Sub-Sahara African Academic
Research Publications
March, 2023, Editions

JASOR
Journal of Advanced Science and Optimization Research
Vol. 27, No.9, ISSN 2418-9325

MOBILE RADIO PROPAGATION: A REVIEW

AFEARE, MARK OISAKHODION; ABRAHAM, USMAN USMAN; AND SULEIMAN, ZUBAIR[1]

Telecommunication Engineering Department, Federal University of Technology Minna, Nigeria

ABSTRACT

Path loss represents the reduction in signal strength of the transmitted signal caused by large scale fading along the communication path. Having accurate path loss models becomes essential during the deployment of wireless systems. Many different propagation models are available for different types of terrain, and their performances are location dependent and site specific. However, in order to obtain a dependable path loss model for a given area, a general model needs to be tuned. The tuned model can then be used by engineers to determine the correct values of parameters such as base station (BS) location, transmitter and receiver antenna height, down tilt angle, transmitted power, and frequency. The four major path loss propagation models, empirical, physical/analytical semi-empirical and deterministic have enjoyed much attention from researchers because of their ease of use, simplicity and less computational efforts. However it failed to take into consideration the physical composition of the target environment thus making them venerable to high prediction error when applied to a similar environment different from which it was designed. The difficulties experienced by the researchers determining the detailed information about the propagation environment prompted the heuristic model. Heuristic models involve nature-inspired computational intelligence in determining path loss also known as computational intelligence (CI). However the need to develop an improved dependable path loss for a given area has been very challenging by most researchers.

This paper reviews both the traditional models and the computational intelligence and incidentally opens new research issues and future research directions.

Keywords: Path loss, traditional models heuristic, computational intelligence,

INTRODUCTION

Since the birth of communications, mankind has always depended on the presence of a communications channel, even before the invention of modern technologies and techniques that replaced more traditional communication channels. The modern communication channel exists both in wired and wireless forms, and a plethora of applications and technologies are able to use both communication media effectively.

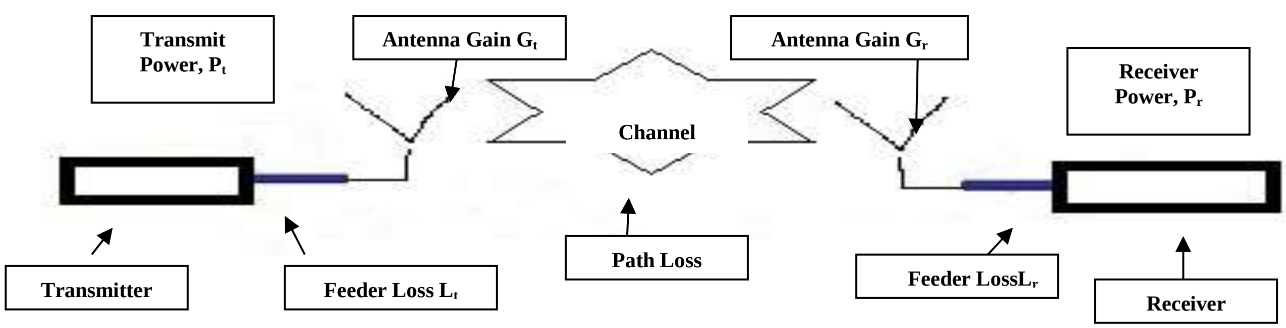


Figure 1.1 Elements of Wireless Communication System

The wireless form of communication techniques has enjoyed a wide acceptance due to its support for mobility. Wireless devices and applications are used for different purposes in various sectors including health, education, e-commerce, transportation, smart agriculture, disaster, social networks, and many others. Wireless systems infrastructure has also been deployed to support broadcasting, public safety communications, and cellular mobile telephony. In particular, the most widely deployed technology is the cellular mobile communications networks. Broadband Internet provision is of particular interest in meeting the sustainable development goals (SDGs), particularly, in the developing economies. Successful deployment of a wireless communications network would require optimum planning and proper design of the entire system, with more focus on its physical layer interface. The physical layer interface is the one that allows to interconnect users and the wired network, defining the quality of service (QoS) delivered by the providers and also the quality of experience (QoE) as perceived by the users, being that such features allow assessing how sophisticated and robust the physical layer interface really is. While designing the physical layer of wireless systems, many different parameters are brought forward for consideration, including QoS, coverage area, transmitted frequency, transmitted power, received power, and system budget. Thus, to determine how effective the values of these parameters can be when performing network planning in a particular topography, a suitable and well optimized radio frequency (RF) path loss propagation model must be applied.

Path loss represents the reduction in signal strength of the transmitted signal caused by large scale fading along the communication path. Hence, having accurate path loss models becomes essential during the deployment of wireless systems. Many different propagation models are available for different types of terrain, and their performances are location dependent and site specific. However, in order to obtain a dependable path loss model for a given area, a general model needs to be optimized and/or tuned. The optimized model can then be used by engineers to determine the correct values of parameters such as base station (BS) location, transmitter and receiver antenna height, down tilt angle, transmitted power, and frequency (Adebowale et al., 2021).

Path loss propagation models are grouped into four (i.e., empirical models, physical/analytical models, semi-empirical models, and deterministic models) (Greenberg et al., 2015). Each of these models contributes significantly to channel propagation modeling. The mentioned groups of the propagation model had contributed to the successful estimation of signal propagation loss for effective design of wireless communication systems. Among the numerous path loss models that exit, the empirical path loss propagation models have been widely used to predict the behavior of radio signals as they propagate throughout a particular environment and location. These models have enjoyed much attention from researchers because of their ease of use and simplicity, and the implementation of these empirical models requires less computational efforts. However, they failed to fully take into consideration the physical composition of the target environment, making them vulnerable to high prediction errors when applied in an environment different from which it was built for (Faruk N et al., 2019).

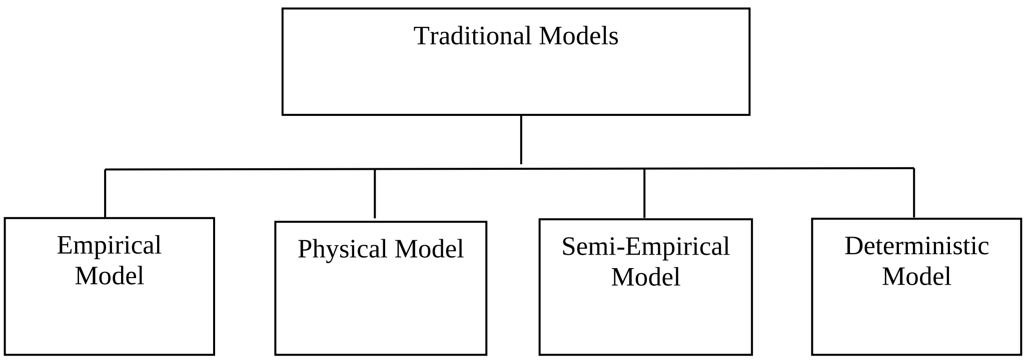


Figure 1.2: Path Loss Traditional Models

Their inability in getting detailed information about the propagating environment leads to the adoption of intelligent algorithms to predict path loss, including the artificial neural networks (ANNs) and fuzzy systems (FSs). These methods learn and adapt to any changes in the environment, thus providing a better prediction when compared with the traditional models. Nature-inspired computational methodologies, also known as computational intelligent (CI), such as the genetic algorithm (GA), particle swarm optimization (PSO), and ant colony (AC), provide a solution to the complex propagation environments where the traditional models failed (Faruk N et al., 2019). In particular, these CI methods integrate neural networks, fuzzy logic, and other natural inspired algorithms to optimize the path loss, thus reducing the errors and improving the prediction accuracy.

