bar{e}_i = \frac{1}{n} \sum_{k=1}^n e_i \quad (15)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{k=1}^n (e_i)^2} \quad (16)$$

Where z_d^k , z_p^k , $\bar{z}_p^k$, e_i and n are the measured path loss, predicted path loss, mean predicted path loss, error between the measured and predicted path losses and the total number of samples considered respectively.

Model Validation

Cross-validation was employed to ascertain the efficacy of the developed model. This is achieved by reserving some of the data set across the frequency band, environmental categories (i.e. open, sub urban and urban) and distances. This is executed in order to mitigate limitations of the existing widely used empirical path loss propagation models such as Okumura-Hata model which is limited to a frequency range of (150–1500 MHz) and a distance between 1km to 20 km. COST 231 model is limited to only frequencies up to 2000 MHz, while Egli for frequency range 90–1000 MHz and distance up to 60 km over irregular terrain environments.

Results and discussion

The performance results of the multi-frequency based ANN path loss models based on different network configurations were observed and obtained. In addition, a single model was identified that provides the best results in terms of the performance metrics discussed in Eqs. (12)–(16). Furthermore, global comparisons with some published models are presented.

Model Development and Performance Evaluation

Fig 3. Predicted path losses for the proposed ANN model against sample index.

Table 3 provides the performance of the training algorithms considered in this work, with respect to the network architecture. The output performances of these configurations were benchmarked with the widely known empirical models. The work considered the SCG and LM algorithms where, for each algorithm, the network was simulated 10 times (iterations) while varying the number of hidden neurons in the hidden layers from 5 to 30 in the steps of 5. The results were observed and recorded. The LM algorithm at 5-20-1 network architecture revealed the least RMSE value of 4.81 dB, -0.028 dB Mean Error, but the highest R-Value of 0.96. When these values are compared with the empirical models, it was discovered that the proposed ANN model produced better outputs for all the metrics considered. The COST 231 and HATA models revealed RMSE values of 22.27 dB and 17.37 dB respectively, thereby providing tangible evidence of the prediction applicability of the proposed ANN-based model. In **Fig. 4**, the output of the R-value (correlation coefficient) from the training, validation and testing stages for the neural network is provided. This value indicates the performance of the developed model.

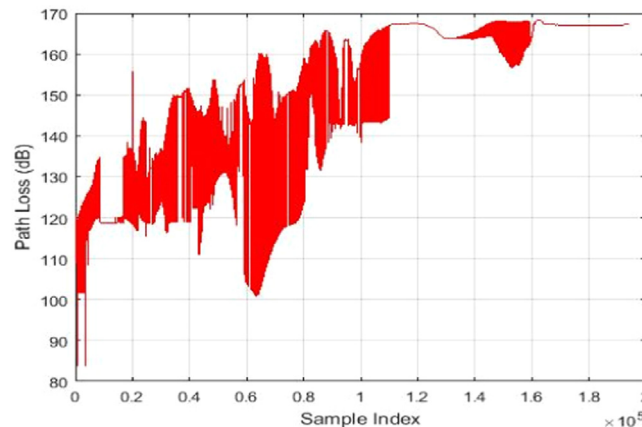
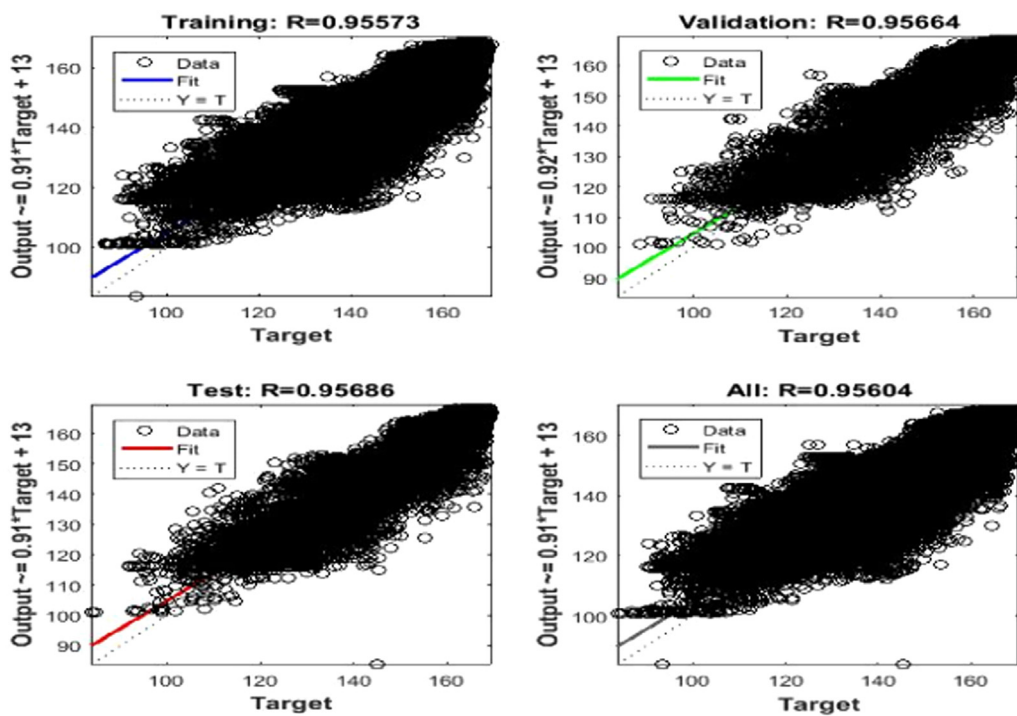


Fig. 3. shows the predicted path losses for the proposed ANN model against the sample index.

Table 3

Performance evaluation for the proposed model and empirical models.

