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Review

Performance of Path Loss Models over Mid-Band and High-Band Channels for 5G Communication Networks: A Review

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Abstract: The rapid development of 5G communication networks has ushered in a new era of high-speed, low-latency wireless connectivity, as well as the enabling of transformative technologies. However, a crucial aspect of ensuring reliable communication is the accurate modeling of path loss, as it directly impacts signal coverage, interference, and overall network efficiency. This review paper critically assesses the performance of path loss models in mid-band and high-band frequencies and examines their effectiveness in addressing the challenges of 5G deployment. In this paper, we first present the summary of the background, highlighting the increasing demand for high-quality wireless connectivity and the unique characteristics of mid-band (1–6 GHz) and high-band (>6 GHz) frequencies in the 5G spectrum. The methodology comprehensively reviews some of the existing path loss models, considering both empirical and machine learning approaches. We analyze the strengths and weaknesses of these models, considering factors such as urban and suburban environments and indoor scenarios. The results highlight the significant advancements in path loss modeling for mid-band and high-band 5G channels. In terms of prediction accuracy and computing effectiveness, machine learning models performed better than empirical models in both mid-band and high-band frequency spectra. As a result, they might be suggested as an alternative yet promising approach to predicting path loss in these bands. We consider the results of this review to be promising, as they provide network operators and researchers with valuable insights into the state-of-the-art path loss models for mid-band and high-band 5G channels. Future work suggests tuning an ensemble machine learning model to enhance a stable empirical model with multiple parameters to develop a hybrid path loss model for the mid-band frequency spectrum.

Keywords: 5G communication; empirical model; high-band; machine learning model; mid-band; path loss

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1. Introduction

Over the past few years, interest in research on fifth-generation (5G) wireless systems has grown significantly in both academia and industry. This surge in interest is driven by the compelling promises that 5G technology holds. Notably, 5G is anticipated to greatly enhance data throughput, enabling faster and more efficient data transmission than ever before. This is particularly important in a world where data consumption continues to escalate with the advent of high-definition multimedia, cloud services, and emerging technologies.

Beyond these performance enhancements, 5G is poised to revolutionize connectivity by offering support for a diverse array of devices. It extends its reach beyond traditional smartphones and computers to create a seamless and interconnected ecosystem for a wide variety of devices, ranging from IoT sensors and smart appliances to industrial machinery and urban infrastructure. The emerging 5G-enabled features that are positioned to transform our lives are presented in Figure 1.

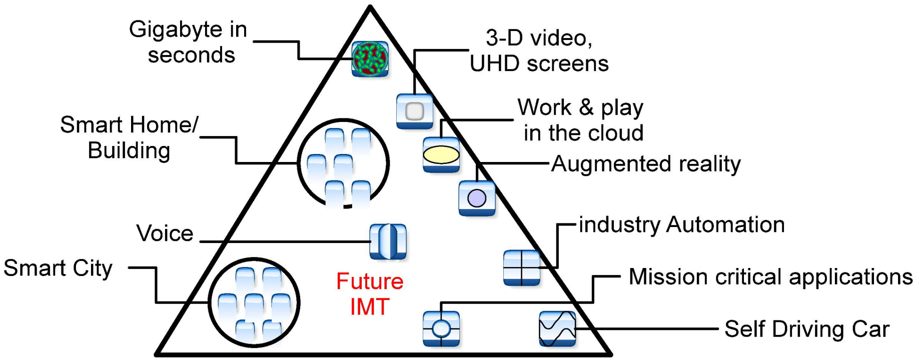

Figure 1. Transformative 5G-enabled features shaping our future.

Table 1 provides a concise list of abbreviations and acronyms with their corresponding definitions used in this review paper.

Table 1. List of abbreviations and acronyms used in the paper.

Abbreviation	Definition
θ	Angle of elevation
3GPP	3rd Generation Partnership Project
5G	5th Generation
ABG	Alpha–Beta–Gamma
CI	Close-In reference
d_{2D}	2D distance between Tx and Rx
d_{3D}	3D distance between Tx and Rx
d_o	Reference distance
dB	Decibel
f_c	Central frequency
FI	Float intercept
FSPL	Free space path loss
GHz	Gigahertz
h_{BS}	Antenna height for the base station
h_{UT}	Antenna height for the user terminal
IMT	International mobile telecommunication
ITU	International Telecommunication Union
LOS	Line-of-sight
MHz	Megahertz
mm-Wave	Millimeter wave
MIMO	Multiple-input multiple-output
NLOS	Non-line-of-sight
PL	Path loss
$PL_{UMa-LOS}$	Path loss for urban macro and line-of-sight scenario
$PL_{UMa-NLOS}$	Path loss for urban macro and non-line-of-sight scenario
Rx	Receiver
T-R	Transmitter to receiver
Tx	Transmitter
UT	User terminal
WRC	World Radio Communication Conference

In 2015, the European Commission launched the 5G Public Private Partnership (5G PPP) initiative [1], which brought together industry and academic partners to develop and test 5G technologies. The same year, the United States Federal Communications Commission (FCC) opened high-frequency spectrum bands for 5G networks.

In 2016, the first 5G standard was released by the International Telecommunication Union (ITU) [2], followed by the 3rd Generation Partnership Project (3GPP) releasing the first 5G New Radio (NR) specifications in 2017. These standards and specifications defined the technical requirements and capabilities of 5G networks, including the use of higher-frequency spectrum, massive multiple-input multiple-output (MIMO) technology, and network slicing [2].

In 2018, the first 5G networks were launched in South Korea, with other countries following suit in the launching of 5G networks for a range of applications, including enhanced mobile broadband, smart cities, connected vehicles, and industrial automation. Trial and commercial system deployments are happening right now in various regions of the world, especially at frequencies below 6 GHz [3].

Delegates from the World Radio Communication Conference (WRC-19), held in Egypt, identified additional radio-frequency bands for deploying 5G mobile networks. According to the WRC-19 resolutions, larger continuous blocks of the spectrum will be needed for International Mobile Telecommunication (IMT-2020) than are currently available in the frequency bands that have already been selected for usage by administrations looking to implement 5G and other wireless communication technologies [4]. Additionally, they emphasized the necessity of uniform international bands for IMT to ease global roaming and the advantages of scale [5].

The spectrum used for 5G is divided into three (3) categories: low-band (<1 GHz), mid-band (1–6 GHz), and high band (>6 GHz); each has merits and demerits. But the mid-band is the most essential (called the priority band), as most deployments are in this band. WRC-23 is considering extending this band due to its importance—its strategic position in achieving both coverage and speed, etc.

The key driver for auctioning more mid-band spectrum, particularly for markets that have not yet introduced commercial 5G services, is the popularity of 3.5 GHz in 5G deployments. The European Union has taken several actions to guarantee a dependable rollout of 5G across European countries. The allocation of the 5G spectrum among the major European countries and a few others is shown in Table 2.

5G mobile wireless communication technology has many advantages, but many obstacles must be overcome before its many advantages can be fully embraced. Among these challenges are high path loss, high penetration loss, interference, and cyber security risk.

To address this issue of high path loss, an accurate channel model is required to accurately predict path loss; aid network planners and researchers in designing, analyzing, and evaluating various proposed wireless technology solutions; and enhance coverage for existing and future deployments. Meanwhile, the use of different bands of frequencies for 5G introduces a new challenge for accurate path loss prediction [8,9].

The high-band frequency spectrum has been highlighted as one of the crucial technologies for reaching extremely high data speeds in 5G mobile networks. Nonetheless, because of the shorter wavelength, the signal suffers from air absorption, increased attenuation loss, and obstruction [10].

The high-band frequency spectrum in the order of millimeter wave (mm-wave) is suitable for 5G mobile system communication in small cell access and backhaul since the frequency spectrum between 28 and 38 GHz demonstrates negligible air absorption in short-range links [11]. Path loss prediction using empirical and deterministic models occasionally leads to undesirable results [12]. Each of the models has its benefits and drawbacks in terms of accuracy, applicability, and computing effectiveness.

