

PAPER 59 – REVIEW ON MOBILE RADIO PROPAGATION

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ABSTRACT

The behaviour of electromagnetic waves in a wireless channel is usually random and highly unpredictable. Its efficiency depends on the physical constituents of the propagation environment obstructing 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 called multipath resulting in path loss. Path loss is the signal intensity reduction that results from extensive fading throughout the transmission path. The placement of base stations (BS) requires the use of accurate path loss models. This paper describes the establishment of a basic mobile radio propagation model which at first presents communication services offered by the cellular telephone system limited to voice, it has gradually expanded to services other than voice such as data, image/video, human-to-human, human-to-machine and machine to machine communication making the mobile technology indispensable of our daily lives. Then it makes extensive reviews of the old traditional models (empirical models), and the new computational intelligence (CI) models and incidentally opens new research issues and future research directions. This review paper will serve as a reference material for researchers in the field of radio propagation and in particular for research in path loss prediction.

Keywords: Multipath, path loss, fading, traditional models, computational intelligence.

1. INTRODUCTION

Since the birth of communications, mankind has always depended on the presence of a communications channel (Faruk *et al.*, 2018 & 2019), 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 can use both communication media effectively (Matthews *et al.*, 2017). The Basic elements of communication are represented in Figure 1.1

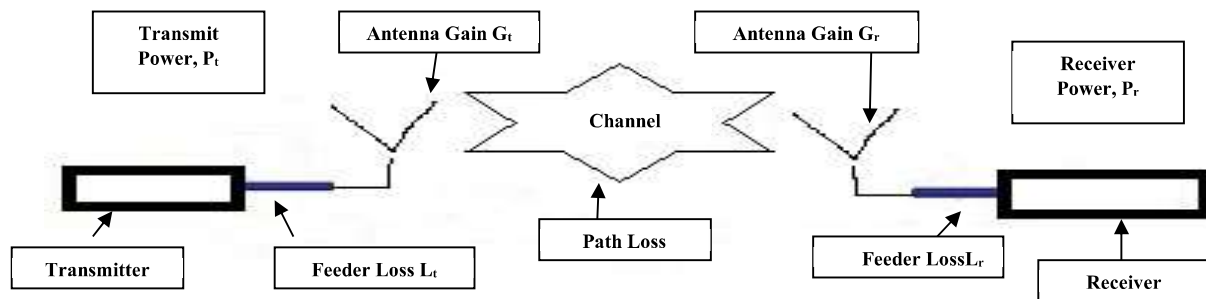


Figure 1.1 Elements of Communication System

The wireless form of communication techniques has enjoyed wide acceptance due to its support for mobility (Castaneda-Miranda, *et al.*, 2020). 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) (Wu *et al.*, 2018), particularly, in developing economies. (Aldossari *et al.*, 2019).

1.1 Background to the Study

Path loss represents the reduction in signal strength of the transmitted signal caused by large-scale fading along the communication path (Rappaport, 2017). 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, 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).

The inability of the traditional models in getting detailed information about the propagating environment leads to the adoption of heuristic models to predict path loss, including 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. Also, an addition to the heuristic models is the nature-inspired computational methodologies, also known as computational intelligence (CI), such as the genetic algorithm (GA), particle swarm optimization (PSO), and ant colony (AC), which provide a solution to the complex propagation environments where the traditional models failed (Faruk *et al.*, 2019). In particular, these CI methods integrate neural networks, fuzzy logic, and other naturally inspired algorithms to optimize the path loss, thus reducing the errors and improving the prediction accuracy.

1.2 Theoretical Background

The Frequency Band

Radio waves are classified into different frequencies in the electromagnetic spectrum. The path of the spectrum that includes the radio spectrum extends from about 30kHz to 300GHz, although radio wave propagation is possible down to a few kilohertz. By international agreement, the radio frequency spectrum is divided into bands and each band is given a designation as represented in Table 1.1.

Table 1.1 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

2. Theoretical Background

2.1 Radio Propagation

The study of the characteristics of radio waves in different propagation environments is needed for effective network planning and 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 Figures 2.1 and 2.2 respectively

2.2 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 the power density of an electromagnetic wave as it propagates from the transmitting antenna to the receiving antenna is of great concern in mobile communication. The major propagation mechanisms are refraction, reflection, diffraction, scattering and absorption (Surajudeen-Bakinde *et al.*, 2018).