The CI techniques can be broadly classified into five major categories; these are depicted in Figure 3. The taxonomy presented in this paper is derived from all the reviewed literature used in this study. The categories are artificial neural networks (ANNs), fuzzy inference systems (FISs), evolutionary computing (EC), swarm intelligence (SI), and artificial immune systems (AISs).

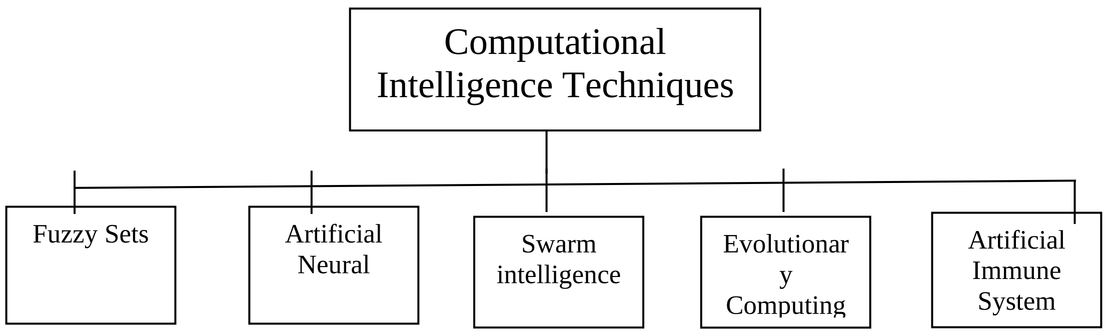


Figure 1.3: Path Loss Computational Intelligence Models

THEORETICAL BACKGROUND

The Frequency Band

Frequency Band		Frequency Range
Extremely low frequency (ELF)		< 3kHz
Very low frequency (VLF)		3-30kHz
Low frequency (LP)		30-300kHz
Medium frequency (MF)		300kHz – 3MHz
High frequency (HF)		3-30MHz
Very high frequency (VHF)		30-300 MHz
Ultra high frequency (UHF)		300MHz -3GHz
Super high frequency (SHF)		3 -30 GHz
Extra high frequency (EHF)		30 - 300GHz

Radio waves are classified into different frequencies in the electromagnetic spectrum. The path of the spectrum that includes that includes radio spectrum extends from about 30kHz to 300GHz, although radio wave propagation is actually possible down to a few kilohertz. By international agreement the radio frequency spectrum is divided into bands and each band is given a designation and in the table below.

Tabble 2.1 the Frequency Band

Path Loss

The path loss between a pair of antennas is the ratio of the transmitted power to the received power, usually expressed in decibels. It includes all of the possible elements of loss associated with interactions between the propagating wave and any objects between transmit and the receive antennas.

The power appearing at the receiver input terminals P_R can be expressed as

$$P_R = \frac{P_T G_T G_R}{L_T L L_R} \qquad (1)$$

Where the parameters are defined in Fig. 1, with all gains G and losses L expressed as power ratios and powers expressed in watts. The antenna gains are expressed with references with references to an isotropic antenna, which radiates the power delivered to it equally in all directions. The values used are those corresponding to the direction of the other antenna and may necessarily be the maximum values. The effective isotropic radiated power (EIRP) is the given by S. Saunders and A. Aragon-Zavala, (2007).

$$EIRP = \frac{P_R L_R}{G_R} \qquad (2)$$

Where P_{TI} is the effective isotropic transmit power similarly, the effective isotropic received power is P_{RI},where

$$P_{RI} = \frac{P_R L_R}{G_R} \qquad (3)$$

The advantage of expressing the powers in terms of EIRP is that the path loss, L, can then expressed independently of system parameters by defining it as the ratio between the transmitted and the received EIRP, or the loss that would be experienced in an idealized system where the feeder losses were zero and the antennas were isotropic radiators($G_{T,R} = 1, L_{T,R} = 1$) S. Saunders and A. Aragon- Zavala, (2007) andRappaport, (1996).

$$Pathloss, L = \frac{P_{TI}}{P_{RI}} = \frac{P_T G_T G_R}{P_R L_T L_R} \qquad (4)$$

The main goal of propagation modeling is to predict L as accurately as possible, allowing the range of a radio system to be determined before installation. The maximum range of the system occurs when the received power drops below a level which provides just acceptable communication quality. This level is often known as the receiver s. the value of L for which this power level is received is the maximum acceptable path loss. It is usual to express the path loss in decibels, so that S. Saunders and A. Aragon-Zavala, (2007).

$$L_{dB} = 10\log\frac{P_{TI}}{P_{RI}} \quad (5)$$

In this paper, path loss models for predicting the propagation loss for mobile network werestudied. Path loss models play a major role in planning of wireless cellular systems. They represent a set of mathematical equations and algorithms that are used for radio signal propagation prophecy in definite areas. There are three kinds of models G. S Bola and G. S Saini (2010). The study of the characteristics of radio waves in different propagation environment is needed for an effective network planning and for the deployment of wireless communication systems. The efficiency of a wireless system depends on the physical constituent of the propagation environment. The presence of building mountain billboards, foliage vehicles and other physical objects in a practical propagation environment usually obstructs the direct 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 Nasir *et al.*, (2019) as represented in Figure 1.4 and 1.5 respectively

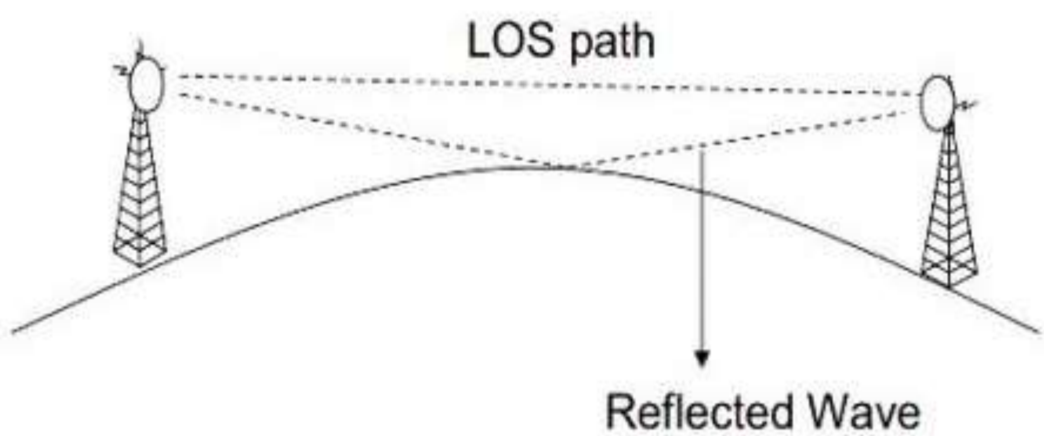


Figure 2.1 Mobile Radio Propagation in a Line of Sight scenario (LOS)

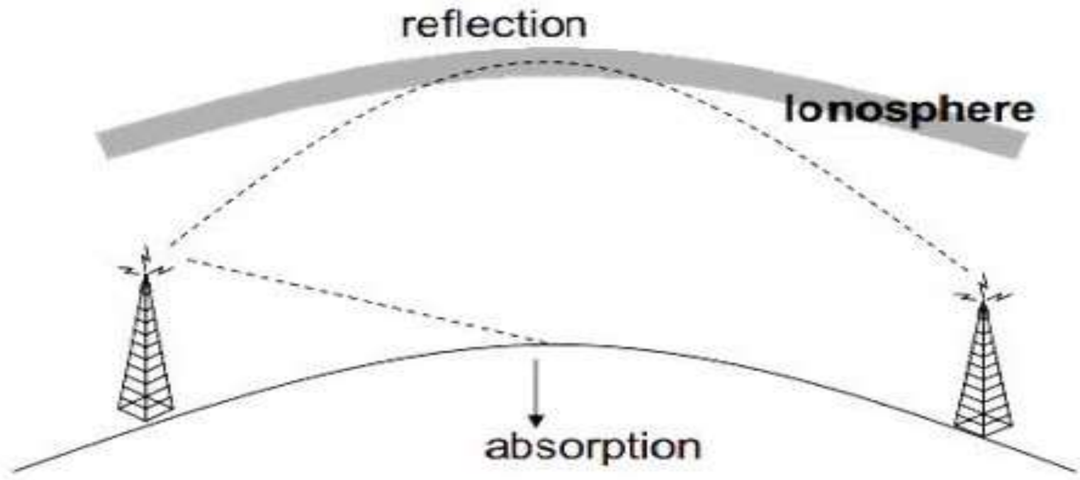


Figure 2.2 Mobile Radio Propagation in a Non-Line of Sight scenario (NLOS)

Propagation Mechanisms

The electric field strength of signals radiated from a transmitter is subject to propagation loss due to reflection, refraction, diffraction, absorption and scattering. Weak received signals and path loss due to the reduction of power density of an electromagnetic wave as it propagates from the transmitting antenna to the receiving antenna is of great concern in mobile communication. This basic propagation mechanism as represented in figure 7.2

Reflection

Radio signal gets *reflected* when it collides with an object whose dimension is large relative to the wavelength of the radiated signal.