Table 2. 5G spectrum allocation in major European countries [6,7].

Country/Region	Frequency Band	Frequency	Auction Status
China	n41 n78 n79 n258	2.515–2.675 GHz 3.4–3.6 GHz 4.8–4.9 GHz 24.75–27.5 GHz	Auctioned Auctioned Auctioned Upcoming
Finland	n78 n258	3.41–3.8 GHz 25.1–27.5 GHz	Auctioned Auctioned
France	n78 n257	3.4–3.8 GHz 26.5–27.5 GHz	Auctioned Upcoming
Germany	n78 n258	3.4–3.7 GHz 24.25–27.5 GHz	Auctioned Upcoming
Ireland	n78 n258	3.4–3.8 GHz 26 GHz	Auctioned Upcoming
Italy	n78 n258 -	3.6–3.8 GHz 26.5–27.5 GHz 700 MHz	Auctioned Auctioned Auctioned
Russia	n40 n79 n248	2.3–2.4 GHz 4.4–4.99 24.25–27.5 GHz	Upcoming Auctioned Upcoming
Spain	n78 n78	3.4–3.6 GHz 3.6–3.8 GHz	Auctioned Upcoming
United Kingdom	n78 n258	3.4–3.8 GHz 24.25–27.5 GHz	Auctioned Upcoming
USA	n258 n258	27.5–28.35 GHz 24–47 GHz	Auctioned Auctioned
Japan	n78 n79 n258	3.6–3.8 GHz 4.4–4.9 GHz 27.5–29.5 GHz	Auctioned Auctioned Upcoming
Republic of Korea	n78 n258 n79	3.4–3.7 GHz 26.5–29.5 GHz 4.8–5.0 GHz	Auctioned Upcoming Auctioned

This paper aims to review current cellular empirical models and machine learning-based path loss modeling for mid-band and high-band channels in rural, urban, and indoor environments. As a result, the following is a summary of the paper's significant contributions.

- We compared the applicability of machine learning models against existing current 5G empirical models at the high-band frequency spectrum.
- We evaluated the applicability of these models in the context of coexistence studies in the selected mid-band and high-band spectrums.
- Considerations for potential scenarios involving additional environmental factors were considered when examining the study of frequency band propagation analysis that are candidates for 6G systems.

The remainder of this paper is organized as follows: Section 2 delves into mid-band and high-band channel propagation. Section 3 examines empirical and machine learning models. Performance metrics used to evaluate the accuracy and effectiveness of path loss models are explored in Section 4. Section 5 conducts a review of empirical-based path loss models. Section 6 reviews machine learning-based path loss models. Section 7 addresses research gaps and future directions. Finally, Section 8 offers concluding remarks and discusses future work.

2. Channel Propagation Characteristics

Wireless communication systems heavily rely on understanding channel propagation characteristics for efficient signal transmission and reception. This section focuses on exploring the characteristics of the mid-band and high-band frequency spectrums, as these frequency ranges have gained significant importance in meeting the ever-growing demand for higher data rates and expanded network coverage. This understanding will aid in developing effective strategies for channel modeling, system design, and performance optimization [13].

2.1. Characteristics of Mid-Band and High-Band Frequency Spectra

The mid-band frequency spectrum provides a balanced combination of coverage and capacity, making it suitable for widespread wireless communication systems. On the other hand, the high-band frequency spectrum offers greater data transfer rates and capacity but requires denser infrastructure due to limitations in signal propagation. Both frequency bands have their own unique advantages and considerations, depending on the specific application and requirements [14].

2.1.1. Short Wavelength

The wavelengths in the mid-band are relatively longer compared to higher frequency ranges, allowing for better signal propagation and penetration through obstacles. The longer wavelength of mid-band frequencies makes them less prone to attenuation and allows for coverage over larger distances [15]. On the other hand, the high-band frequency spectrum, which encompasses frequencies above the mid-band range, has shorter wavelengths. For example, in the case of millimeter-wave frequencies used in 5G communication, the wavelength can be in the range of a few millimeters to a few centimeters. However, they also result in reduced distance range and limited penetration through buildings and other obstacles due to their higher susceptibility to attenuation [16].

2.1.2. Abundant Bandwidth

Abundant bandwidth in the mid-band and high-band frequency spectrums for 5G communication refers to the availability of large portions of the radio frequency spectrum within these frequency ranges. The mid-band spectrum for 5G typically covers frequencies between 1 GHz and 6 GHz. It offers a good balance between coverage and capacity. The specific frequency bands that fall within the mid-band spectrum can vary from country to country, but common examples include the 2.5 GHz, 3.5 GHz, and 4.9 GHz bands [15], as presented in Table 1. The high-band spectrum, also known as the mm-wave spectrum, provides extremely high data rates and low latency but has limited coverage compared to the mid-band spectrum [16].

2.1.3. Propagation Loss

Propagation loss in the context of mid-band and high-band for 5G communication refers to the reduction in signal strength as the electromagnetic waves travel through the wireless medium [17,18]. In the mid-band spectrum, propagation loss is primarily caused by atmospheric absorption, terrain, and foliage. As the frequency increases, the absorption of radio waves by the atmosphere also increases, leading to higher propagation loss. Additionally, the presence of obstacles such as buildings, trees, and hills can further attenuate the signal, reducing its strength and coverage [19]. This is illustrated in Figure 2.

In the high-band spectrum, propagation loss becomes more significant due to the short-wavelength characteristics of these frequencies. Millimeter wave (mm-wave) signals have high propagation loss when they encounter obstacles like walls, buildings, and even rain or foliage. Moreover, they experience rapid signal attenuation over long distances due to their high absorption by atmospheric gases [15,20]. This has historically been a significant weakness in mm-wave technology, but with the employment of beamforming techniques, advanced antenna systems, and small-cell deployments, this issue may be mitigated in both mid-band and high-band frequencies. These techniques aim to direct and amplify the signal towards the intended receiver and compensate for the loss experienced during propagation, improving coverage and overall network performance.

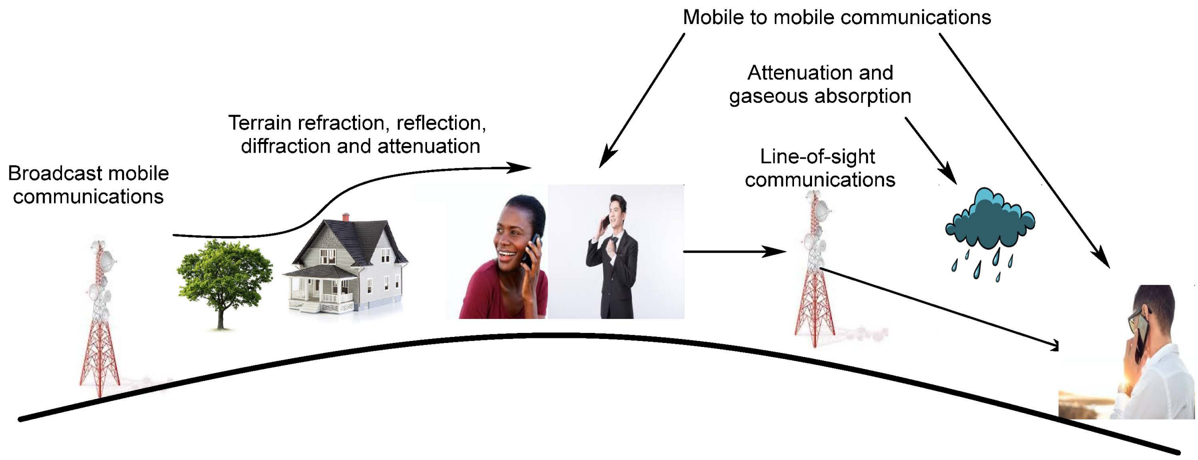

Figure 2. Propagation mechanism effect along a terrestrial path.