The propagation of electromagnetic waves is usually influenced by the atmospheric conditions of the propagation environment; different copies of transmitted radio waves arrive at the receiver using various propagation mechanisms. This phenomenon is known as multipath propagation and this causes signal fading at the receiver (Rappaport 2017). 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.

2.3 The Path Loss Models

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

$$P_R = \frac{P_T G_T G_R}{L_T L_R} \quad (2.1)$$

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 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 given by S. Saunders and A. Aragon- Zavala, (2007).

$$EIRP = \frac{P_T L_T}{G_T} \quad (2.2)$$

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

$$P_{RI} = \frac{P_R L_R}{G_R} \quad (2.3)$$

The advantage of expressing the powers in terms of EIRP is that the path loss, L , can then be 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) and Rappaport, (2002).

$$Pathloss, L = \frac{P_{TI}}{P_{RI}} = \frac{P_T G_T G_R}{P_R L_T L_R} \quad (2.4)$$

The main goal of propagation modelling 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 S. Saunders and A. Aragon- Zavala, (2007).

$$L_{dB} = 10 \log \frac{P_{TI}}{P_{RI}} \quad (2.5)$$

2.4 Propagation Models

To solve the problem of capacity and coverage in cellular mobile networks, 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 the 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 the analysis and design of the 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. Propagation models to be discussed include traditional propagation models such as geostatistical, geospatial, electrodynamic, statistical, empirical, deterministic and stochastic while the newer propagation models include heuristic models and computational intelligence.

2.5 LITERATURE REVIEW

In (Benmus *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. Also in (Ofure *et al.*, 2016), an ANN was used to develop path loss propagation models that considered atmospheric parameters, relative humidity, and dew point, as input 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. In (Eichie *et al.*, 2017), developed an ANN-based path loss model for signal quality estimation in rural and urban areas. They relied on a feed-forward 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 (Popoola *et al.*, 2019) for path loss prediction in VHF and UHF bands for wireless communications. 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 (Y. Zhang *et al.*, 2019) reported the principle, method, and data expansion methods of machine learning for 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 to generate considering the amount of training samples for the system were presented. It was shown that the machine learning algorithms exhibit better performance than the log distance propagation model. However, open research areas to be exploited were also reported. In (Popoola *et al.*, 2019) conducted a study on the characterization of path loss in the very high frequency (VHF) band by exploiting the neural network modelling technique. The article reported how the propagation loss through frequency band 30–300 MHz is characterized based on the 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 from researchers within the path loss prediction area, where several works report the use of evolutionary algorithms. Similarly, in (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 a resemblance of the model's predictions with the actual measurement data. 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 with three different algorithms. The most widely used, as found in the literature, is particle swarm optimization.

In (He *et al.*, 2016). It was reported that 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 to create a self-adaptive PSO-RBF NN algorithm for path loss estimation. Furthermore, in (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. The measurement campaign was conducted in the urban areas of Port Harcourt, Nigeria. The 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.

Usman *et al.* (2015) examined the change in wireless mobile communication signal strength with weather and environmental factors in Bauchi. The investigation caused signal intensity to vary in different areas, although similar results were achieved at different times in the same location. Similarly, Ayekomilogbon *et al.* (2013) discovered seasonal variability in the influence of trees on radio waves due to variations in the electrical constants (conductivity and permittivity) of the trees in their research of signal degradation as a function of leaf density. Similarly, Nwawelu *et al.* (2012) discovered that trees and buildings have a considerable impact on wireless mobile network received power levels.

Ogbulezie *et al.* (2013) studied the applicability of two fundamental propagation models for GSM 900 and 1800MHz for the cities of Port Harcourt and Enugu, as well as Abuja, Kaduna, and Kano in Nigeria. Measurements from cities were compared to estimates from the Okumura Hata and COST-231 Hata models, and the classical models were shown to overestimate route loss in all cities. Similarly, due to the effect of terrain, the research indicated that route loss is not consistent at diverse sites for a constant distance surrounding the corresponding Base Transceiver Station (BTS) Benmus *et al.* (2016) used an ANN technique to construct an empirical model for predicting propagation path loss at 900MHz, 1800MHz, and 2100MHz in Tripoli, Libya. The results showed that the ANN path loss model agreed with the desired 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 scenarios

using the 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.