Algorithm	Network Architecture	ME (dB)	RMSE (dB)	SDE (dB)	R-Value
Scale Conjugate	5-5-1	4.72	7.15	5.33	0.90
Levenberg- Marquardt	5-5-1	4.66	7.10	5.35	0.90
Scale Conjugate	5-10-1	4.62	7.06	5.34	0.90
Levenberg- Marquardt	5-10-1	4.11	6.39	4.90	0.92
Scale Conjugate	5-15-1	4.22	6.55	5.01	0.92
Levenberg- Marquardt	5-15-1	3.58	5.74	4.49	0.94
Scale Conjugate	5-20-1	-0.06	6.66	6.66	0.92
Levenberg- Marquardt	5-20-1	-0.03	4.81	4.81	0.96
Scale Conjugate	5-25-1	0.071	6.25	6.25	0.92
Levenberg- Marquardt	5-25-1	-0.029	4.83	4.83	0.95
Scale Conjugate	5-30-1	-0.061	6.58	6.58	0.92
Levenberg- Marquardt	5-30-1	-0.075	5.40	5.40	0.94
COST 231	-	20.23	22.27	9.32	-
HATA	-	15.22	17.37	8.38	-
EGLI	-	25.75	27.36	9.25	-

**Fig 4.** Best R-value performance for the proposed ANN model (Levenberg- Marquardt: 5-20-1)

The global performance of the model relative to the empirical models is provided in Table 4. The proposed ANN model revealed the smallest values of MAE, RMSE, ME and SDE of 3.11 dB, 4.81dB, -0.028 dB and 4.81 dB, respectively. These values satisfy the global recommendation for an urban environment, as reported in various articles, including [45,70,81]. Among the empirical models used, the Hata model reported the lowest RMSE and ME values of 17.37 dB and 16.21 dB respectively, thus outperforming the other empirical models when subjected to the same environmental conditions. However, the RMSE value obtained for Hata is far above the acceptable range of 6 dB in urban areas, and up to 10 dB in rural environments ([13] & [82]). This demonstrates the model's generalisation weakness in predicting path loss in different complex environments.

Validation of the proposed ANN-based model

The proposed ANN-based model was validated across different frequency bands, environmental categories and distances.

Frequency Validation

Table 5 provides also the results of the statistical analysis of the proposed model deployed for different frequency bands. In order to test the performance, a validation test was performed across frequency bands. This was achieved by testing

Table 4

Global performance across all routes for the proposed and empirical models.

Models/Metrics	COST 231	Hata	Egli	Proposed Model
MAE (dB)	21.22	16.21	25.87	3.11
RMSE (dB)	22.27	17.37	27.36	4.81
ME (dB)	20.23	15.21	25.75	-0.02
SDE (dB)	9.32	8.38	9.25	4.81
R-Value (%)	-	-	-	0.96

Table 5

Validation per frequency bands for existing empirical and proposed model

Bands [MHz]	HATA				EGLI				PROPOSED MODEL			
	ME(dB)	RMSE(dB)	MinE(dB)	MaxE(dB)	ME(dB)	RMSE(dB)	MinE(dB)	MaxE(dB)	ME(dB)	RMSE(dB)	MinE(dB)	MaxE(dB)
89.3	2.51	7.77	-18.76	22.8	14.77	16.22	-6.75	35.21	-2.43	7.69	-20.64	23.8
103.25	-3.68	9.42	-23.37	15.3	6.31	10.16	-14.93	23.75	2.58	7.84	-22.7	15.05
203.5	1.98	6.41	-9.55	17.85	15.01	16.21	3.25	30.95	14.85	5.82	-30.24	3.62
479.25	-10.8	10.8	-12.53	-8.09	-0.91	1.59	-2.81	2.59	0.08	0.81	-4.01	4.58
559.25	-4.93	6.62	-21.28	0.08	5.89	7.34	-11.15	12.49	-1.25	4.89	-17.02	8.19
615.25	-4.82	7.42	-18.11	16.22	11.3	13.85	-2.48	42.56	4.31	6.54	-57.55	25.46
695.25	-8.86	9.49	-17.53	0.48	4.88	6.57	-1.96	17.36	3.17	8.49	-15.72	14.15
1800	-9.95	10.98	-14.51	7.74	15.76	16.5	11.37	34.73	0.19	3.22	-6.07	11.51
2100	-4.26	12.05	-27.82	18.5	21.27	24.03	-2.91	42.74	1.6	11.88	-24.34	23.22
ARG	-4.75	8.99	-18.16	10.09	10.47	12.49	-3.15	26.93	2.56	6.35	-22.03	14.39

the model with data sets for different frequencies. Statistics for validation per frequency band for empirical and proposed ANN model, with the performance metrics of ME, RMSE, Min Error (MinE), and Max Error (MaxE), were considered. The proposed ANN model was trained with data set consisting of many frequencies. This makes it ideal for path loss prediction across multiple frequencies. It is revealed from Table 5 that the RMSE and ME for 479.25 MHz has recorded the least value of 0.81dB and 0.08dB respectively. Hata model produced the least RMSE value of 6.62 dB at 559.25 MHz band, while Egli has 1.59 dB at 479.25 MHz. As expected, the frequency limitation of Hata model is 1500 MHz, hence the reason for very the high RMSE of 10.98 dB and 12.05dB when validated for 1800 MHz and 2100 MHz respectively. This is expected to go higher at higher frequencies. Furthermore, findings from Table 5 reveal that the RMSE values for the proposed ANN-based model fall within the widely acceptable range for both rural, suburban and urban environments, with an average RMSE of 6.35 dB. The respective average RMSE for Hata and Egli models were 8.88 dB and 12.49 dB. Even, on band-on-band basis, the proposed model outperformed the empirical models in terms of the RMSE which is the most widely and acceptable metrics used to gauge the performance of the models. The average ME of the proposed model was found to be the lowest among the contending models. The Hata model produced the least value in comparison with Egli empirical model. However, the RMSE for the Hata could still be acceptable for open areas, with about 1 dB higher than the threshold limit for urban areas, and the ME revealed that the model underestimated the losses. The Egli model's average RMSE is far above the recommended threshold limit but could still be accommodated for open areas where RMSE up to 15 dB is within the acceptable range. The average mean error for the proposed model is 2.56 dB this indicates that the proposed model mostly overestimated the losses.