2.2. Path Loss in Wireless Communications

Path loss describes the attenuation or loss a wave (or electromagnetic signal) goes through as it moves from the transmitter to the receiver [21]. The received power is therefore less than the broadcast power [21]. Nevertheless, several pertinent factors come into play, including antenna gains, operating frequency, transmitted power, and the separation distance between the transmitter and the receiver [22]. Decibels (dB) are the most popular unit of measurement for path loss [23].

Fortunately, the short wavelengths of mm-wave signals allow for the integration of numerous antenna elements into a small area, resulting in significant spatial processing improvements that, in principle, can at least offset the related isotropic path loss [10].

Using a combination of computational algorithms [24] and approximations based on empirical measurements obtained from channel-sounding experiments, path loss models are created. In general, propagation path loss rises with both frequency and distance, shown as follows [25]:

$$P_l = 10\log_{10}\left(\frac{16\pi^2 d^n}{\lambda^2}\right), \tag{1}$$

where P_l, d, n, and λ represent the path loss, length of the path between the transmitter and receiver, path loss exponent [26], and the free space wavelength in meters [25], respectively.

As we can see, (1) can thus be transformed into (2), as follows [27]:

$$P_l(f,d) = 32.5 + 10n\log_{10}(d) + 20\log_{10}(f) \tag{2}$$

where d and f represent the distance between the Tx and the Rx in km and the frequency of operation in MHz [28].

In the mm-wave spectrum, a variety of propagation mechanisms contribute to multipath propagation [29], but their significance differs from that in frequency bands below 6 GHz [30]. The measured path loss can thus be written as follows [30]:

$$Path\ loss,\ P_l\ in\ dB = EIRP - R_p, \tag{3}$$

where R_p and $EIRP$ are the received power in dBm and the effective isotropic radiated power, which can thus be written as follows [30]:

$$EIRP = P_T + G_T + G_R - C_l - A_l - A_{fl}\ , \tag{4}$$

where P_T, G_T, and G_R, are the transmitting power in dBm, the gain of the transmitting antenna, and the gain of the receiving antenna, and C_l, A_l, A_{fl} represent the losses that comprise the feeder cable, antenna, and filter, respectively.

5G cellular has been the focus of considerable study and development over the past few years because it promises to greatly enhance data throughput, has very low latency, and offers connectivity capabilities to support and connect a new array of devices. Trial and commercial system deployments are happening right now in various regions of the world, especially at frequencies below 6 GHz.

3. Path Loss Models

Path loss models are mathematical models used to predict the attenuation of radio signals as they propagate through a medium. These models consider factors like distance, frequency, environmental conditions, and obstacles to estimate the signal strength at a receiver. They are essential for network planning and optimization in wireless communication systems. The transition from one path loss model to another occurs to improve accuracy and account for more relevant factors like frequency, environment, technological advancements, and standardization requirements [31].

3.1. Empirical Models

Empirical models used to predict path loss rely on recorded measurements of signal strength in various environmental conditions. These models use empirical data to establish a relationship between the transmitter and receiver. Numerous empirical models have been created for the measured environment, but when used in other measurement contexts and experimental setups, they are found to be ineffective. To enable its services and use cases, the 5G standard provided significant improvements. The empirical model is categorized into early and current empirical models [32].

3.1.1. Early Empirical Models

These early models were based on simple empirical formulas that related path loss to distance, frequency, and other factors such as antenna height and terrain type. Some of the early models included the Okumura–Hata model (developed in 1968) [33], the COST 231 model (developed in 1991), and the Walfisch–Ikegami model (developed in 1992). These models were based on extensive measurements in urban, suburban, and rural environments and were widely used in the design of cellular networks [34]. Some of these early empirical models include the Okumura model [35], Okumura–Hata model [36], and COST-231 Hata model [37,38]. They are discussed as follows:

A. Okumura Model

This widely adopted empirical radio propagation model serves as a valuable tool for predicting path loss in urban environments. The model's foundation lies in the collection of signal strength measurements across various frequencies and distances within urban environments [35]. The Okumura model leverages a series of empirical equations to estimate path loss, factoring in the signal's frequency, the transmitter–receiver separation distance, and environmental characteristics. These characteristics encompass terrain type, building height, and vegetation density. The model operates under the assumption that the radio signal follows a straight-line path from the transmitter to the receiver, encountering attenuation due to reflection, diffraction, and scattering in the process [39].

The model can thus be written as follows [33,37]:

$$L_{50}(dB) = L_F + A_{mu}(f,d) - G(h_{te}) - G(h_{re}) - G_{AREA}, \tag{5}$$

where A_{mu}, $G(h_{te})$, L_F, $G(h_{re})$, and G_{AREA} are the median attenuation relative to free space, base station antenna height gain factor, the free space propagation loss, and the mobile antenna height gain factor and gain due to the type of environment.

B. Okumura–Hata Model

The Okumura–Hata model stands as a frequently employed empirical model for path loss prediction within the realm of wireless communication systems, specifically designed for urban and suburban environments. Variants of this model have been tailored to address diverse frequency bands and environmental scenarios. Presented in (6) is the foundational representation of the Okumura–Hata model, serving as a valuable reference for its general form [38]:

$$Path\ Loss\ (L) = A + B \times \log 10(f) - C + (D \times \log 10(h)) + E \times (\log 10(h))^2 + F \times \log 10(d), \tag{6}$$

where A, B, C, D, E, and F are model-specific constants that depend on factors like the frequency of operation, the type of environment (urban or suburban), and the receiver height; f is the frequency of the signal in MHz; h is the height of the transmitting antenna in meters; and d is the distance between the transmitter and receiver in kilometers.

The constants A, B, C, D, E, and F vary depending on the specific version of the Okumura–Hata model and the frequency range in use.

C. COST-231 Hata Model

This model is an extension of the Okumura–Hata model to a higher frequency (2 GHz) [40,41]. The COST 231 model relies on empirical data acquired through measurements of signal propagation in diverse urban and suburban environments. It considers the effects of building density, street width, and antenna height, among other factors. This model offers a formula for path loss computation between a transmitter and receiver, taking into account factors such as signal frequency, the transmitter–receiver separation distance, and multiple environmental parameters [25]. The formula includes separate terms for line-of-sight and non-line-of-sight propagation, and it can be adapted for use in different frequency bands and environments [36]. As seen in (7), the formula can thus be written as follows [42]:

$$PL = 46.33 + 33.9\log f - 13.82\log h_{tx} + C_m - a(h_{rx}) + (44.99 - 6.55\log(h_{tx}))\log d, \tag{7}$$

where f, d, h_{tx}, h_{rx}, and C_m are the frequency in MHz, distance from the transmitting station to the receiving antenna, transmitting antenna height, and receiver antenna height, respectively. The correction factor is thus written as follows [39]:

$$a(h_{rx}) = (1.1\log_{10}(f) - 0.7)h_{rx} - (1.56\log_{10}(f) - 0.8) \quad for\ 1500\ MHz \le f \le 2000\ MHz. \tag{8}$$

The COST-231 Hata model has been widely used in the telecommunications industry for path loss predictions and for designing mobile communication networks in urban areas. However, it is important to note that the model has limitations and may not accurately predict path loss in every specific scenario [39].

3.1.2. Current Empirical Models

In light of new standards (such as new frequency bands and beamforming antennas), the propagation modeling for 5G has been updated, establishing new empirical path loss models. Some of these empirical models include the Close-In (CI) reference model [23], Alpha–Beta–Gamma (ABG) model [23], 3GPP model [39], and Float Intercept (FI) model [43]. These models are briefly discussed below, concerning the illustration of important parameters in Figure 3.