Refraction

Refraction occurs when the transmitted electromagnetic waves move from one medium to another medium whose refraction index is different from that of the former. Refraction also occurs when radio wave propagating in one medium impinges upon another medium with different electromagnetic properties. The amplitude and phase of the reflected wave are strongly related to the medium's intrinsic impedance, incident angle, and electric field polarization. Part of the radio wave energy may be absorbed or propagated through the reflecting medium, resulting in a reflected wave that is attenuated.

Diffraction

Diffraction of radio signals takes place when the transmission path is obstructed by large objects, causing the bending of the radio wave .It is a phenomenon by which propagating radio waves bend or deviate in the neighborhood of obstacles. Diffraction results from the propagation of wavelengths into a shadowy region caused by obstructions such as walls, buildings, and mountains.

Absorption

Radio signals could also be *absorbed* when it passes through dense materials like walls or floors, trees and foliage.

Scattering

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. The event happens when a radio signal hits a rough surface or an object having a size much smaller than or on the order of the signal wavelength. This causes the signal energy to spread out in all directions. Scattering can be viewed at the receiver as another radio wave source. Typical scattering objects are furniture, lamp posts, street signs, and foliage (Akpado *et al.,* 2013).

The propagation of electromagnetic waves is usually influenced by the atmospheric conditions of the 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 (Rappaport, 1996). 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 (Faruk*et al.,* 2013). For large-scale fading, the mean received signal strength will significantly reduce as the distance increases (Greenberg and Klodzh, 2015). The large scale fading concept is also referred to as *path loss*. Several propagation models have been developed for path loss estimations under different propagation scenarios.

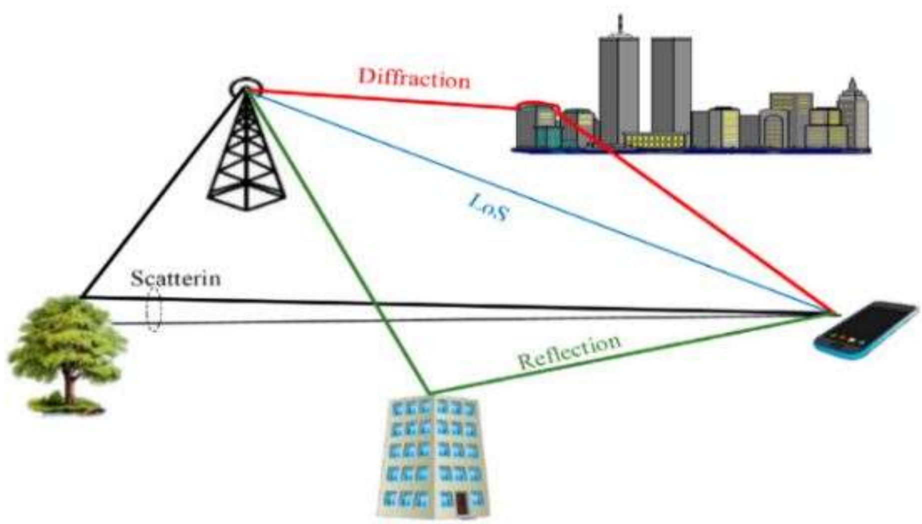


Figure 2.3 Mobile Radio Propagation in a Line of Sight LOS and Non-Line of Sight scenario (NLOS)

Propagation path loss models are useful for prediction of received signal strength at a given distance from the transmitter, estimation of radio coverage areas of Base Transceiver Stations (BTS), frequency assignments, interference analysis, handover optimization, and power level adjustment (Julia *et al.,* 2017). Due to the differences in environmental structures, local terrain profiles and weather conditions, the signal strength and path loss prediction model for a given environment using any of the existing basic path loss models such as the Okumura-Hata's model has been shown to differ from the optimal empirical model. (Julia *et al*., 2017).

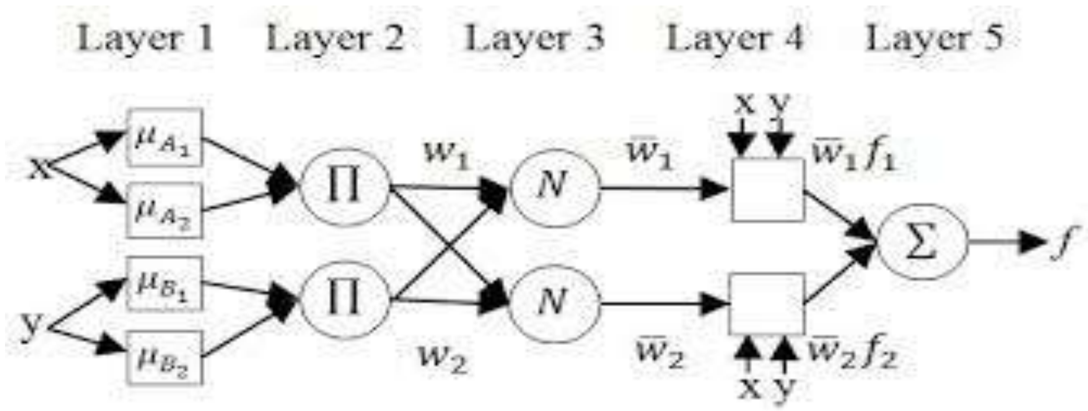


Figure 2.4 The ANFIS Structure
(Sources: Telecommunication online journals)

ANFIS Model

The Fuzzy Logic as shown in figure 2.3 is adopted as the Neuro-Fuzzy modeling approach which involves the use of expert knowledge to train a neural network structure to map a given set of input data correctly to their corresponding path loss values. In particular, it is a Fuzzy Inference System (FIS) which prepares the mapping of inputs to the respective outputs. The ANFIS method is not just a simulation method; the technique can actually be used for predicting values of a dependent variable based on a given set of values of independent variable(s). ANFIS techniques have been widely applied to solve prediction (or regression) problems in different fields of study. In this study, the input variables that determine the output variable (path loss) are the separation distance between transmitter and receiver, and the frequency of transmission. The NF model structure consists of both the Fuzzy Logic (FL) and Artificial Neural Network (ANN), which complement one another in the development of mapping the supplied inputs to their corresponding outputs. The most significant reason for this combination is that the FL system makes use of the learning ability of the ANN. The most complex part of the FL technique is in deciding on the most suitable membership functions (generalized bell, Gaussian, triangular, trapezoidal, pi, etc.) to be adopted for the inputs, as well as generating the fuzzy rules (fuzzification) for the desired outputs. The membership function defines how each point in the input space (universe of discourse)

is mapped to a membership value or degree of membership between 0 and 1. The input (antecedent) parameters are generated initially using a trial and error method. These parameters are therefore tuned by the learning ability of the ANN, which makes the errors reduction easier, as well as optimizing the output (consequent) parameters (Adebowale et al., 2021).
The structure consists of five layers, as shown in Fig. 2. The nodes in these layers are either fixed or adaptive. The adaptive nodes are symbolized by the square shapes, while the fixed nodes are represented by the circular shapes. To describe the structure, a first order Sugeno model has been used because the output is crisp, which does not require defuzzification. A Sugeno-based ANFIS has a rule of the form as given by Eqs. (6)–(7)
Rule 1: If x is A_1, and y is B_1, then:

$$f_1 = p_i x + q_i y + r_i \tag{6}$$

Rule 2: if x is A_2, and y is B_2, then:

$$f_2 = p_2 x + q_2 y + r_2 \tag{7}$$

Layer 1 : A node in this layer is adaptable, and is given as:

$$L_i^1 = \mu A_i(x), \qquad i = 1,2 \tag{8}$$

x is the input to the ith node, A_i is the alterable language related to this node, and the membership function of A_i is $lA_i(x)$, usually taken as:

$$\mu A_i(x) = \frac{1}{1+\left[\left(\frac{x-c}{a_i}\right)^2\right]^{b_i}} \tag{9}$$