Environmental Categories (Open, Suburban and Dense Urban)

We have also investigated the performance of the proposed ANN-based model across different environmental categories, that is, rural (open) areas, sub urban and dense urban areas for wider applicability. The aim is to test the model's generalisation and prediction accuracy in practice. For this experiment, no recourse was made on a particular band; however, attention was paid to only the environment where the data was collected in order to make accurate categorisation. Table 6 reports the statistical results of the proposed ANN model and the empirical models. The proposed ANN model produces average values for RMSE for urban, suburban and rural environments as 6.47 dB, 10.56 dB and 8.00 dB (dB) respectively. The Hata produces an average RMSE of 12.52 dB, 21.65 dB and 11.24 dB while the corresponding values for the Egli model were 23.35 dB, 18.61dB and 17.83 dB respectively for the three categories. Based on these findings, the proposed model can be deployed across all categories since the average RMSE values are all within the acceptable thresholds. The Hata model only satisfied the conditions for open areas, while the Egli model's RMSE values are all outside the approved thresholds across all the categories. However, based on site-specific performance of the models, the Hata model can be deployed in URBAN-1, Egli model in SUB URBAN-2, and ANN-based model across all the sites categorised. The inconsistent and site-specific performance of Hata model was further proven in the works of [13,82], its failure mainly attributed to the inability of the model to cater for environmental peculiarities, hence the reasons for high prediction errors. Table 7

Table 6

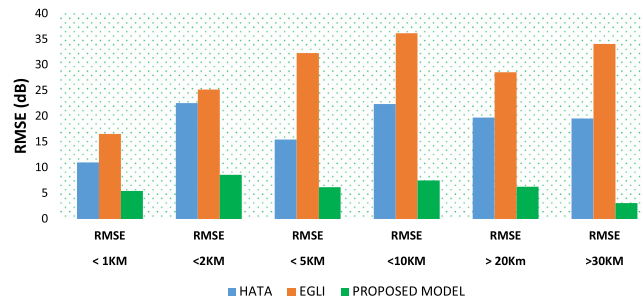
Validation per environmental Category for empirical and proposed ANN model

Category	Hata				Egli				Proposed Model			
	ME (dB)	RMSE (dB)	MinE (dB)	MaxE (dB)	ME (dB)	RMSE (dB)	MinE (dB)	MaxE (dB)	ME (dB)	RMSE (dB)	MinE(dB)	MaxE (dB)
Urban-1	-4.09	6.44	-14.32	10.46	20.87	21.43	10.9	35.23	0.41	5.18	-10.33	15.34
Urban-2	9.82	17.22	-6.39	40.54	38.65	41.92	19.83	74.34	-3.43	6.84	-16.48	8.27
Urban-3	-9.95	10.98	-14.51	7.74	15.76	16.5	11.37	34.73	-3.38	5.43	-11.51	6.07
Urban-4	-13.85	15.46	-25.29	0.96	11.5	13.55	-1.15	27.04	-5.27	8.43	-18.07	8.02
Sub Urban-1	-15.7	18.64	-32.89	5.21	8.63	15.21	-8.49	29.39	-10.1	14.34	-27.41	10.97
Sub Urban-2	-19.65	21.2	-32.82	-8.24	4.85	9.36	-8.39	16.34	-14.3	8.41	-27.41	-3.08
Sub Urban-3	-12.24	22.29	-31.84	31.08	12.88	24.72	-8.72	61.18	-1.95	8.94	-14.45	21.51
Sub Urban-4	-11.66	22.53	-38.07	32.29	13.49	25.16	-15.25	61.94	-2.32	8.59	-19.09	21.66
Rural-1	-9.03	12.07	-23.19	15.12	17.56	19.11	4.22	40.69	-9.09	10.25	-27.25	18.27
Rural-2	-9.61	10.41	11.69	30.77	16.06	16.56	11.69	30.77	-3.27	5.76	-12.03	5.64

Table 7

Comparison of RMSE and R-Values with other published works from till date

Author/Year	Algorithm	Case Study/Band	RMSE (dB)	R-Value Obtained
[33]	ANN/ BPN/Feed-Forward Network	1835–1850 MHz	-	0.90
[67]	ANN/ BPN/Feed-Forward Network	900, 1800, 2100, and 2400	-	0.95
[83]	ANN/ BPN/Feed-Forward Network	450 MHz, 850 MHz, 1850 MHz, 2100 MHz, 2600 MHz	-	0.85
[64]	ANN/ BPN/Feed-Forward Network	189.25 MHz and 479.25 MHz	6.06	0.87
[34]	ANN/ BPN/Feed-Forward Network	450 MHz, 1450 MHz and 2300 MHz	8.52	0.81
[37]	Feed-forward DNN	800 – 70,000 MHz	8.27	0.77
Proposed Model (Faruk et. al., 2022)	ANN/ BPN/Feed-Forward Network	89.3 MHz, 103.5 MHz, 203.25MHz, 429.25 MHz, 529.25MHz, 615.25MHz, 629.25MHz, 900MHz, 1800 MHz	4.81	0.96

**Fig 5.** Graph of cross validation of the models against distances

Distance Validation

Performance of the models were tested across distances. Six distance categories were considered during the validation process; and, these include (i) distances less than 1 km which is applicable for typical microcells deployment, i.e. $d > 1\text{km}$, (ii) distances above 1 km but less than 2 km (i.e. $1\text{km} < d < 2\text{km}$), (iii) $d < 5\text{ km}$, (iv) $d < 10\text{ km}$, (v) $d > 20\text{ km}$, and (vi) $d > 30\text{ km}$.

Fig. 5 illustrates the performance of the proposed ANN model compared to the empirical models across distances. The proposed model produces a better result of RMSE at distance $d < 1\text{km}$ compared to both Hata and Egli models. The proposed ANN model demonstrated a better performance than that of Hata and Egli models for distance $1\text{ km} < d < 30\text{ km}$, and ANN model shows the least value of an RMSE of 3.06 dB compared to Hata model which gives an RMSE of 19.54 dB for a distance above 30 km. This may be attributed to the fact that Hata model has a distance validity of 20 km; hence, a high prediction error is expected to manifest [13]. As such, the proposed model has better prediction applicability for higher distances. Table 9 reports a global comparison of some of the highest correlation coefficients (R-values) obtained from the literature. The proposed ANN model revealed the highest R-value of all times, with an R-value of 0.96 which indicates a better prediction performance for the developed model despite its multi-frequency attributes. Eqn 1-16