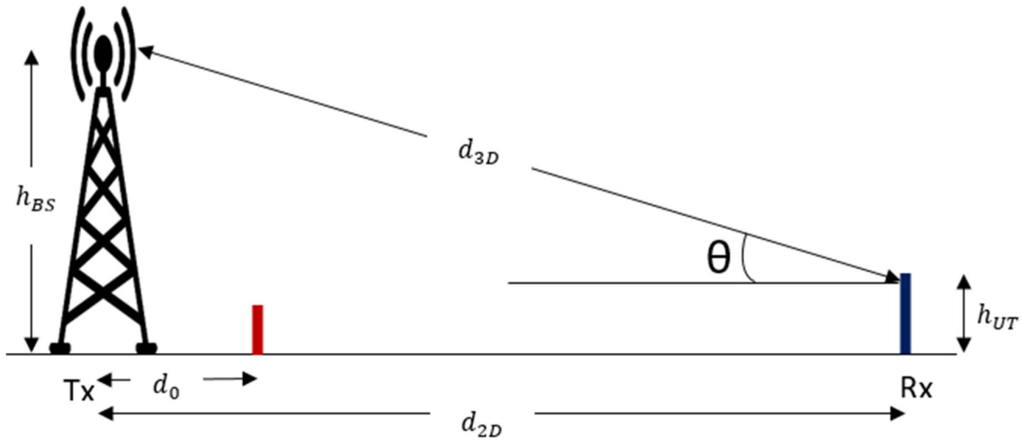

Figure 3. Definition of d_{2D} and d_{3D} for outdoor UT_S.

A. 3GPP TR 38.901 Model [39]

This model is considered in two scenarios: LOS and NLOS [44].

i. For the urban macro and line-of-sight (LOS) scenario, the model expression is written as follows [44,45]:

$$PL_{UMa-LOS} = \begin{cases} PL_1 & 10\,m \leq d_{2D} \leq d'_{BP} \\ PL_2 & d'_{BP} \leq d_{2D} \leq 5\,km' \end{cases} \quad (9)$$

$$PL_1 = 28.0 + 22\log_{10}(d_{3D}) + 20\log_{10}(f_c), \quad (10)$$

$$PL_2 = 28.0 + 40\log_{10}(d_{3D}) + 20\log_{10}(f_c) - 9\log_{10}\left((d'_{BP})^2 + (h_{BS} - h_{UT})^2\right), \quad (11)$$

$$Elevation\ angle,\ \theta = tan^{-1}\left(\frac{(h_{BS} - h_{UT})}{d_{2D}}\right). \quad (12)$$

ii. For the NLOS scenario [45], the path loss expression is thus written as follows [45]:

$$PL_{UMa-NLOS} = max\left(PL_{UMa-LOS},\ PL'_{UMa-NLOS}\right)\ for\ \ 10m \leq d_{2D} \leq 5\,km, \quad (13)$$

$$PL'_{UMa-NLOS} = 13.54 + 39.08\log_{10}(d_{3D}) + 20\log_{10}(f_c) - 0.6(h_{UT} - 1.5). \quad (14)$$

B. Close-In (CI) Free Space Reference Distance Path Loss Model [23]

For a single frequency, the CI free space reference distance model can thus be written as follows [23]:

$$P_L^{CI}(f,d)[dB] = P_L(f,d_0)|_{1\,m} + 10n\log\left(\frac{d}{d_0}\right) + W_\sigma^{CI}, \quad (15)$$

where $P_L(f,d_0)$, f, n, d_0, and W_σ^{CI} are the free space path loss at a T-R separation distance of 1 m, carrier frequency, path loss exponent, initial separating path, and zero-mean Gaussian-distributed random variable, respectively. Shadow fading standard deviation, σ_{SF} is set to 6 dB, and the range of applicability includes default antenna heights of $1.5\,m \leq h_{UT} \leq 22.5\,m$ and $h_{BS} = 25\,m$, which are valid for (14) and (15), respectively.

C. Alpha–Beta–Gamma (ABG) Model [23]

This model includes frequency-dependent terms such as the γ, α, and β to describe the path loss at various frequencies. The ABG model is presented in (16) as follows [23]:

$$P_L^{ABG}(f,d)[dB] = 10\alpha\log_{10}\left(\frac{d}{d_0}\right) + \beta + 10\gamma\log_{10}\left(\frac{f}{f_{ref}}\right) + W_\sigma^{ABG}, \tag{16}$$

where α and γ, β, and $P_L^{ABG}(f,d)$ are coefficients illustrating the dependence of path loss on distance and frequency, respectively; the optimal offset value for path loss in dB; and the path loss in dB over frequency and distance, respectively. The 3D transmitter–receiver (T-R) separation distance is denoted as d in meters, f is the carrier frequency in GHz, and W_σ^{ABG} is the SF standard deviation representing large-scale signal fluctuations regarding the mean path loss over distance [46].

D. FI Model [46]

In this model, the intercept parameter can vary based on the environment or specific scenario to present a more accurate estimation of the path loss [47]. Traditional path loss models assume a fixed intercept value for a particular environment. However, in real-world scenarios, environmental factors can significantly affect the path loss, such as building density, terrain, foliage, and other obstructions. A floating intercept model takes these factors into account by allowing the intercept value to adjust accordingly.

The FI model is presented in (17) as follows [47,48]:

$$P_L^{FI}(f,d)[dB] = \alpha + 10.\beta^{FI}\log_{10}(d) + X_\sigma^{FI}, \quad d > 1\ m, \tag{17}$$

where $P_L^{FI}(f,d)$, f, d, α, β, and X_σ^{FI} represent the FI path loss in dB; frequency in GHz; separation distance between the transmitter and receiver; the floating intercept in dB; the slope of the line, which represents the path loss' dependence on distance; and the randomly distributed variable having a Gaussian distribution and a zero mean.

$$\overline{PL}(d)[dB] = \alpha + 10\beta\log_{10}(d) \tag{18}$$

The tilt is represented by the floating intercept in the path loss model of (19) [47], measured in dB.

$$\alpha = \overline{PL}(d)[dB] + 10\beta\log_{10}(d) \tag{19}$$

The slope of the line, β, is given as in (20) below:

$$\beta = \frac{\sum_i^n \left(d_i - \overline{d}\right) x \left(PL_i - \overline{PL}\right)}{\sum_i^n \left(d_i - \overline{d}\right)^2}, \tag{20}$$

The path loss models' standard deviation can be determined, using (21), as follows:

$$\sigma(dB) = \sqrt{\frac{\left(PL_i - \overline{PL}\right)^2}{N}}. \tag{21}$$

3.2. Machine Learning Models

Machine learning encompasses a collection of methods for making predictions by utilizing datasets and modeling algorithms. These techniques find application across numerous domains [49]. In the realm of path loss modeling for prediction, machine learning techniques have gained prominence. Some researchers are exploring the idea that path loss models based on machine learning may outperform traditional empirical and analytical models.

Machine learning models utilize algorithms and techniques to automatically learn and extract patterns and relationships from a large dataset. These models can analyze vast amounts of empirical or measured data to identify complex patterns and dependencies that may not be easily captured by deterministic or statistical models. Machine learning models can be trained using historical data to accurately predict path loss in various environments based on input parameters like transmitter–receiver distance, frequency, antenna heights, and other relevant factors [35].

Empirical models are based on observed measurements; deterministic models use physical principles and equations; statistical models consider statistical properties; and machine learning models learn patterns and relationships from large datasets.

4. Performance Metrics for Path Loss Models

Performance metrics for path loss models are essential in evaluating the accuracy and effectiveness of models used to predict signal propagation and attenuation in wireless communication systems [21,35,50,51]. These models play a critical role in various applications, such as network planning, resource allocation, and the optimization of wireless communication systems. Some common performance metrics for path loss models include, e.g., mean square error (MSE), mean absolute error (MAE), mean error (ME), and R2 score [50,51].

These performance metrics help researchers, engineers, and network planners assess the suitability of a path loss model for specific applications. The choice of which metrics to use depends on the specific goals of the study and the nature of the path loss modeling problem. These common performance metrics are discussed below.

A. Mean Square Error (MSE)

The mean square error (MSE) in path loss predictions serves as a statistical measure, quantifying the average squared disparity between predicted and observed path loss values. It stands as a prevalent performance metric employed to evaluate the precision and suitability of path loss models within the domain of wireless communication systems [52].