$\{a_i, b_i, c_i\}$ forms a set called the antecedent parameters set. Eq. (5) represents the generalized bell membership function. Other membership functions used in the paper are the triangular, trapezoidal, Gaussian, and pi functions..
Layer 2: This layer is comprised of fixed nodes, and it solves the firing power w_i of a rule. The multiplication of the incoming signals is the output of each node, and is given by Eq. (10):

$$L_i^2 = \mu A_i(x) \times \mu B_i(y), \quad i = 1,2 \tag{10}$$

Layer 3:Each node is constant in this layer is given by Eq (11)

$$L_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i \;, \quad i = 1,2 \tag{11}$$

{p_i, q_i and r_i} also forms a set called the consequent parameters set, which are established by the least squares method.

Layer 5: The output of this layer is the summation of all incoming signals, and it is given by Eqs. (12) and (13):

$$L_i^5 = \sum_{i=1}^{2} \overline{w_i} f_i = \frac{\sum \overline{w_i} f_i}{\sum \overline{w_i} f_i} \tag{12}$$

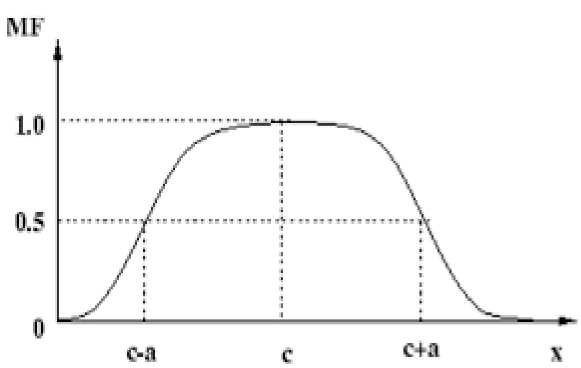
$$L_i^5 = z_p = \sum_{i=1}^{2} \overline{w_i} f_i \tag{13}$$

$$(\overline{w_1} x)p_1 + (\overline{w_1} y)q_1 + (\overline{w_1} x)r_1 + (\overline{w_1} x)p_2 + (\overline{w_1} y)q_2 + (\overline{w_2} y)r_2$$

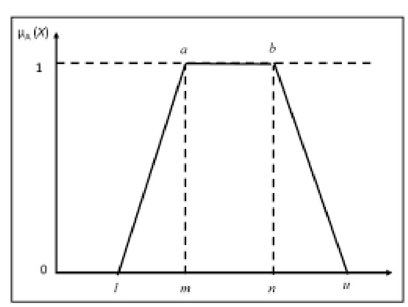
where z_p is the network predicted output.

Membership function (MF)

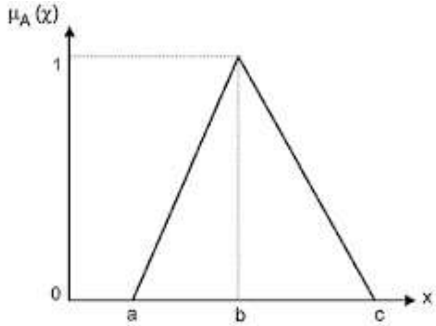
In the Membership Function (MF), m refers to the degree or grade of membership of an element in a fuzzy set, and it must vary between 0 and 1. The most commonly used membership functions are the triangular, trapezoidal, generalized bell, Gaussian, and pi functions as shown in Figure 2.5 below[34]. In this paper, we explore the impact of MF on the training RMSE for the model.



Generalized



Trapezoidal



Traiangular

Bell

Propagation Models

In order to solve the problem of capacity and coverage in cellular mobile network, network operators develop propagation models in predicting receive signal strength in the world. Propagation models are mathematical attempts to model the real radio environment as closely as possible. The propagation path loss which is a major limiting factor to coverage prediction is derived from all losses encountered by the signal in its propagation from base station (BS) tower to the mobile user or mobile station (MS)

Propagation models are useful for predicting signal attenuation or path loss which is the reduction in power of an electromagnetic wave as it propagates through space. It is a major component in analysis and design of link budget of a communication system. It depends on frequency, antenna height, receive terminal location relative to obstacles and reflectors, and link distance, among many other factors. These models can be broadly categorized into three types; empirical, deterministic and stochastic.

Empirical models

Empirical models are those based on observations and measurements alone. This model takes into account all environmental influences, but its accuracy depends on the similarities between the environment to be analyzed and the environment used in the development of the model

Deterministic models

Deterministic models make use of the laws governing electromagnetic wave propagation to determine the received signal power at a particular location. This model deals with the fundamental principles of radio wave propagation. It utilizes the governing laws of wave propagation to determine the received signal level at a particular location. The model can be applied to different environments without altering the accuracy but it is usually very complex and lack computational efficiency.

The Heuristic Models

Artificial Intelligence is a method of making a computer, a computer-controlled robot, or a software think intelligently like the human mind. AI is accomplished by studying the patterns of the human brain and by analyzing the cognitive process. The outcome of these studies develops intelligent software and systems. AI systems work by merging large with intelligent, iterative processing algorithms. This combination allows AI to learn from patterns and features in the analyzed data. Each time an Artificial Intelligence system performs a round of data processing, it tests and measures its performance and uses the results to develop additional expertise **(Barr & Feigenbaum, 1981).**

Stochastic Models

Stochastic models on the other hand, model the environment as a series of random variables.

Macro cells are generally large, providing a coverage range in kilometers and used for outdoor communication (Rappaport, 1996). Several empirical path loss models have been determined for macro cells. Among numerous propagation models, the following are the most significant ones, providing the foundation of mobile communication services. The empirical models are:

Empirical Models

Yoshihisa Hata Okumura model

The Hata-Okumura model is measurement provided by Yoshihisa Okumura, and is valid from 150 MHz to 1500 MHz; Hata presented the urban area propagation loss as a standard formula, along with additional correction factors for application in other situations such as suburban, rural among others. The computation time is short and only four parameters are required in Hata model. However, the model neglects terrain profile between transmitter and receiver, i.e. hills or other obstacles between transmitter and receiver are not considered.