Conclusion

In this study, an ANN-based model for multi-frequency path loss prediction is presented. Metrics such as RMSE, ME, MAE and SDEs were used to gauge the performance of the model and compared to those of three widely used empirical models: Hata, COST 231 and Egli models. In the development, frequency, elevation, distance, and heights of the transmitter and receiver were used as inputs, while, network parameters such as a number of neurons used in the hidden layer and activation function were varied. The Scale Conjugate and the Levenberg-Marquardt algorithms were examined for the model development, of which the Levenberg-Marquardt algorithm, specifically when having a 5-20-1 network architecture, logsig activation in the hidden layer, and tansig at the output layer, was shown to provide the optimal combination. The following conclusions are drawn from this research:

- The global performance of the ANN-based model is found to be better than the empirical models. The global performance of the model relative to the empirical models revealed the smallest values of MAE, RMSE, ME and SDE of 3.11 dB, 4.81dB, -0.028 dB and 4.81 dB respectively. These values satisfy the global recommendation for an urban environment, as reported in various articles. COST 231 and HATA models revealed RMSE values of 22.27 dB and 17.37 dB respectively, thereby providing tangible evidence of the prediction applicability of the proposed ANN-Based model.
- On band-on-band basis, the proposed model outperformed the empirical models in terms of the RMSE.
- The average mean error for the proposed model is 2.56 dB, indicating that the proposed model generally, overestimated the losses. Hata and Egli models could still be used to predict path loss in open areas. the proposed model can be de-

ployed across all categories (open, suburban and urban) since the average RMSE values are all within the acceptable thresholds.

- The proposed ANN model demonstrated a better performance than that of Hata and Egli model for distances $1 \text{ km} < d < 30 \text{ km}$. The proposed model has better prediction applicability for higher distances.
- The proposed ANN model revealed the highest R-value of all times, with an R-value of 0.96 which indicates a better prediction performance for the developed model despite its multi-frequency attributes.

Declaration of Competing Interest

All co-authors have seen and agreed with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original unpublished work, is not being submitted for publication elsewhere at the same time and it is not under review at any other publication.

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References

- [1] ITU, Measuring digital development: Facts and figures 2021 (2022) <https://www.itu.int/en/ITU-D/Statistics/Pages/facts/default.aspx>.
- [2] CISCO, Cisco Annual Internet Report (2018–2023) White Paper, IEEE Trans. Antennas Propag. (2022) <https://www.cisco.com/c/en/us/solutions/collateral/executive-perspectives/annual-internet-report/white-paper-c11-741490.html>.
- [3] S.I. Popoola, N. Faruk, C.T. Calafate, L.A. Olawoyin, V.O. Matthews, A.A. A. Standard Propagation Model Tuning for Path Loss Predictions in Built-Up Environments, Computational Science and Its Applications – ICCSA 2017 (2017) 363–375, doi:[10.1007/978-3-319-62407-5_26](#).
- [4] N. Faruk, N.T. Surajudeen-Bakinde, A. Abdulkarim, S. I. Popoola, A. Abdulkarim, L. A. Olawoyin, A. A. Atayero, ANFIS Model for Path Loss Prediction in the GSM and WCDMA Bands in Urban Area, ELEKTRIKA- Journal of Electrical Engineering 18 (1) (2019) 1–10, doi:[10.11113/elektrika.v18n1.140](#).
- [5] Faruk Abdulkarim, A., Surajudeen-Bakinde, N. T., & Popoola, S. I., N. (2019). Energy Efficiency of Backhauling Options for Future Heterogeneous Networks. In Advances on Computational Intelligence in Energy. In C. H. Herawan T. Abawajy J. (Ed.), *Advances on Computational Intelligence in Energy: The Applications of Nature-Inspired Metaheuristic Algorithms in Energy, Green Energy and Technology* (pp. 169–194). Springer, Cham. Green Energy and Technology. doi:[10.1007/978-3-319-69889-2_9](#).
- [6] Faruk Oloyede, A. A., Abdulkarim, A., Olawoyin, L. A., & Adediran, Y. A., N. (2019). Energy Savings in Heterogeneous Networks with Self-Organizing Backhauling. In Advances on Computational Intelligence in Energy. In C. H. Herawan T. Abawajy J. (Ed.), *Advances on Computational Intelligence in Energy: The Applications of Nature-Inspired Metaheuristic Algorithms in Energy, Green Energy and Technology*. Springer. doi:[10.1007/978-3-319-69889-2_6](#).