The formula for calculating MSE is presented in (22), as follows [51–53]:

$$MSE = \frac{1}{N_{test}} \sum_{i=1}^{N_{test}} \left(PL_i^{msd} - PL_i^{pred} \right)^2, \tag{22}$$

where PL_i^{msd}, PL_i^{pred}, N_{test}, and i are the measured path loss value, predicted path loss values, total number of samples to be tested, and the index of the measured sample, respectively.

The MSE is calculated by taking the squared differences between the predicted and observed values for each data point, summing those squared differences, and then averaging them by dividing by the total number of data points. A lower MSE indicates a path loss model with better predictive accuracy. In other words, a lower MSE suggests that the predicted path loss values are closer to the actual observed values, indicating a better fit of the model to the data.

However, it is essential to note that MSE gives more weight to large errors due to the squaring operation. As such, the root mean square error (RMSE), which is the square root of the MSE, is often used to provide a measure of the average magnitude of prediction errors, and it is presented in (23) as follows [52,54]:

$$RMSE = \sqrt{\frac{1}{N_{test}} \sum_{i=1}^{N_{test}} \left(PL_i^{msd} - PL_i^{pred} \right)^2}. \tag{23}$$

B. Mean Absolute Error (MAE)

The mean absolute error (MAE) is a statistical metric used to measure the average absolute difference between the predicted path loss values and the actual or observed path loss values. It is a common performance metric used to assess the accuracy of path loss models in the context of wireless communication systems.

The mathematical expression for the MAE is thus presented in (24) as follows [52,55]:

$$MAE = \frac{1}{N_{test}} \sum_{i=1}^{N_{test}} \left| PL_i^{msd} - PL_i^{pred} \right|. \tag{24}$$

Mean Absolute Error (MAE) calculates the average absolute differences between the predicted and observed values for each data point without squaring the differences. This means that all errors, whether they are overestimations or underestimations, are treated equally in the calculation of MAE. A lower MAE indicates a path loss model with better predictive accuracy. A lower MAE suggests that the predicted path loss values are closer to the actual observed values, indicating a better fit of the model to the data [55].

C. Mean Error (ME)

The mean error (ME), alternatively referred to as the mean bias or mean prediction error, is a statistical measurement employed to assess the average variance between predicted path loss values and the actual path loss values within a path loss model. This metric offers valuable insight into the model's systematic or average prediction errors.

The formula for calculating ME is presented in (25) as follows [54,55]:

$$ME = \frac{1}{N_{test}} \sum_{i=1}^{N_{test}} \left(PL_i^{pred} - PL_i^{msd} \right). \tag{25}$$

Mean error computes the mean of disparities between predicted and observed values for individual data points without employing absolute values or squared differences. It offers insights into both the direction and magnitude of the average error. A positive ME implies a tendency for the model to overestimate path loss values, while a negative ME signifies a tendency to underestimate path loss values [56].

D. R2 Score

The R2 score, alternatively referred to as the coefficient of determination, serves as a statistical measure for evaluating the quality of fit in regression models, including those used in path loss prediction. This metric quantifies the model's ability to explain the variances observed in path loss data. It operates on a scale from 0 to 1, with 1 signifying a model that precisely predicts the dependent variable and 0 indicating a lack of predictive capability. The proximity to 1 indicates a stronger fit in the regression [57]. The mathematical expression to calculate the R2 score is presented in (26) and (27) as follows [58,59]:

$$R2 = 1 - \frac{\sum_{i=1}^{N_{test}} \left(PL_i^{msd} - PL_i^{pred} \right)^2}{\sum_{i=1}^{N_{test}} \left(PL_i^{msd} - \overline{PL} \right)^2}, \tag{26}$$

$$\overline{PL} = \frac{1}{N_{test}} \sum_{i=1}^{N_{test}} PL_i^{msd}, \tag{27}$$

where PL_i^{msd}, PL_i^{pred}, N_{test}, $\overline{PL}$, and i are the measured path loss value, predicted path loss values, total number of samples to be tested, mean values, and the index of the measured sample, respectively.

For a more comprehensive assessment of the overall prediction accuracy, metrics such as mean absolute error (MAE) and root mean square error (RMSE) are often used in combination with ME to evaluate path loss models.

5. Reviewed Papers on Empirical-Based Path Loss Models

Numerous studies have sought optimal path loss models for signal attenuation prediction in 5G communication scenarios [60], especially in mid-band and high-band frequencies. A case in point is the work of [61], which devised a model for indoor environments at 3.5 GHz. Using two omnidirectional antennas in building measurements, this research highlighted the utility of path loss parameters for describing coverage and large-scale fading in propagation channels. However, the development of representative models calls for extensive measurement campaigns across comparable buildings.

Phaiboon et al. [62] introduced a path loss prediction model for 5G mm-wave applications using Grey modeling. They trained this model with 28 GHz path loss data and compared it to four existing empirical models, revealing its strong performance, particularly in high-band frequencies [63]. Additionally, a comparison between the single-frequency FI model and the single-frequency CI models indicated their similar performance across all frequencies under line-of-sight scenarios [64–66]. However, it is important to note that the measurement did not account for material properties, which may have contributed to the symmetrical behavior of the data due to potential reflection and diffraction effects. The associated investigation for these empirical path loss models spanning mid-band and high-band frequencies are presented in Table 3.

Table 3. Related studies of 5G empirical path loss models at mid and high bands.

Ref.	Freq. (GHz)	Model	Scenario	Environment	Area of Focus/Methodology	Important Results	Drawback
[61]	3.5	Model fit, FSPL, and ITU-R	LOS and NLOS	Indoor	Conduction of large-scale fading, using an omnidirectional antenna and a spectrum analyzer under two different scenarios.	The FSPL overestimates path loss whereas the ITU-R model performed better, therefore recommended to be used.	It will be necessary to conduct extensive measurement campaigns across similar structures to obtain a representative model.
[62]	28	Grey model, 5GCM, 3GPP, METIS, and mm-MAGIC	LOS and NLOS	Outdoor–urban	The suggested path loss model was tested against four 5G empirical models after being trained using measured path loss data.	In contrast to the linear regression model, it is discovered that the proposed model has a good prediction.	There is need to test the comparative analysis beyond the mean absolute error (MAE)
[48]	14, 18, and 22	CI and FI	LOS and NLOS	Indoor	Measurement campaigns were carried out to examine the models and path loss exponent (PLE).	The LoS comparison demonstrates that for the chosen frequency bands, the two models produce precise estimates that fit the actual measured data.	The impact of the materials surrounding the symmetry of the environment were not considered.
[47]	28	CI, FI, and RMSE	LOS and NLOS	Outdoor–urban	Two 5G models were employed to evaluate the best path loss model. Additionally, five distinct path loss scenarios were analyzed during this process.	The FI model performed better with the lowest value of RMSE.	A live measurement campaign should be carried out for proper investigation

Table 3. *Cont.*

Ref.	Freq. (GHz)	Model	Scenario	Environment	Area of Focus/Methodology	Important Results	Drawback
[66]	26	3GPP, ABG, and CI	LOS and NLOS	Outdoor–rural	A comprehensive measurement campaign was conducted in two rural areas using a crane to assess path loss at transmite antenna heights of 30, 50, and 70 m.	The height of the cell site antenna appears to be a crucial design factor for network planning.	There is need to test the models in another frequency to know the stability at multiple frequencies.
[67]	28	FSPL, CIB, and CI	LOS	Outdoor–urban	Based on the data collected during measurement campaigns, some selected models were employed to look into the channel loss for the 5G system.	The CIB path loss model is suitable for the LOS scenarios as it aligns with the data from the environment.	There is a need to investigate the effect of return and mismatch losses along the feed line.
[68]	28, 38, 60, 73, 100, and 120	NYUSIM and CI	LOS and NLOS	Urban microcell	Large-scale simulation analysis on geometric parameters and environmental conditions for the proposed millimeter wave channels.	Geometric parameters and external factors affect the statistical channel modeling's parameters.	For the suggested model's performance to be verified and assessed, more experimental data are needed.
[69]	1.8, 3.5, and 28	FI and CI	LOS	Outdoor–urban	Modeling of path loss from wideband measurement campaign.	A guiding effect was noticed in the 1.8 GHz frequency band, which is not observed in other bands.	To check the stability of the models, a non-line-of-sight (NLoS) scenario should be taken into account.
[70]		PEF and Log-distance	LOS	Suburban	The "drive test" and "walk test" experiments were conducted to investigate propagation loss along distinct paths.	With an RMSE that was 1.4 dB lower, the suggested model performed better than the log-distance model.	The proposed model needs to be tested on other frequency bands to accurately determine the stability of the models.
[71]	28	CI, FI, and ZMS	LOS and NLOS	Indoor	Simulation for all possible polarization at NLoS and LoS scenarios per meter over 47 m.	The straightforward model that is suggested, which only has one parameter called ZMS, can forecast expansive path loss across distance.	To develop a model that is representative, a comprehensive measuring campaign across comparable buildings will be necessary.