This is because both Hata and Okumura made the assumption that transmitter would normally be located on hills (Yukihiko Okumura, 2017). The path loss in dB for the various environments is given in equations below:

Path loss for each measurement location is given by (Segun*et al.,* 2019) as:

$$PL_m(\text{dB}) = \text{EIRP}(\text{dBm}) - P_r(\text{dBm}) \quad (14)$$

where:

$EIRP_t$ = Effective Isotropic Radiated Power

P_r= received signal level

$$EIRP_t = P_{BTS} + G_{BTS} + G_{MS} - L_{FC} - L_{AB} + L_{CF} \quad (15)$$

The computation of path loss for all routes:

$$PL_m(\text{dB}) = P_{BTS} + G_{BTS} + G_{MS} - L_{FC} - L_{AB} + L_{CF} - Pr \quad (16)$$

where:

P_t = received signal level
P_{BTS} = transmitter power (dBm)
G_{BTS} = transmitting antenna gain (dBi)
G_{MS} = receiving antenna gain (dBi)
L_{AB} = antenna body loss (dB)
L_{FC} = feeder cable loss (dB)
L_{CF} = combiner and filter loss (dB)

Since this research would be based on observations and measurements, empirical models will be considered, and some of the most frequently used basic empirical path loss model equations (Julia *et al.,* 2017) are as follows:

Hata Model

PL(suburban)$_{Hata}$= $+\{44.9 - 6.55\ \log_{10}(h_b)\}\log_{10}(d) - 2[\log_{10} f/28]^2$ - 5.4 (17) $= 69.55\ +\ 26.16\log_{10}(f) - 13.82\, log_{10}(h_b)$
$+\{44.9 - 6.55\ \log_{10}(h_b)\}\ \log_{10}(d) -\ 4.78(\log_{10}(f))^2\ +$
$18.33(\log_{10}(f)) - K(9.5)$

PL(suburban)$_{Hata}$= $69.55 + 26.16\log_{10}(f) - 13.82\log_{10}(hb)$ (18)

PL(Rural)$_{Hata}$

where k
= 35.94

Egli Model

$PL_{Egli} = 20\log_{10} f + 40\log_{10} d - 20\log_{10} hb + 76.3 - 10\log_{10} hm$ (19)

COMPREHENSIVE LITERATURE REVIEW

Fuzzy Sets: This aspect of computational techniques was introduced and defined by means of a membership function. It can be applied to various practical applications as shown in [Ref].A fuzzy set makes its determination based on truth factors which take in the probabilities input in order to provide a definite output. In a fuzzy set A, an object x may belong to this set with varying membership degrees in the range [0, 1], where 0 and 1 denote lack of membership and full membership, respectively (M. Jezewski and P. Prokopowicz, 2017).

A fuzzy inference system (FIS) model is based on fuzzy set theory, fuzzy “if/then” rules, and fuzzy reasoning as shown in Figure 4. The FIS approximate functions are based on a rule base, a database, and a reasoning mechanism. The adaptive neuro-fuzzy inference system (ANFIS) is a class of adaptive networks that are functionally equivalent to FIS. An adaptive network is a multilayer feed forward network where each node performs a particular function on incoming signals. ANFIS has five layers, as shown in Figure 5. The description of the structure above is done with a first-order sugeno because the output is a crisp value. A sugeno-based ANFIS has a rule of the form (R. DasMahapatra, 2015).

In like manner, (W. Bhupuak and S. Tooprakai, 2018) the authors proposed the use of K-means clustering and fuzzy logic for the minimization of prediction path loss error. The research studied an urban area of Thailand's Nonthaburi Province, where the training area used consisted of man-made buildings with variable heights and dense and large vegetation, and the study focused on both the 900 and 1800 MHz frequency bands. The path loss prediction between the transmitter and the receiver associated with the empirical prediction models was carried out using MATLAB. The results show that the prediction path loss of the newly developed k-mean fuzzy scheme was only 2.67% in comparison with the test-drive measurement, for which it reveals the lowest error alongside the other compared models. Supachai and Pisit (M. A. Salman et al., 2018) adopted the neuro-fuzzy (NF) model for the prediction of path loss in the Ilorin metropolitan area focusing on the VHF band. Four different routes were used during the measurement to obtain the received signal strength using the NTA Ilorin transmitter, which operates on the frequency of 203.25 MHz; the developed model was alongside compared with widely used empirical path loss models (Hata, Egli, Ecc33, and COST 231). The performance was measured using the root mean square error (RMSE) across all the routes visited. The results indicated an average RMSE of 5.23 dB, 9.487 dB, 18.696 dB, and 27.890 dB, respectively, for the neuro fuzzy, ECC-33, HATA, COST 231, and Egli models. The newly developed model achieved more accuracy and improvement on the predictions of path loss. The study is limited to NTA with four routes. Jafri et al. In (N. T. Surajudeen-Bakinde, N. Faruk, S. I. Popoola et al., 2017), a propagation path loss algorithm with the use of one classification out of fuzzy set techniques was proposed, and data set was generated using a multi-transmitter (i.e., three different transmitters) radiating radio signals in the VHF bands. The prediction model was developed within an urban terrain in Ilorin, Kwara State, Nigeria. A five-layer optimized approach ANBFIS network was used for the training of the measured data centered on the backpropagation gradient descent algorithm. The performance of the ANBFIS developed model was tested and achieved an error reduction for the correlation coefficient (R), RMSE, and standard deviation error (SDE), with values of 0.92 dB, 4.47 dB, and 4.45 dB, respectively. +e developed algorithm achieves a better estimation accuracy while remaining simple. Reference

(O. O. Shoewu et al., 2018) relied on a fuzzy logic algorithm to estimate propagation path loss for urban, suburban, exurban, dense-urban, microurban, and periurban terrains in the Lagos metropolitan environment, for both the 900 MHz and the 1800 MHz frequency bands. The results revealed that the mean path loss in these different environments is higher in the 900 MHz band in comparison to the 1800 MHz band. Furthermore, the urban terrain achieves the highest value for the constant offset (60 dB for the 900 MHz band), and the exurban terrain shows a constant offset of 64 dB in the 1800 MHz band. In general, the literature focuses on the 900 and 1800 MHz frequency spectrum. (N. Faruket al., 2019) performed experimental investigation on heuristic, geospatial, and empirical models after the use of the artificial neural network (ANN) method, Aaptive Neuro-Fuzzy Inference System (ANFIS), and Kriging technique for the development of the compared models for path loss prediction in the VHF and UHF frequency bands. The models were compared with reference to its RMSE value in which it was reported that the root mean square errors of all aforementioned compared models are considered acceptable. The first artificial neural network was created in the year 1951 (Wikipedia, 2018). ANN is an artificial intelligence technique which can effectively be used for the development of path loss models, providing a solution for prediction problems. A neural network has the competence to learn, and it has no need of an explicit knowledge of the input and output process relationship (J. E. Ofure et al., 2016).