- [7] K. Faruk Ruttik, E. Mutafungwa, R. Jäntti, N. Energy savings through self-backhauling for future heterogeneous networks, Energy 115 (1) (2016) 711–721, doi:[10.1016/j.energy.2016.09.059](#).
- [8] E.P. Angeles, C.D. J. D, Neural network-based path loss prediction for digital TV macrocells, in: 2015 International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), 2015, pp. 1–9, doi:[10.1109/HNICEM.2015.7393223](#).
- [9] B.O.H. Akinwale, J.B. J. Comparative Analysis of Empirical Path Loss Model for Cellular Transmission in Rivers State, American Journal of Engineering Research (AJER) 02 (08) (2013) 24–31.
- [10] N Popoola Faruk, A Aderemi, M. Atayero, Adeyeye Oshin, W. Olayiwola, Bello, S.I. Matthew Adigun, Radio Access Technologies for Sustainable Deployment of 5G Networks in Emerging Markets, International Journal of Applied Engineering Research (IJAER) 12 (24) (2017) 14154–14172 https://www.ripublication.com/ijaer17/ijaerv12n24_27.pdf.
- [11] S.I. Faruk Popoola, N.T. Surajudeen-Bakinde, A.A. Oloyede, a. Abdulkarim, L.A. Olawoyin, M. Ali, c.T. Calafate, A.A. Atayero, N, Path loss predictions in the VHF and UHF bands within urban environments: experimental investigation of empirical, heuristics and geospatial models, IEEE Access 7 (2019), doi:[10.1109/ACCESS.2019.2921411](#).
- [12] E. Greenberg, E. Klodzh, Comparison of Deterministic, Empirical and Physical Propagation Models in Urban Environments, in: IEEE International Conference on Microwaves, Communications, Antennas and Electronic Systems, 1, 2015, pp. 659–663, doi:[10.1109/COMCAS.2015.7360394](#).
- [13] N Faruk, A.A. A, A.A. YL Karadzinov, T Capuder, K Mokhtar (Eds.), Error Bounds of Empirical Path Loss Models at VHF/UHF Bands in Kwara State, Nigeria, Eurocon 2013 (2013), doi:[10.1109/EUROCON.2013.6625043](#).
- [14] N. Jimoh Faruk, N.T. Surajudeen-Bakinde, O.W. Bello, A.A. Ayeni, A A, Assessment of Multipath and Shadowing Effects on UHF Band in Build-Up Environments, ATBU Journal of Environmental Technology 10 (1) (2017) 1–11.
- [15] N.T. Jimoh Surajudeen-Bakinde, N Faruk, A.A. Adeseko, O.O. Obiyemi, O.W. Bello, A A, Performance Analysis of Empirical Path Loss Models in VHF and UHF Bands, 2015 6th International Conference on Information and Communication Systems (ICICS), 2015, doi:[10.1109/IACS.2015.7103226](#).
- [16] N. Onidare Faruk, O.W. Bello, M.Y. Muhammad, O. Sowande, A.A. Ayeni, O S, Practical Error Bounds of Empirical Models at VHF/UHF Bands, Bayero Journal of Engineering and Technology 11 (1) (2016) 28–39 https://www.bayerojet.com/wp-content/uploads/journal/published_paper/volume-11/issue-1/bjett_zYOfq4m9.pdf.
- [17] N. Afolayan Faruk, O.W. Bello, A.A. Ayeni, M.H. Ali, M.O. Olufemi, B. G, Error Analysis for Empirical Path-Loss Models in GSM and WCDMA Bands in the Urban Area, Journal of Science, Technology, Mathematics and Education (JOSTMED) 11 (1) (2015) 38–46 https://jostmed.futminna.edu.ng/images/JOSTMED/jostmed_11_1_April_2015/Error_Analysis_For_Empirical_Path_Loss_Models_in_GSM_and_WCDMA_Bands_in_Kano_Metropolis_of_Nigeria.pdf.
- [18] O.W. Faruk Bello, A.A. Oloyede, N.T. Surajudeen-Bakinde, O. Obiyemi, L.A. Olawoyin, M Ali, A. Jimoh, N, Clutter and terrain effects on path loss in the VHF/UHF bands. IET Microwaves, Antennas & Propagation, The Institution of Engineering and Technology 12 (1) (2018) 69–76, doi:[10.1049/iet-map.2016.0809](#).
- [19] N.T. Jimoh Surajudeen-Bakinde, N. Faruk, O.W. Bello, A.A. Ayeni, A A, Clutter Height Variation Effects on Frequency Dependent Path Loss Models at UHF Band in Build-Up Areas, Science, Technology & Arts Research (STAR) Journal 4 (4) (2016) 138–147, doi:[10.4314/star.v4i4.21](#).
- [20] N Oloyede Faruk, O.W. Bello, A A, Variation of clutter height and its impact on path loss in the VHF/UHF band, 2016 Advances in Wireless and Optical Communications (RTUWO), 2016, doi:[10.1109/RTUWO.2016.7821870](#).
- [21] N. Surajudeen-Bakinde Faruk, S.I. Popoola, M.A. Salman, A.A. Oloyede, L.A. Olawoyin, C.T. Calafate, T N, Path loss predictions for multi-transmitter radio propagation in VHF bands using Adaptive Neuro-Fuzzy Inference System, Engineering Science and Technology, an International Journal 21 (4) (2018) 679–691, doi:[10.1016/j.jestech.2018.05.013](#).
- [22] I.Y. Faruk Abdulrasheed, N.T. Surajudeen-Bakinde, E. Adetiba, A.A. Oloyede, A. Abdulkarim, A.A. Atayero, N, Large-Scale Radio Propagation Path Loss Measurements and Predictions in the VHF and UHF Bands, Heliyon, E07298 7 (6) (2021), doi:[10.1016/j.heliyon.2021.e07298](#).