Table 3. *Cont.*

Ref.	Freq. (GHz)	Model	Scenario	Environment	Area of Focus/Methodology	Important Results	Drawback
[42]	1.8	FSPL and COST-231 Hata	LOS	Urban	With the dataset gathered from drive tests, the proposed model was tuned using the magnetic optimization algorithm (MOA).	With a lower RMSE value, the proposed augmented model outperformed and was more representational of the data than its traditional counterparts.	The magnetic optimization algorithm that was used has deficiencies in handling non-linearity and may suffer from convergence issues to provide an accurate model.
[72]	2.5	FSPL, SUI, Okumura, and COST-231 Hata.	LOS	Urban	Five different empirical models were tested with actual data measurements to find the most performed model to predict path loss.	The COST-231 Hata model proved to be more suitable than the other chosen models, with a minimal RMSE of 5.27 dB.	The COST-231 Hata model needs to be fine-tuned to suit the special scenario of the urban environment that comprises old and modern buildings.

To investigate five alternative path loss scenarios in an urban environment, the authors in [47] adopted the FI and CI models to evaluate the best path loss model for Lagos Island. In comparison to the CI model, they discovered that the FI model had the lowest RMSE value for the situations they were evaluating. As a result, the FI model offers the most accurate prediction model to describe the environment.

A thorough measuring campaign at 26 GHz was conducted over the course of the summer in two remote areas of southern Finland, according to Saba et al. [66]. The collected data demonstrate that the mean path loss increased from 4 to 6 dB for every 20 m increase in antenna height. As a result, while planning a fixed wireless access type 5G rural network, transmitter antenna height is a critical factor. The 3GPP RMa model has the largest shadow fading, ranging from 8 to 10 dB, when the specified path loss models are compared. As a result, the ABG and CI models fit data more accurately than the 3GPP RMa model. The CI model appears appropriate for modeling various antenna heights in an RMa environment, even though the chosen models were not compared based on an indoor measurement experiment.

In [67], path loss models were thoroughly examined for the outdoor environment in a tropical climate while considering two distinct scenarios. For the (LoS) case study, the 3D T-R separation distances ranged from 16.5 m to 70 m, with data line-of-sight being gathered every 10 m. An omnidirectional antenna emulator was used to calculate the results. Although the impedance matching technique between the feed line and the horn antennas was not investigated, it might influence the effect of return and mismatch losses within the system. The result revealed that co-polarization decays rapidly in line-of-sight (LOS) scenario.

To assess mmWaves and sub-tetra hertz propagation for outdoor urban microcells (UMi), the authors of [68] took into account several possible scenarios. The findings of their research showed that the 60, 100, and 120 GHz channels are more sensitive to the effects of changing environmental circumstances than the 38 and 73 GHz channels. Nevertheless, there was no actual measuring campaign run on the channels in question.

In [69], it was shown that it is possible to model path loss in the frequency ranges of 1.8, 3.5, and 28 GHz by using wideband measurements made in the middle of a street. The atmosphere was static, and there was no breeze during the measuring campaign. The outcome shows that after a certain distance between the transmitter and receiver, the multiple-scattering contributions from trees in the 1.8 GHz and 3.5 GHz bands must be considered.

An improvement on the widely used log-distance model was presented in [70] to predict path loss in areas with raster map data, especially in suburban environments. In this case, instead of one PLE as in the case of the log-distance model, the proposed model contains multiple exponents, and each stands for a parameterized environmental factor (PEF). To verify the proposed model, parameters via measurement were extracted, and its performance was compared with the log-distance model. The results demonstrate that the proposed model is a better-performed model. Meanwhile, the proposed model needs to be tested on other frequency bands to accurately determine its stability.

The authors in [71] suggested a novel large-scale propagation model for 5G wireless communication systems, which is expected to be reliable for indoor environments. Simulations were run for all polarizations at two distinct scenarios per meter over 47 m to compare and validate the proposed model with current models. The findings demonstrated that the straightforward ZMS model, which only included one parameter, allowed for a more accurate prediction of path loss over a distance. To get a representative model, however, an extensive measuring effort across comparable structures will be necessary.

The authors in [42] optimized the conventional COST 231 Hata model in the city of Limbe in Cameroon using an optimization algorithm, such as the magnetic optimization algorithm (MOA), to predict path loss within the mid-band of 2 GHz. Even though reasonable prediction results were achieved with the proposed model, the magnetic optimization algorithm that was used has deficiencies in handling non-linearity and may suffer from convergence issues to provide an accurate model.

In another paper presented by [72], five different empirical models—the FSPL, SUI model, Ericsson model, Okumura model, and COST-231 Hata model—were compared with empirical data measurements to find the best suitable model to predict path loss in the urban environment of Cologne, Germany, at 2.5 GHz. The analytical results showed that the COST-231 Hata model was the most suitable, with a minimum RMSE of 5.27 dB. Meanwhile, the COST-231 Hata model needs to be fine-tuned to suit the special scenario of the urban environment that comprises old and modern buildings. In this case, novel indicators from the measurement campaign will be used to tune the model.

5.1. Performance Evaluation of Empirical Path Loss Models in Urban Environment

In assessing the performance of empirical models in the mid-band and high-band frequency ranges in urban environments, several studies have been done, especially in [69], which demonstrated that path loss could be effectively modeled across the frequency ranges of 1.8, 3.5 and 28 GHz using wideband measurements. The CI model performed excellently in both bands, having the minimum RMSE value of 1.95 dB across the frequencies under consideration, as shown in Figure 4.

The stability of the same early empirical models, including FSPL and COST-231 Hata, was examined against empirical data measurements for path loss prediction at 1.8 GHz in [42] and 2.5 GHz in [72]. The analytical results concluded that the COST-231 Hata model was the most suitable choice, exhibiting a minimum RMSE of 4.64 dB in the case of 1.8 GHz and 5.27 dB in the case of 2.5 GHz. Conversely, in various frequency bands and scenarios, CI and FI models were scrutinized, with the CI model showing exceptional performance, particularly in line-of-sight (LOS) scenarios across both mid-band (1.8 GHz and 3.5 GHz) and high-band (28 GHz) frequencies.

Considering the empirical models for high-band frequency ranges, the stability of the FI and CI models was tested in [47,69] to determine the best path loss prediction at 28 GHz in an urban environment. In comparison to the NYUSIM model in [68], they discovered that the CI model had the lowest RMSE value for the situations they were evaluating, with 2.25 dB in [47], 3.54 dB in [68], and 1.95 dB in [69].