. In (Benmus T. A. et al., 2015), an ANN was used to develop a model for estimating path loss in the Great Tripoli area considering five different area types (dense urban, urban, dense suburban, suburban, and rural) in the 900, 1800, and 2100 MHz frequency bands. The study relies on real RSS measurements to train and evaluate the model. The results of the developed ANN model were compared with the real values. The RMSE for the ANN varies from 3.0 to 6.7 depending on the area type and frequency of operation, achieving values that are better than those obtained with the Hata model. The comparison results show that the proposed model recorded higher prediction accuracy when compared with real measurements. Also in (J. E. Ofure et al., 2016), an ANN was used to develop a path loss propagation models that considered atmospheric parameters, relative humidity, and dew point, as inputs parameters. The models were used in estimating the reception power of GSM signals. An MLP network architecture and the weight and bias value were used in the development of the models. The performance of the proposed models was tested and found to be efficient with a mean squared error (MSE) of 0.056. Eichie et al. in (J. O. Eichie et al,. 2017), developed an ANN-based path loss model for signal quality estimation in rural and urban areas. They relied on a feedforward network topology and the Matlab Network Toolbox learning algorithm; specifically, they used the Levenberg–Marquardt approach with 31 to 39 neurons in incremental steps of 2. The model performance was then compared with existing techniques. Performance results show that the proposed model outperforms basic empirical models. The proposed method demonstrated significant improvements, comparable to analytical models, and revealed faster computation time due to the intrinsic parallelism of an ANN architecture. Neural network parameters were derived in (S. I. Popoola et al., 2019) for path loss prediction in VHF and UHF bands for wireless communications. +e authors conducted a field measurement in an urban environment for the purpose of obtaining network information about the losses radio signals transmitted through 189.25 MHz and 479.25 MHz. +e obtained network information was used to develop an artificial neural network (ANN) model which was evaluated using the mean squared error (MSE), root mean squared error (RMSE), standard deviation (SD), mean absolute error (MAE), and regression coefficient (R). +e study reported statistical output of MAE, MSE, RMSE, SD, and R of 0.58 dB, 66 dB, 0.81 dB, 0.56 dB, and 0.99, respectively. Also, the developed model was compared with known empirical models, and it was observed that the model shows a better performance in prediction, accuracy, and generalization ability. Authors in (Y. Zhang et al,. 2019) reported the principle, method, and data expansion methods of machine learning for the purpose of path loss prediction for fifth-generation (5G) mobile networks. Measured data were used to estimate the performance of different propagation models such as the artificial neural network (ANN), support vector regression (SVR), and random forest (RF) alongside the log-distance model. Also, methods on how data expands in order to generate considering amount of training samples for the system were presented. It was shown that the machine learning algorithms exhibit better performance than the logdistance propagation model. However, open research areas to be exploited were also reported. Popoola et al. in (S. I. Popoola et al., 2019) conducted a study on the characterization of path loss in the very high frequency (VHF) band exploiting the neural network modeling technique. +e article reported how the propagation loss through frequency band 30–300 MHz is characterized based on ANN algorithm and its attributes such as the activation functions and training algorithms based on the measured data at 203.25 MHz. The developed model was compared with the widely used empirical models, and it was observed that the ANN developed model outperformed the empirical models based on the statistical analysis results which also recorded a correlation coefficient (R) of 0.95. 3.3. Evolutionary Computing. Evolutionary computing has also experienced significant attention by researchers within the path loss prediction area, where several works report the use of evolutionary algorithms. Similarly, in (B. J. Cavalcanti et al., 2017) a genetic algorithm (GA) path loss models were developed for the prediction of losses for LTE and LTE advance networks. The GA was used in tuning the Free Space and Ericsson models. Findings from the work revealed resemblance of the models' predictions with the actual measurement data. Table 5 provides the summary of the evolutionary algorithms' computational process. 3.4. Swarm Intelligence. The swarm intelligence expression was introduced in the cellular robotic systems context by Beni and Wang in 1989. Swarm intelligence has also been utilized in various areas in which it has gained attention, including problem forecasting. Swarm intelligence is typically associated to three different algorithms, as categorized in Figure 1. The most widely used, as found from the literature, is particle swarm optimization.

Furthermore, particle swarm optimization (PSO) algorithm is a population-based quest procedure where the individuals, known as particles, are clustered into a swarm. PSO is a stochastic optimization method that is modeled on the fundamental social behavior of bird flocks, which is then used to solve nonlinear problems. The particle for search in space consists of the personal best vector, position vector (x), and velocity vector (v), and a fitness value. The PSO algorithm can be deployed at the initialization and iteration phases (T. He et al., 2016). Each particle is randomly allotted through an n-dimensional search space at the initialization phase of the velocity and position vectors, while in iterations each particle looms towards the best solution by modifying its velocity and position in accordance with equation. PSO can be applied in various aspects, such as function approximation, optimization of mechanical structures, clustering, and solving systems of equations. Essentially, two different PSO algorithms were developed, namely, the global best PSO (gbest) and the local best PSO (lbest). 3.4.2. Global Best PSO. For the global best PSO, the neighborhood for each particle is the entire swarm. For the star neighborhood topology, the social component of the particle velocity update reflects information obtained from all the particles in the swarm

He et al. in (T. He et al., 2016). reported the adoption of particle flight path information, which is used by the particle swarm optimization algorithm to train a radial basis function (RBF)-based neural network model in order to create a self adaptive PSO-RBF NN algorithm for path loss estimation. +e performance of the developed model prediction indicated a convergence speed and prediction accuracy better than the traditional RBF neural network. Tahat and Taha applied statistical tuning technique based on particle swarm optimization (PSO) to adjust the COST 231 WalfischIkegami for path loss prediction. +e data measurements were carried out to measure the received signal power in a deployed 3G network at 2.125 GHz FDD mode. +e received signal power, roof height, road orientation angle, and buildings separation variables were all considered for the tuning of the COST 231 WI model. The PSO technique was used for the tuning and revealed lowest standard deviation error when compared with measured data. Even though, the work recorded least error, the model was limited to only 2.125 GHz frequency band. Furthermore, in (A. A. Olukunle et al., 2017), PSO was used to optimize some empirical path loss models for urban outdoor path loss estimation at the 2300 MHz frequency for LTE network systems. Measurement campaign was conducted in the urban areas of Port Harcourt, Nigeria. +e modified model was compared with Okumura-Hata, COST 231, Ericsson 999, ECC-33, and Egli models for the specified environments. For the performance metrics, the RMSE and the MAE were used to gauge the models' efficacies. The results obtained were promising with RMSE and MAE values of 3.030 dB and 0.00162 dB, respectively. Hence, the PSO modified model could be used for the deployment of the long-term evolution (LTE) wireless communication systems in the study locations.

The work of Usman *et al*. (2015) investigated wireless mobile communication signal strength variation with weather and environmental factor in Bauchi. The research brought about variation of signal strength in different locations but close results were obtained at different times in the same location. Similarly, Ayekomilogbon *et al*., (2013) study of signal degradation as a function of leaf density uncovered seasonal variability in the effect of trees on radio waves due to variation in the electrical constants (conductivity and permittivity) of the trees. Likewise, Nwawelu *et al*.,(2012) established that trees and buildings have significant effect on the received power level of wireless mobile network.

The work of Ogbulezie *et al*., (2013) investigated the suitability of two basic propagation models for GSM 900 and 1800MHz respectively for Port Harcourt and Enugu cities, and for Abuja, Kaduna and Kano cities in Nigeria. Measurements taken in cities were compared against predictions made by the Okumura Hata and COST-231 Hata models, and the classical models were seen to overestimate the path loss in all the cities. Similarly, the research revealed that path loss is not constant at various locations for a constant distance around the respective Base Transceiver Station (BTS) due to the effect of terrain. Benmus *et al.,* (2016) developed an empirical model, using ANN approach, for the prediction of propagation path loss at 900MHz, 1800MHz and 2100MHz in Tripoli, Libya. Results revealed that the ANN path loss model had acceptable agreement with the target path loss with MSE values ranging from 3.7 to 6.7.

Recently, different ANN approaches were introduced to predict signal path loss in wireless communication networks Ayadi *et al.,*(2017) developed a new method for multi-band heterogeneous wireless network scenario using ANN technique. In Eichie *et al*., (2017) 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.

In Angeles *et al*., (2015) 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, Eichie e*t al.,* (2017) and Popescu *et al.,* (2005*)* investigated the analysis of empirical models and ANN model for path loss prediction. The ANN inputs were propagation parameters and the radio network data sets were measured through drive test along preferred suburban and rural routes. The prediction results of the ANN model were compared with the ones obtained based on the use of basic empirical path loss models namely: Egli, COST-231, Hata and Ericsson models. ANN based path loss model yielded better results when compared to basic models. The authors concluded that ANN model is useful for accurate path loss prediction in rural and suburban propagation environments.

Sotiroudis and Siakavara., (2015) also proposed the use of ANN models for prediction of path loss in urban areas. Their work seems similar to other general research works but they aimed at discovering the needed amount and kind of information to be used as network inputs. The network input information is the terrain profile of the propagation environment and the data provided is of minimal amount. The results of the proposed ANN model proved that the model was capable of predicting path loss in urban (randomly-built) environment. More importantly, working with a small number of inputs with detailed specifications of the propagation also yielded significant accuracy, which turned to be better than previously proposed ANN methodologies. The work revealed that the developed model is effective in performing path loss prediction.