- [23] M.M. Banimelhem Al-Zu'bi, M.S.O. Al Salameh, Hata path loss model tuning for cellular networks in Irbid City, in: 2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing IEEE, 2015, pp. 1646–1650, doi:[10.1109/CIT/IUCC/DASC/PICOM.2015.248](https://doi.org/10.1109/CIT/IUCC/DASC/PICOM.2015.248).
- [24] A.G. Cavalcanti Assuncao, L.M. Mendonca, J. B. Optimizing Empirical Propagation Models for LTE and LTE - Using Genetic Algorithms at 879 MHz, 2017 IEEE-APS Topical Conference on Antennas and Propagation in Wireless Communications (APWC), 2017, doi:[10.1109/APWC.2017.8062313](https://doi.org/10.1109/APWC.2017.8062313).
- [25] A.A. Faruk Ayeni, Y.A. Adediran, N.T. Surajudeen, N. Improved Path Loss Model for Predicting DTV Coverage for Secondary Access, Int. J. Wireless and Mobile Computing 7 (6) (2014) 565–576, doi:[10.1504/IJWMC.2014.065607](https://doi.org/10.1504/IJWMC.2014.065607).
- [26] N. Faruk, A.A. A. A. Y. Optimization of Davidson Model Based On RF Measurement Conducted In UHF/VHF Bands, Proceeding 6th IEEE Conference on Information Technology, Jordan, IEEE ICIT, 2013.
- [27] Hanci, I.H. Cavdar, Y. B. Mobile radio propagation measurements and tuning the path loss model in urban areas at GSM-900 band in Istanbul-Turkey, in: In IEEE 60th Vehicular Technology Conference, 2004. VTC2004-Fall. 2004, 1, 2004, pp. 139–143, doi:[10.1109/VETECF.2004.1399948](https://doi.org/10.1109/VETECF.2004.1399948).
- [28] S.E. Greenberg Greenberg, Simulations and measurements of the radio channel propagation parameters in urban and industrial environments for emergency localization, 2011 IEEE Int. Conf. on Microwaves, Communications, Antennas and Electronics Systems (COMCAS) (2011) 1–7, doi:[10.1109/COMCAS.2011.6105943](https://doi.org/10.1109/COMCAS.2011.6105943).
- [29] R. Benmus Abboud, M.K. Shater, A. T. Neural Network Approach to Model the Propagation Path Loss for Great Tripoli Area at 900, 1800, and 2100 MHz Bands, in: 16th International Conference on Sciences and Techniques of Automatic Control & Computer Engineering Monastir, IEEE, 2015, pp. 793–798, doi:[10.1109/STA.2015.7505236](https://doi.org/10.1109/STA.2015.7505236).
- [30] G. Cerri, M. Cinalli, F. Michetti, P. Russo, Feed forward neural networks for path loss prediction in urban environment, IEEE Trans. Antennas Propag. 52 (11) (2004) 3137–3139, doi:[10.1109/TAP.2004.835252](https://doi.org/10.1109/TAP.2004.835252).
- [31] F.S. Dela Cruz Caluyo, C. J. Heuristic Modelling of Path Loss Inside Residences at 677 MHz, 7th IEEE International Conference Humanoid, Nanotechnology, Information Technology, Palawan: IEEE, 2014, doi:[10.1109/HNICEM.2014.7016246](https://doi.org/10.1109/HNICEM.2014.7016246).
- [32] E.P. Delos Angeles Dadios, C. J. Heuristic Modelling of Path Loss Inside Residences at 677 MHz, 8th IEEE International Conference Humanoid, Nanotechnology, Information Technology, Cebu: IEEE (2015), doi:[10.1109/HNICEM.2015.7393223](https://doi.org/10.1109/HNICEM.2015.7393223).
- [33] D.O. Eichie Oyedum, O.M. Ajewole, M.A. Aibinu, J. O. Comparative Analysis of Basic Models and Artificial Neural Network Based Model for Path Loss Prediction, Progress In Electromagnetics Research (2017) 133–146, doi:[10.2528/PIERM17060601](https://doi.org/10.2528/PIERM17060601).
- [34] C. Jo Park, E. Lee, H.K. Choi, J. Park, S. H. Path Loss Prediction based on Machine Learning Techniques: Principal Component Analysis, Artificial Neural Network and Gaussian Process, Sensors 20 (7) (2020), doi:[10.3390/s20071927](https://doi.org/10.3390/s20071927).
- [35] A. Muhammed, N. Salman Faruk, T. N. Surajudeen-Bakinde, A. Abdulkarim, A. Oloyede, Lukman, S.I.P. Olawoyin, Adaptive Neuro-Fuzzy Model for Path Loss Prediction in the VHF Band, in: In Pro. IEEE International Conference on Computing, Networking and Informatics (ICCNi 2017), 2017, pp. 1–6, doi:[10.1109/ICCNi.2017.8123768](https://doi.org/10.1109/ICCNi.2017.8123768).
- [36] Nadir, M., Z. Idrees Ahmad, A. Swiątek Grzech, P. Swiątek, J. Tomczak, J. RF Coverage and Pathloss Forecast Using Neural Network, Advances in Systems Science, 240, Springer, Cham, 2014, doi:[10.1007/978-3-319-01857-7_36](https://doi.org/10.1007/978-3-319-01857-7_36).
- [37] Nguyen, A.A. Cheema, C. A deep neural network-based multi-frequency path loss prediction model from 0.8 GHz to 70 GHz, Sensors 21 (15) (2021), doi:[10.3390/s21155100](https://doi.org/10.3390/s21155100).
- [38] OMAR AHMADIEN TUNCER BAYKAS, K. BAHADIR, H.F.A. GUNTURK, Predicting Path Loss Distribution of an Area From Satellite Images Using Deep Learning, IEEE Access 8 (2020) 64982–64991, doi:[10.1109/ACCESS.2020.2985929](https://doi.org/10.1109/ACCESS.2020.2985929).
- [39] H.-J. Oustlin Zepernick, H. Suzuki, E. Macroccl Path-Loss Prediction Using Artificial Neural Network, IEEE Trans. on Vehicular Technology 59 (6) (2010) 2735–2747, doi:[10.1109/TVT.2010.2050502](https://doi.org/10.1109/TVT.2010.2050502).
- [40] M. Ozdemir Alkan, M. Kabak, M. Gulsen, M.H. Sazli, R. A. The Prediction of Propagation Loss of FM using Artificial Neural Network, J. Electromagn. Anal. Appl. 6 (11) (2014) 358–365, doi:[10.4236/jemaa.2014.611036](https://doi.org/10.4236/jemaa.2014.611036).