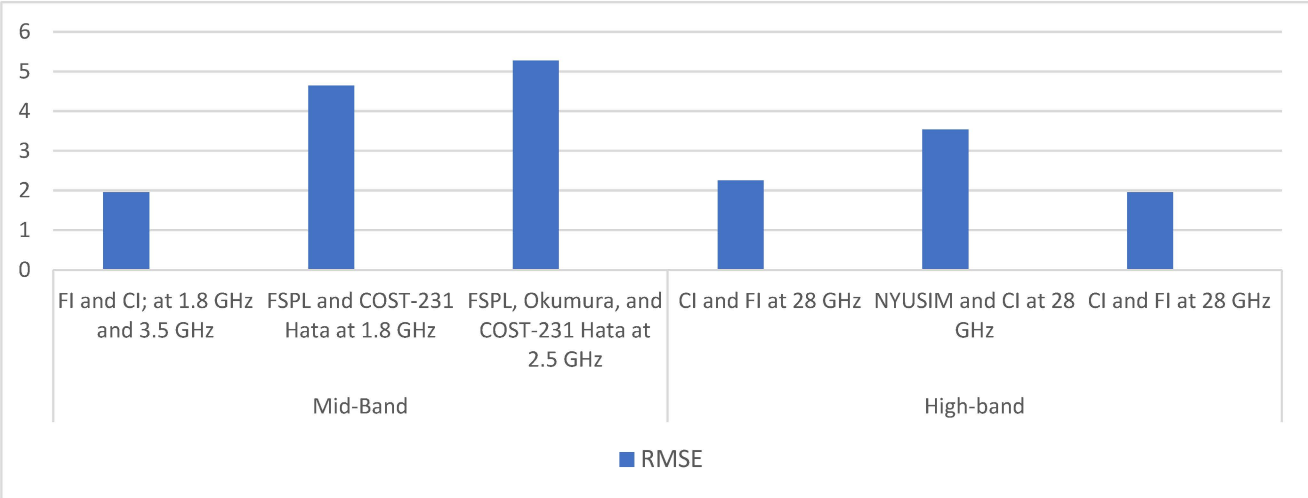

Figure 4. Performance analysis of empirical path loss models in mid-band and high-band frequencies within urban environments.

5.2. Performance Evaluation of Empirical Path Loss Models in Indoor Environment

Considering the deployment of empirical models for path loss prediction in indoor environments in the mid-band frequency spectrum, quite a lot of the proposed models have outperformed the conventional ones, like in the case of [70], where the proposed model outperformed the log-distance model with the minimum value of RMSE at 2.1 GHz. On the contrary, the ITU-R model was overestimated at 3.5 GHz in [61] with a MAPE value of 10.71, while FSPL was underestimated with a MAPE value of 4.83, as shown in Figure 5.

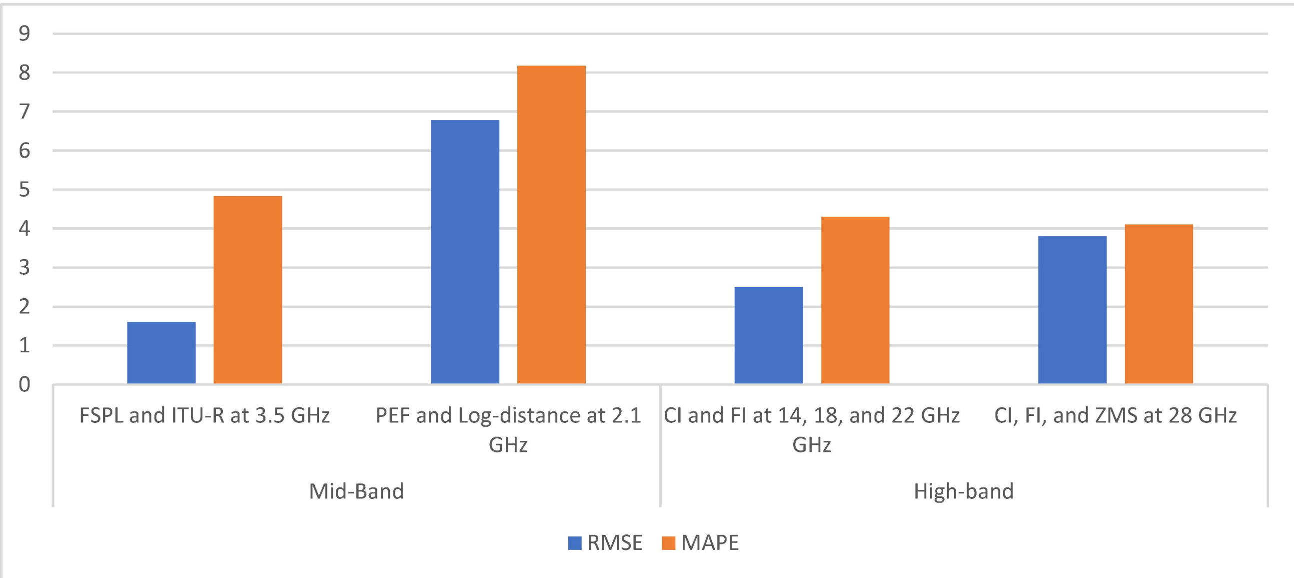

Figure 5. Comparative assessment of empirical path loss models in mid-band and high-band frequencies for indoor environments.

On the high-band spectrum, CI and FI models performed excellently well in the work of [48] at 14, 18, and 22 GHz, and [71] at 28 GHz. Both models provided accurate estimates that fit the real measured data, with CI having the lowest RMSE value of 2.5 dB in [48] and 3.8 dB in [71].

6. Reviewed Papers on Machine-Learning-Based Path Loss Models

Numerous frequencies are covered by various studies on machine learning path loss models, which take place in urban, suburban, rural, and indoor environments [73].

For example, in [74], it was suggested to create a new convolutional neural network (CNN) structure with four subnetworks and incorporate feature sharing between the convolution layers. The suggested techniques show higher accuracy and complexity compared to empirical and deterministic models. The feasibility of predicting channel characteristics in a cellular network with aerial base stations using deep convolutional neural networks and images from satellites was investigated in [75]. In this study, it was discovered that, among other variables influencing the effectiveness of the suggested method, transmitter height and channel parameter quantization are the most crucial. Additional factors that influence path loss were not considered.

Preliminary features were built into [76] to increase the proposed model's training effectiveness. Test data were collected from three distinct types of terrains: high-building cities, dense cities, and inland lakes. The models were put to the test on these distinct types of terrains, and RMSE was used to measure how well the models were generalized. When compared to the other chosen model, the suggested model was more suitable for the measured data and worked well in a range of settings. Nevertheless, the proposed model was not validated using the NLOS scenario.

A measurement effort described in [77] that was conducted at 3.7 GHz in a variety of rural Greek locales was utilized to create various machine learning models, which were then contrasted with a few chosen empirical models. However, the comparison was only made using information gathered from a thorough measurement in a rural setting. The results provided an RMSE in the range of 4.2–4.3 dB, demonstrating a higher prediction accuracy than those empirical models.

In a previous study [78], an innovative approach was proposed for developing path loss models using convolutional neural networks (CNN), specifically through meta-learning, referred to as the CNN model with meta-learning. This approach was compared to existing CNN and FI models. It is important to note that the application of this method was limited to the smart factory environment and the specific frequency of 28 GHz.

The most popular artificial neural network (ANN) multilayer perception (MLP) neural network was utilized in [79] to reliably predict path loss. It was built by combining the data from the transmitting antenna and that of the receiver (Rx), including 3D locations and environmental characteristics. To assess the model's performance, a comparison was made between the actual measured outcomes and the predicted results, excluding considerations for losses from the base station (BS). Notably, the inclusion of environmental variables led to enhancements in the precision and reliability of the prediction models.

Utilizing a dataset of field measurements at 28 GHz in a suburban environment, Cheng et al. [80] introduced an innovative path loss modeling technique based on convolutional neural networks (CNN). In their research, they proposed two key components: the enhanced local area multi-scanning method (E-LAMS) and a unique CNN architecture incorporating four subnetworks with shared features between convolution layers. Nonetheless, it is worth noting that further improvements are required to enhance the performance of this model, particularly in line-of-sight scenarios. The study's results indicate that the proposed CNN-based approach outperforms existing empirical models.

In [81], KNN, SVR, RF, and AdaBoost were employed as four machine learning techniques to simulate the radio coverage offered by a flying base station in the urban city of Tripoli. The chosen algorithms were trained on a dataset produced by a ray tracing method. Even though only a line-of-sight (LOS) scenario was used in the investigation, the performance of each model was contrasted. The most accurate predictions came from the tree-based ensemble models, with AdaBoost achieving the lowest MAPE value of 2.72%. Table 4 compiles key findings from studies that examined path loss modeling with machine learning techniques.