Angeles *et al.* (2015) used a three-stage technique to construct an ANN model for the GSM spectrum. The model included 33 neurons in the hidden layer, as well as a tansig (hyperbolic tangent sigmoid) transfer activation function.

Similarly, machine learning is a technique for enhancing system performance that is based on a flexible model architecture and a large amount of relevant data. Machine learning has recently acquired popularity in a variety of sectors, including autonomous driving, computer vision, and speech recognition. Previous research has looked into the feasibility of several machine-learning techniques for path loss prediction (Popoola *et al.*, 2018). Finally the principle of ANFIS was introduced to path loss predictions to overcome the shortcomings of the empirical and deterministic models (Popoola *et al.*, 2019).

3. Review Methodology

This section describes the research processes used to review existing publications in the domain of mobile radio propagation for path loss prediction. In addition, we described how the selected papers were chosen using a set of inclusion and exclusion criteria.

3.1 Literature Search and Data Sources.

The systematic review was strategic in that the primary search terms were carefully chosen to find the appropriate works for the study. The following terms are specifically used to search for relevant research on mobile radio propagation for route loss prediction from relevant academic databases as they pertain to the study.

3.2. Study Selection Procedure.

The study selection approach was carefully developed to ensure a thorough examination of the literature. papers relevant to this study were acquired from several academic databases; specifically, 711 papers were retrieved and analyzed. This collection was reduced to 200 after a title check and 72 after an abstract check. Based on the full contents of the papers, 72 articles were thoroughly edited to provide a final list of 36 articles. Table 3.1 shows the database and its data sources.

3.3. Studies Inclusion/Exclusion Criteria.

Both inclusion and exclusion criteria were established to choose the most relevant publications for the investigation. The main literature elements were chosen by reading through the title, abstract, and complete content of the selected articles to arrive at the final list.

Table 3.1 Database Used as Data Source

Academic Database	URL Address
IEEE Explorer	http://ieeexplore.ieee.org/
Springer	http://www.springer.com/
Taylor & Francis	http://taylorandfrancis.com/
ISI Web of Science	https://apps.webofknowledge.com/
Science Direct	http://www.sciencedirect.com/
Scopus	https://www.scopus.com/
ACM Digital Library	https://www.dl.acm.org/
Google Scholar	https://scholar.google.com/

4. Results And Discussion

To pick the most relevant papers for the study, both inclusion and exclusion criteria were established. To arrive at the final list, the main literature aspects were chosen by reading the title, abstract, and complete content of the selected papers.

4.1. Application of Deep Learning. Deep learning is the new generation of the ANN which is currently attracting tremendous attention from the research community. However, surprisingly deep learning remains unexploited in propagation path loss prediction notwithstanding its effectiveness, efficiency, and robustness in solving real-world problems. Empirical evidence from the literature has proven that deep learning architectures such as the deep belief network, convolutional neural network, attentive deep neural network, stack auto encoder, generative

adversarial network, deep reinforcement learning, deep long short-term memory, and deep recurrent neural network among many others can handle machine learning problems such as prediction, clustering, and classification better than the shallow ANN currently in use for propagation path loss prediction especially when the amount of the data size is large. As such, this survey suggests researchers explore these architectures of the new generation ANN in the domain of propagation path loss.

4.2. Multi-terrain Model. Observations from the survey pointed out that propagation path loss prediction is mainly conducted for a single terrain. Therefore, the model developed based on any CI algorithm for a particular terrain is limited for the prediction of path loss within the terrain. The result obtained from such a model cannot be generalized to other terrains. The multi-terrain propagation path loss prediction model remains an open issue. It is suggested researchers apply deep learning architecture because of its ability to handle large-scale data to investigate the possibility of propagation path loss prediction for multiple terrains.

5. Conclusion

This study presents a systematic literature review on mobile radio propagation path losses for different environments and spanning different operating frequencies. The literature review covered different classes of mobile propagation models as follows: fuzzy sets, artificial neural networks (ANNs), evolutionary algorithms, swarm intelligence (SI), and artificial immune systems (AISs). The current status of the application of AI and CI techniques for path loss prediction, research trends in the past few years, open research problems and future research areas and expectations are outlined in the paper. It was also discovered that the efforts made by researchers to propose a better model for the prediction of path loss in different terrains have 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 modelling. Also, expert researchers in channel modelling or radio propagation can use this review to gain further insight when suggesting a novel approach for path loss prediction.

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