- [41] D.K. Park Tetey, H.-S. Jo, C. Artificial neural network modeling for path loss prediction in urban environments, ArXiv Preprint ArXiv (2019), doi:[10.48550/arXiv.1904.02383](https://doi.org/10.48550/arXiv.1904.02383).
- [42] E. Popoola Adetiba, A.A. Atayero, V.O. Mathews, N. Faruk, C.T. Calafate, I. S. Optimal Path Loss Prediction Model For Rural Propagation Environments Using Feed-Forward Neural Networks, Cogent Engineering, Taylor and Francis (2018) 144–434, doi:[10.1080/23311916.2018.1444345](https://doi.org/10.1080/23311916.2018.1444345).
- [43] N. Popoola Faruk, N.T. Surajudeen-Bakinde, A.A. Atayero, S. Misra, I. S. S. Tripathi Upadhyaya, M. Artificial Neural Network Model for Path Loss Predictions in the VHF Band, in: Conference Proceedings of ICDLAIR2019. ICDLAIR 2019. Lecture Notes in Networks and Systems, 175, Springer, Cham, 2021, doi:[10.1007/978-3-030-67187-7_18](https://doi.org/10.1007/978-3-030-67187-7_18).
- [44] A. Popoola Jafia, A.A. Atayero, O. Kingsley, N. Faruk, O.F. Oseni, R.O. Abolade, I. S. Determination of neural network parameters for path loss prediction in very high frequency wireless channel, IEEE Access 7 (2019) 150462–150483, doi:[10.1109/ACCESS.2019.2947009](https://doi.org/10.1109/ACCESS.2019.2947009).
- [45] S.K. Sotiroudis Goudos, K.A. Gotsis, J. Siakavara, J.N. Sahalos, P. S. Application of a composite differential evolution algorithm in optimal neural network design for propagation path-loss prediction in mobile communication systems, IEEE Antennas and Wireless Propagation Letter 12 (2013) 364–367, doi:[10.1109/LAWP.2013.2251994](https://doi.org/10.1109/LAWP.2013.2251994).
- [46] N. Surajudeen-Bakinde Faruk, A. Oloyede, A. Abdulkarim, L. Olawoyin, S. Popoola, E. Adetiba, N. Effect of Membership Functions and Data Size on the Performance of ANFIS-Based Model for Predicting Path Losses in the VHF and UHF Bands, Journal of Engineering Research (2021) 1–37, doi:[10.36909/jer.10457](https://doi.org/10.36909/jer.10457).
- [47] T. Tahat Edwan, H. Al-Sawwaf, J. Al-Baw, M. Amayreh, A. Simplistic Machine Learning-Based Air-to-Ground Path Loss Modeling in an Urban Environment, in: 2020 Fifth International Conference on Fog and Mobile Edge Computing (FMEC), 2020, pp. 158–163, doi:[10.1109/FMEC49853.2020.9144965](https://doi.org/10.1109/FMEC49853.2020.9144965).
- [48] D. Wu He, B. Ai, J. Wang, H. Qi, K. Guan, Z. Zhong, L. Artificial neural network based path loss prediction for wireless communication network, IEEE Access 8 (2020) 199523–199538, doi:[10.1109/ACCESS.2020.3035209](https://doi.org/10.1109/ACCESS.2020.3035209).
- [49] G. Wu Zhu, B. Ai, D. Application of artificial neural networks for path loss prediction in railway environments, in: 2010 5th International ICST Conference on Communications and Networking in China, 2010, pp. 1–5.
- [50] J. Zhang Wen, G. Yang, Z. He, J.Y. Wang, Path Loss Prediction Based on Machine Learning: Principle, Method, and Data Expansion, Applied Sciences 9 (9) (2019), doi:[10.3390/app9091908](https://doi.org/10.3390/app9091908).
- [51] Z.K. Adeyemo, T.O. A. O.F. O. O. S.I. Development of a Path-loss Prediction Model Using Adaptive Neurofuzzy Inference System, International Journal of Wireless and Microwave Technologies 9 (6) (2019) 40–53, doi:[10.5815/ijwmt.2019.06.05](https://doi.org/10.5815/ijwmt.2019.06.05).
- [52] P. Phaiboon Phokharatkul, S. Somkuarnpanit, S. Boonpiyathud, S. Microwave line-of-sight path loss prediction on urban street by fuzzy logic model, in: 2005 Asia-Pacific Microwave Conference Proceedings, 2005, doi:[10.1109/APMC.2005.1606797](https://doi.org/10.1109/APMC.2005.1606797).
- [53] Hojjat, S. Nazmul, A. Computational Intelligence Synergies of Fuzzy Logic, Neural Networks and Evolutionary Computing (First), John Wiley & Sons, 2013, doi:[10.1002/9781118534823](https://doi.org/10.1002/9781118534823).
- [54] J. Jafri, J. Ely, J. L. Vahala, M. L. Interference Path Loss Prediction in A319/320 Airplanes Using Modulated Fuzzy Logic and Neural Networks, NAFIPS 2007 - 2007 Annual Meeting of the North American Fuzzy Information Processing Society, 2007, doi:[10.1109/NAFIPS.2007.383861](https://doi.org/10.1109/NAFIPS.2007.383861).
- [55] C.O. Mgbe, J.M. Mom, G.A. Igwe, Performance evaluation of generalized regression neural network path loss prediction model in macrocellular environment, Performance Evaluation 2 (2) (2015).
- [56] D.C. Abraham, Development and Comparison of Artificial Neural Network Techniques for Mobile Network Field Strength Prediction across the Jos-Plateau, Nigeria. Development 3 (6) (2016).
- [57] J. Idogho, G. George, Path Loss Prediction Based On Machine Learning Techniques: Support Vector Machine, Artificial Neural Network, And Multilinear Regression Model, Open Journal of Physical Science 3 (2) (2022) 1–22 (ISSN: 2734-2123).
- [58] V.C. Ebhota, V.M. Srivastava, Effect of Architectural Composition of MLP ANN in Neural Network Learning for Signal Power Loss Prediction, J. Commun. 16 (1) (2021) 20.