Machine learning is a technique aimed at improving system performance based on a flexible model architecture and good amount of appropriate data. Recently, machine learning has gained recognition in several fields including autonomous driving, computer vision, speech recognition etc. Previous studies have considered the suitability of different machine learning techniques for path loss prediction (Popoola *et al*., 2018)

Artificial Neurofuzzy Inference System (ANFIS) is an adaptive system which makes modifications to its structure and response characteristics in the course of a training process (Benmus *et al*., 2015)

The ideology behind the neural network is derived from the biological nervous system. ANFIS are referred to as adaptive statistical tools which are capable of modeling the behavior of the biological nervous systems in information processing. ANFIS behaves in a similar way to human beings in the sense that, with the aid of some examples related to a given process, they are able to represent that process. In essence, ANFIS learns by example. Due to their flexibility and simplicity, their applications in tough areas (such as pattern recognition, regression) have proven to be successful in several fields like physics, medicine, engineering, statistics and econometrics. A suitable algorithm is employed for training the preferred model in a controlled manner, bearing the generalization factor in mind. Generalization in a neural network occurs when developed ANFIS model demonstrates the ability to properly obtain the input-output mapping for test data excluded from the training data set. In general, the generalization ability of an Artificial Neuro-fuzzy Inference System is strictly associated its complex-ability. In fact, the more complex a network is, the poorer its process approximation on points not included in the training set (that is, the testing set). The phenomenon is regarded as over fitting. However, a simple model is also not ideal due to its inability to provide a good fit to the training data.

The principle of ANFIS was introduced to path loss predictions with the aim of overcoming the shortcomings of the empirical and deterministic models (Popoola *et al.,* 2019).

CONCLUSION

This study presents mobile propagation path losses for different environments and spanning different operating frequencies. The literature review covered different classes of path loss, propagation mechanisms propagation path loss models, and CI techniques as follows: fuzzy sets, artificial neural networks (ANNs), evolutionary algorithms, swarm intelligence (SI), and artificial immune systems (AISs). The current status on the application of CI techniques for path loss prediction, research trends in the past few years, and open research problems and future research areas and expectations are outlined in the paper. It was discovered that the efforts made by researchers to propose a better model for the prediction of path loss in different terrains has at times led to the testing and simultaneous application of two different CI techniques in a specific environment. The comprehensive review presented in this paper can thus become a first point of reference for new researchers interested in radio propagation and channel modeling. Also, expert researchers in channel modeling or radio propagation can use this review to gain further insight when suggesting a novel approach for path loss prediction.

REFERENCES

M. Jezewski and P. Prokopowicz, 2017 "Theory and applications of ordered fuzzy numbers," Studies in Fuzziness and Soft Computing, Springer, Berlin, Germany.

R. DasMahapatra, 2015. "Optimal power control for cognitive radio in spectrum distribution using ANFIS," in Proceedings of the 2015 IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES), Kozhikode, India.

W. Bhupuak and S. Tooprakai, 2018 "Minimizing path loss prediction error using k means clustering and fuzzy logic," Turkish Journal of Electrical Engineering & Computer Science, vol. 26.

M. A. Salman, S. I. Popoola, N. Faruk, N. T. Surajudeen-Bakinde, A. A. Oloyede, and L. A. Olawoyin, 2017 "Adaptive neuro-fuzzy model for path loss prediction in the VHF band," in Proceedings of the 2017 Conference on Computing, Networking and Informatics, Ota, Nigeria.

N. T. Surajudeen-Bakinde, N. Faruk, S. I. Popoola et al., 2018 "Path loss predictions for multi-transmitter radio propagation in VHF bands using adaptive neuro-fuzzy inference system," Engineering Science and Technology, an International Journal, vol. 21, no. 4, pp. 679–691.

A. Danladi and P. G. Vasira, 2018 "Path loss modeling for next generation wireless network using fuzzy logic—spline interpolation technique," Journal of Engineering Research and Reports.

O. O. Shoewu, M. A. Adedoyin, L. A. Akinyemi, and L. I. Oborkhale, 2018 "Fuzzy-logic based path loss models for Metropolitan environment," in Proceedings of the 2018 IEEE International Workshop on Signal Processing Systems (SiPS), Cape Town, South Africa. .

N. Faruk, Y. A. Adeniran, and A. A. Ayeni, 2019 "Error bounds of empirical path loss models on VHF/UHF bands in Kwara state," in Proceedings of the 2019 EUROCON, Ilorin, Nigeria.

W. S. McCulloch and P. Walter, 1943 "A logical calculus of the ideas immanent in nervous activity," Fe Bulletin of Mathematical Biophysics, vol. 5, pp. 115–133.

"History of artificial intelligence," 2018, https://en.wikipedia. or/wiki/history_of_artificial_intelligence.

J. E. Ofure, O. O. David, A. M. Oludare, and A. A. Musa, 2016. "Artificial neural network model for the determination of GSM Rxleve from atmospheric parameters," Engineering Science and Technology: An International Journal.

T. A. Benmus, R. Abboud, and M. K. Shater, 2015 "Neural network approach to model the propagation path loss for great Tripoli area at 900, 1800, and 2100 MHz bands," in Proceedings of the 16th International Conference on Sciences and Techniques of Automatic Control & Computer Engineering, Monastir, Tunisia.

J. O. Eichie, O. D. Oyedum, M. O. Ajewole, and A. M. Aibinu, 2017 "Comparative analysis of basic models and artificial neural network based model for path loss prediction," Progress in Electromagnetics Research, vol. 61, pp. 133–146.

D. Wu, G. Zhu, and B. Ai, 2010 "Application of artificial neural networks for path loss prediction in railway environments," in Proceedings of the 2010 5th International ICST Conference on Communications and Networking in China, Beijing, China.

S. I. Popoola, A. Jefia, A. A. Atayero et al., 2019 "Determination of neural network parameters for path loss prediction in very high frequency wireless channel," IEEE Access, vol. 7, pp. 150462–150483,.

Y. Zhang, J. Wen, G. Yang, Z. He, and J. Wang, 2019 "Path loss prediction based on machine learning: principle, method, and data expansion," Applied Sciences, vol. 9, no. 9, p. 1908,

S. I. Popoola, N. Faruk, N. T. Surajudeen-Bakinde, A. A. Oloyede, A. A. Atayero, and L. A. Olawoyin, 2019 "Characterization of path loss in the VHF band using neural network modeling technique," in Proceedings of the 2019 19th International Conference on Computational Science and Its Applications (ICCSA), Saint Petersburg, Russia.

B. J. Cavalcanti, A. G. d'Assunção, and L. M. Mendon, 2017 "Optimizing empirical propagation models for LTE and LTEA using genetic algorithms at 879 MHz," in Proceedings of the 2017 IEEE-APS Topical Conference on Antennas and Propagation in Wireless Communications (APWC), Verona, Italy,https://ieeexplore.ieee.org/author/37531408200.

T. He, D. Tangren, W. Yong, L. H. X. Chen, and G. Qin, 2016 "Particle swarm optimization RBF neural network model for internet traffic prediction," in Proceedings of the 2016 International Conference on Intelligent Transportation, Big Data & Smart City, Changsha, China.

A. A. Olukunle, N. C. Onyebuchi, A. K. Cosmos, and O. C. Reginald, 2017 "Implementation of particle swarm optimization technique for enhanced outdoor network coverage in long term evolution network in Port Harcourt Nigeria," European Journal of Engineering Research and Science, vol. 2.

Abraham U.U., Okpo U. O. & Elijah E. O. (2015) Macrocel Path Loss Prediction Using Artificial Intelligence Techniques. *International Journal of Electronics,* 101:4, 500-515, DOI:10.1080/00207217.2013.792040

Angeles J.C.D., E.P. Dadios, (2015) "Neural network-based path loss prediction for digital TV macrocells, Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), 2015 International Conference on, IEEE.Ayadi M,.A. B. Zineb, and S. Tabbane, (2017) ''A UHF path loss model using learning machine for heterogeneous networks,'' *IEEE Trans. Antennas Propag.*, vol. 65, no. 7, pp. 3675–3683, Jul. 2017.

Ayekomilogbon, O., O. Famoriji, and O. Olasoji, (2013) "UHF band radio wave propagation mechanismin forested environments for wireless communication systems," *Journal of Information Engineering and Applications*, Vol. 3, No. 7, 11–16, 2013.

Bakinde, N. T., N. Faruk, A. A. Ayeni, M. Y. Muhammad, and M. I. Gumel, (2012) "Comparison ofpropagation models for GSM 1800 and WCDMA systems in selected urban areas of Nigeria," *International Journal of Applied Information Systems (IJAIS)*, Vol. 2, No. 7, 6–13, 2012.

Benmus, T. A., R. Abboud, and M. K. Shater, (2016) "Neural network approach to model the propagation path loss for great Tripoli area at 900, 1800 and 2100MHz bands," *International Journal of Sciences and Techniques of Automatic Control and Engineering*, Vol. 10, No. 2, 2121–2126, 2016.

Benmus T. A, R. Abboud, and M. K. Shatter,(2015) ''Neural network approach to model the propagation path loss for great Tripoli area at 900, 1800, and 2100 MHz bands,'' in *Proc. 16th Int. Conf. Sci. Techn. Autom. Control Comput. Eng. (STA)*, 2015, pp. 793–798

Chebil, J., A. K. Lwas, M. R. Islam, and A. Zyoud, (2011). "Investigation of path loss models for mobilecommunications in Malaysia," *Australian Journal of Basic and Applied Sciences*, Vol. 5, No. 6, 365–371, 2011.

Dalkiliç T. E, B. Y. Hanci, and A. Apaydin,(2010) ''Fuzzy adaptive neural network approach to path loss prediction in urban areas at GSM-900 band,'' *Turkish J. Electr. Eng. Comput. Sci.*, vol. 18, no. 6, pp. 1077–1094, Dec. 201c

Eichie J. O., O. D. Oyedum, M. O. Ajewole, and A. M. Aibinu, (2017). ''Comparative analysis of basic models and artificial neural network based model for path loss prediction,'' *Prog. Electromagn. Res. M*, Vol. 61, pp. 133–146, 2017. doi: 10.2528/PIERM17060601.

Eichie J. O., O. D. Oyedum, M. O. Ajewole, and A. M. Aibinu,(2017). ‘‘Artificial neuralnetwork model for the determination of GSM rxlevel from atmospheric parameters,’’ *Eng. Sci. Technol., Int. J.*, vol. 20, no. 2, pp. 795–804, Apr. 2017.

Faruk, N., Adediran, Y. A., &Ayeni, A. A. (2013) "*Error bounds of empirical path loss models at vhf/uhf bands in kwara state, Nigeria.* Paper presented at the EUROCON, 2013 IEEE

Faruk N., A. A. Ayeni, and Y. A. Adediran,(2013) ‘‘Characterization of propagation path loss at VHF/UHF bands for Ilorin city, Nigeria,’’ *Nigerian J. Technol.*, vol. 32, no. 2, pp. 253–265, 2013.

Faruk N., S. I. Popoola, N. T. Surajudeen-Bakinde, A. A. Oloyede, A. Abdulkarim, M. Ali, C. T. Calafate, A. A. Atayero, and L. A. Olawoyin,(2019). ‘‘Path loss predictions in the VHF and UHF bands within urban environments: Experimental investigation of empirical, heuristics and geospatial models,’’ *IEEE Access*, vol. 7, pp. 77293–77307, 2019.

G. S Bola and G. S Saini (2010), Path Loss Measeurement and Estimation Using Emperical Modes for WiMax in Urban Area.

Greenberg E. and E. Klodzh, (2015) ‘‘Comparison of Deterministic, Empirical and Physical Propagation Models in Urban Environments,’’ in *Proc. IEEE Int. Conf. Microw., Commun., Antennas Electron. Syst. (COMCAS)*, Nov. 2015, pp. 1–5.

Matthews, V. O., Osuoyah, Q., Popoola, S. I., Adetiba, E., &Atayero, A. A. (2017) "C-BRIG: A Network Architecture for Real-Time Information Exchange in Smart and Connected Campuses" In*Lecture notes in engineering and computer science: Proceedings of the world congress on engineering 2017* (pp. 398–401). London.

Nwawelu, U. N., A. N. Nzeako, and M. A. Ahaneku, (2012) "The limitations of campus wirelessnetworks: A case study of University of Nigeria, Nsukka," *International Journal of Networks and Communications*, Vol. 2, No. 5, 112–122, 2012.

Nwalozie, G. C., S. U. Ufoaroh, C. O. Ezeagwu, and A. C. Ejiofor, (2014) "Pathlossprediction for GSMmobile networks for urban region of Aba, South-East, Nigeria," *International Journal of Computer Science and Mobile Computing*, Vol. 3, No. 2, 267–281, 2014.

Obot, A., O. Simeon, and J. Afolayan, (2011) "Comparative analysis of path loss prediction models forurbanmacrocellular environments," *Nigerian Journal of Technology*, Vol. 30, No. 3, 50–59,

Ogbulezie, J. C., M. U. Onuu, J. O. Ushie, and B. E. Usibe, (2013) "Propagation models for GSM 900 and 1800MHz for Port Harcourt and Enugu, Nigeria," *Network and Communication Technologies*, Vol. 2, No. 2, 1–10, 2013b.

Ostlin E., H.-J. Zepernick, and H. Suzuki,(2010). ‘‘Macrocell Path-Loss Prediction using Artificial Neural Networks,’’ *IEEE Trans. Veh. Technol.*, vol. 59, no. 6, pp. 2735–2747, Jul. 2010

Popoola, S. I., Atayero, A. A., Okanlawon, T. T., Omopariola, B. I., &Takpor, O. A. (2018). Smart campus: Data on energy consumption in an ICT-driven university. *Data in Brief,16*, 780–793 https://doi.org/10.1016/j.dib.2017.11.091

Rappaport T.S. (1996). Wireless Communications: Principles and Practice. Upper Saddle River, NJ, USA: Practice-Hall.

Sharma, P. K. and R. K. Singh, (2010) "Comparative analysis of propagation path loss," *International Journal of Engineering Science and Technology*,Vol. 2, No. 6, 2008–2013,

Segun. I. Popoola, S. Misra, and A. A. Atayero,(2018). ''Outdoor path loss predictions based on extreme learning machine,'' *Wireless Pers. Commun.*, vol. 99, no. 1, pp. 441–460, Mar.

Segun. I. Popoola, A. Jefia, A. A. Atayero, O. Kingsley, N. Faruk, O. F. Oseni and R. O. Abolade, (2019) "Determination of nueral Network Parameters for Path Loss Prediction in Very High Frequency Wireless Channel," *IEEE Access*, vol. 7, pp. 150462–150482)

Sir William Crookes (1892) Some Posibilities of electricity For Mighty Review 173-81

Sotiroudis, S. P., and Siakavara, K. (2015). "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), 1453–1463

SugunI.Popoola, Emmanuel Adetiba, Aderemi A. Atayero, NasirFaruk and Carlos T.Calafate, (2018) "Optimal Model for Path Loss Predications Using Feed-Forward Neural Networks" Cogent Endineering 5: 1444345 https://doi.org/10.1080/23311916.2018.1444345.

Wu J., S. Guo, H. Huang, W. Liu, and Y. Xiang,(2018). "Information and communications technologies for sustainable development goals: State-of-theart, needs and perspectives" *IEEE Commun. Surveys Tuts.*, vol. 20, no. 3, pp. 2389–2406, 3rd Quart.,)