- [59] A.R. Igwe, V.I.E. Anireh, N.D. Nwaibu, A Predictive Optimization Model for Path Loss Minimization for GSM Based Network Using Neuro-Swarm Intelligence (2022).
- [60] J. Isabona, V.M. Srivastava, A neural network based model for signal coverage propagation loss prediction in urban radio communication environment, *International Journal of Applied Engineering Research* 11 (22) (2016) 11002–11008.
- [61] J.A. Fernández Anitzine Romo Argota, F.P. Fontán, I. Influence of training set selection in artificial neural network-based propagation path loss predictions, *International Journal of Antennas and Propagation* (2012), doi:[10.1155/2012/351487](https://doi.org/10.1155/2012/351487).
- [62] M. Gómez-Pérez Crego-García, I. Cuiñas, R.F. Caldeirinha, P. Modeling and inferring the attenuation induced by vegetation barriers at 2G/3G/4G cellular bands using Artificial Neural Networks, *Measurement* 98 (2017) 262–275, doi:[10.1016/j.measurement.2016.12.014](https://doi.org/10.1016/j.measurement.2016.12.014).
- [63] K. Kalakh Kandil, N. Hakem, M. Neural Networks Model of an UWB Channel Path Loss in a Mine Environment, 2012 IEEE 75th Vehicular Technology Conference (VTC Spring), 2012, doi:[10.1109/VETECS.2012.6240318](https://doi.org/10.1109/VETECS.2012.6240318).
- [64] Popoola, N. Faruk, A. Oloyede, A. Atayero, N. Surajudeen-Bakinde, L. Olawoyin, I S, Characterization of Path Loss in the VHF Band using Neural Network Modeling Technique, in: 19th International Conference on Computational Science and Its Applications (ICCSA), 2019, pp. 166–171, doi:[10.1109/ICCSA.2019.00017](https://doi.org/10.1109/ICCSA.2019.00017).
- [65] Y. Wen Zhang, G. Yang, Z. He, W. Zhang, J. Path loss prediction based on machine learning methods for aircraft cabin environments, *IEEE Access* 7 (2019) 159251–159261, doi:[10.1109/ACCESS.2019.2950634](https://doi.org/10.1109/ACCESS.2019.2950634).
- [66] N. Zaarour Kandil, N. Hakem, C.N. Despins, Comparative experimental study on modeling the path loss of an UWB channel in a mine environment using MLP and RBF neural networks, 2012 International Conference on Wireless Communications in Underground and Confined Areas, 2012, doi:[10.1109/ICWCUCA.2012.6402503](https://doi.org/10.1109/ICWCUCA.2012.6402503).
- [67] M. Zineb Ayadi, B. A. A multi-wall and multi-frequency indoor path loss prediction model using artificial neural networks, *Arabian Journal for Science and Engineering* 41 (3) (2016) 987–996, doi:[10.1007/s13369-015-1949-6](https://doi.org/10.1007/s13369-015-1949-6).
- [68] Piacentini, F. Rinaldi, M. Path loss prediction in urban environment using learning machines and dimensionality reduction techniques, *Computational Management Science* 8 (4) (2011) 371–385, doi:[10.1007/s10287-010-0121-8](https://doi.org/10.1007/s10287-010-0121-8).
- [69] I. Popescu Nafornta, P. Constantinou, I. Comparison of Neural Network Models for Path Loss Prediction, in: IEEE International Conference on Wireless And Mobile Computing, Networking And Communications, 2005, pp. 44–49, doi:[10.1109/WIMOB.2005.1512814](https://doi.org/10.1109/WIMOB.2005.1512814).
- [70] K. Sotiroidis Siakavara, J.N. Sahalos, P S, A Neural Network Approach to the Prediction of the Propagation Path Loss For Mobile Communications Sysstems in Urban Environments, in: PIERs Proceedings, 2007, pp. 162–166, doi:[10.2529/PIERS070220023434](https://doi.org/10.2529/PIERS070220023434).
- [71] I. Popescu Nafomita, P. Constantinou, A. Kanatas, N. Moraitis, I. Neural networks applications for the prediction of propagation path loss in urban environments, in: IEEE VTS 53rd Vehicular Technology Conference, Spring 2001. Proceedings (Cat. No. 01CH37202), 1, 2001, pp. 387–391, doi:[10.1109/VETECS.2001.944870](https://doi.org/10.1109/VETECS.2001.944870).
- [72] X. Liu Jin, F. Dong, L. He, H. Liu, J. Fading channel modelling using single-hidden layer feedforward neural networks, *Multidimension. Syst. Signal Process.* 28 (3) (2017) 885–903, doi:[10.1007/s11045-015-0380-1](https://doi.org/10.1007/s11045-015-0380-1).
- [73] O.D. Eichie Oyedum, M.O. Ajewole, A.M. Aibinu, O. J. Artificial Neural Network model for the determination of GSM Rxlevel from atmospheric parameters, *Engineering Science and Technology, an International Journal* 20 (2) (2017) 795–804, doi:[10.1016/j.jestch.2016.11.002](https://doi.org/10.1016/j.jestch.2016.11.002).
- [74] R. Bhuvaneshwari Hemalatha, T.A. Satyasavithri, Performance evaluation of dynamic neural networks for mobile radio path loss prediction, in: 2016 IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics Engineering (UPCON), 2016, pp. 461–466, doi:[10.1109/UPCON.2016.7894698](https://doi.org/10.1109/UPCON.2016.7894698).
- [75] L.J. Ferreira Matos, J.M. Silva, P. G. Improvement of outdoor signal strength prediction in UHF band by artificial neural network, *IEEE Trans. Antennas Propag.* 64 (12) (2016) 5404–5410, doi:[10.1109/TAP.2016.2617379](https://doi.org/10.1109/TAP.2016.2617379).
- [76] X. Zhang Wen, L. Wang, Z. Lu, L.C. Ma, Performance Evaluation of Candidate Protocol Stack for Service-Based Interfaces in 5G Core Network, in: 2018 IEEE International Conference on Communications Workshops (ICC Workshops), 2018, pp. 1–6, doi:[10.1109/ICCW.2018.8403675](https://doi.org/10.1109/ICCW.2018.8403675).
- [77] Sotiroidis, K. Siakavara, P S, Mobile radio propagation path loss prediction using artificial neural networks with optimal input information for urban environments, *AEU-International Journal of Electronics and Communications* 69 (10) (2015) 1453–1463, doi:[10.1016/j.aeue.2015.06.014](https://doi.org/10.1016/j.aeue.2015.06.014).
- [78] M. Hata, Empirical formula for propagation loss in land mobile radio ser-vice, *IEEE Trans. on Vehicular Technology* VT-29 (1980) 317–325, doi:[10.1109/T-VT.1980.23859](https://doi.org/10.1109/T-VT.1980.23859).
- [79] COST 231, Urban transmission loss models for mobile radio in the 900 and 1800 MHz bands (revision 2), COST 231. TD (90) 119 Rev. 2 (1991).
- [80] J.J. Egli, Radio propagation above 40 MHz over irregular terrain, *Proc IRE* 45 (10) (1957) 1381–1391, doi:[10.1109/JRPROC.1957.278224](https://doi.org/10.1109/JRPROC.1957.278224).
- [81] S.K. Sotiroidis Goudus, K.A. Gotsis, K. Siakarva, J.N. Sahalos, P S, Optimal Artificial Neural Networ Design for Propagation Path-Loss Prediction Using Adaptive Evolutionary Algorithms, in: 2013 7th European Conference on Antennas and Propagation (EuCAP), 2013, pp. 3795–3799.
- [82] Y.A. Faruk Adediran, A.A. Ayeni, N. On the study of empirical path loss models for accurate prediction of TV signal for secondary users, *Progress in Electromagnetic Research (PIER) B*, Published by Electromagnetics Academy, USA 49 (2013) 155–176, doi:[10.2528/PIERB13011306](https://doi.org/10.2528/PIERB13011306).
- [83] M. Ayadi, A. Ben Zineb, S. Tabbane, A UHF Path Loss Model Using Learning Machine for Heterogeneous Networks, *IEEE Trans. Antennas Propag.* 65 (7) (2017) 3675–3683, doi:[10.1109/TAP.2017.2705112](https://doi.org/10.1109/TAP.2017.2705112).