Table 4. Related studies of ML-based PL prediction models.

Reference	Freq. (GHz)/Scenario	ML. Algorithm	Input Features	Performance Indicators	Important Results	Limitations/Area of Improvement
[74]	28/ Urban	CNN	Tx, Rx, floor plan image matrix	RMSE	The proposed model outperformed the chosen models, demonstrating a root mean square error of 8.59 dB.	To accurately determine the model stability, the result should be modeled with multiple parameters.
[75]	3.5/ Urban	*D*-CNN	Satellite image, pl exponent, and shadow factor	MSE	The results made public demonstrate a high degree of real-time channel parameter prediction accuracy.	In commercial environments with more impediments, the path loss model needs to be tested.
[76]	28/ Urban	RF	Tx power, Tx antenna gain, terrain profile, and site coordinates	RMSE and cost time	This study recommends employing the RF model, as it was proven to be reliable with high accuracy.	There is a need to compare the proposed model with any of the widely used models in the same environment to test its validity.
[77]	3.7/ Rural	ANN, RF, SVR, and B-*k*NN	Distance between Tx and Rx, Tx height, and Rx height	RMSE, ME, MAPE, MAE, and σ	The ML models outperformed the empirical ones with remarkably low RMSE on the order of 4.2 to 4.3 dB after a comparison between the proposed ML models and those of the chosen empirical models.	It only takes path loss and distance into consideration. Another important element that must be taken into consideration is frequency.
[78]	28/ Indoor	CNN	LAMS images	RMSE	The suggested model solved the few-shot data problem and implemented path loss prediction in a smart factory.	There is a need to test the proposed model in a non-line-of-sight scenario to deduce its stability in the indoor environment.
[79]	2.5/Suburban, Urban	ANN	3D locations, frequency, transmitted and receiver power, antenna information, and feeder loss	AME, MAE, STD, and TR	These PL prediction models become more accurate and stable when environmental data are included, with unweighted rectangular environmental features performing better.	The suggested model's viability needs to be examined in a commercial environment with a higher level of obstruction.

Table 4. *Cont.*

Reference	Freq. (GHz)/Scenario	ML. Algorithm	Input Features	Performance Indicators	Important Results	Limitations/Area of Improvement
[80]	28/Suburban, Urban	AE—CNN	GPS Tx and Rx coordinates, DE-LAMS image size, and Google map image matrix	RMSE	Modern deterministic and empirical techniques cannot match the proposed innovative AE-CNN path loss model in suburban environments.	Improvements must be made to the suggested model's performance in the line-of-sight (LoS) situation.
[81]	2.1/ Urban	KNN, SVR, RF, and AdaBoost	Vertical and horizontal coordinates (x,y) for FBS height	RMSE, MAE, and MAPE	The most accurate predictions came from the tree-based ensemble models, with AdaBoost achieving the lowest MAPE value of 2.72%.	Distinct scenarios should be examined for the comparative examination of the models.
[82]	2.2, 4.7, and 26.4/Urban	RNN	Path loss and gate layer	RMSE	With an RMSE of 2dB, the suggested method outperformed the standard method for predicting path loss using LSTM, a type of RNN utilized in time series prediction.	To verify the performance of the suggested model at various frequencies, more performance indicators should be implemented.
[83]	1.5/ Urban	XGBoost, CNN	Data in tabular form, pictures (Tr_to_R_area), and pseudo images.	MAE, MAPE, and RMSE	The proposed strategy produced superior results than prior fusion methods, with an MAE value of 3.07 dB as opposed to the 3.15 dB of the traditional bimodal approaches.	For the performance of the suggested model to be verified, more experimental data are needed.
[84]	3.5/ Urban	*D*-NN, ABG, and CI	Tx height, Tx-Rx pair separation, and path profile.	RMSE	According to simulation data, the proposed model performs better than traditional models and has an accuracy of 72%.	There is a need to investigate the applicability of the proposed model in a commercial environment.
[85]	2.5/ Urban	DL	3D image	MAE, MAPE, and RMSE	It has been demonstrated that for lower transmitter heights, texture's influence is more significant. The features are consistently provided by the SFTA algorithm.	It will be necessary to conduct an extensive measurement campaign to obtain a representable model.

Table 4. *Cont.*

Reference	Freq. (GHz)/Scenario	ML. Algorithm	Input Features	Performance Indicators	Important Results	Limitations/Area of Improvement
[86]	28/ Urban	3D—CNN	3D—LAMS image	RMSE	When the data were extracted into a 40 m square, the best performance was attained.	To know the stability at multiple frequencies, the result should be modeled with more input features.
[87]	3.5/ Urban	CNN	Building height, image, and distance from Tx and Rx	RMSE	The region where the NN model's estimation accuracy declined was concentrated close to Tx, according to the proposed CNN model, which was built using the same principle as the NN model.	To validate the performance of the suggested model at various frequencies, performance measures should go beyond RMSE.
[88]	5.9/ Urban	MLP, CNN, and RF	Coordinates for Tx and Rx, the number of buildings on the path, the distances covered inside and outside of structures, the widths of the streets where Tx and Rx are located, and the separations between Tx and Rx from side corners	MAE, MAPE, and RMSE	RF performed better than the MLP model, which had a maximum RMSE value of 11 ns, among the machine learning models used to characterize the impacts of radio wave propagation in dynamic vehicle situations.	Testing the proposed model in an environment with more obstacles, such as a commercial one, is necessary.
[31]	28/ Urban	LR, MLR1, and MLR2	Distance between T and R, time delay, received power, RMS delay spread, azimuth and elevation AoDs, and elevation AoAs	MAE, MSE, RMSE, and R-squared	Prediction of the model for new communication scenarios with the reduction in the required number of measurements and complexity.	For the proposed model's performance to be verified, more input features are needed.
[89]	60/ Urban	CNN and MLP	3D image	MAE, RMSE, and RMSLE	The suggested model, which utilizes building footprint and top-view photos to forecast path loss, was presented.	Training features from a physical measurement campaign are required to validate the performance of the model.
[90]	3.5/ Urban	GLMs, NNs, and *k*-NN	Image, TX power, and coordinates of the transmitter	MAE	Simpler models with higher performance and lower computational cost are GLM and KNN.	More performance indicators should be used to validate each model's performance for comparison.

Table 4. *Cont.*

Reference	Freq. (GHz)/Scenario	ML. Algorithm	Input Features	Performance Indicators	Important Results	Limitations/Area of Improvement
[91]	2.5/ Indoor	LR and ANN	Reflections of the ground, ceiling, and walls	MSE and MAE	With the lowest MSE and MAE values, the ANN model outperformed the linear model in terms of performance.	It just takes into account the surface of the reflection area. Another important factor that needs to be taken into account is obstruction.
[92]	2.3/ Indoor	GPR, LG, and KNN	Received power, T-R separation distance, elevation, and azimuth AoD	MSE and MAE	A multi-dimensional GPR-based model that is capable of estimating path loss was proposed.	Varied environments need to be used to test the stability of the proposed model.
[93]	7/ Urban	NN, FI, CI, WINNER II, and 3GPP	3D distance between Tx and Rx, center frequency, Tx height, Rx height, latitude, longitude, and satellite image	RMSE	When compared to the selected traditional models, the proposed model provided superior accuracy in predicting path loss.	The model needs to be improved in the context of the environment with more obstructions.
[94]	1.8/ Urban	RF	Cell distance, vertical angle, horizontal angle from Rx, total height of Tx, total height of Rx, road width, and height of nearby buildings	MAPE and RMSE	Employing hyperparameter tuning for the suggested model leads to enhanced predictive accuracy performance.	Exploratory data analysis (EDA) is important and should be improved on the available data.
[95]	3.5/ Urban	RF	Geographical coordinates, distance, azimuth, and antenna gain	MAE and RMSE	The use of an RF model with the given attributes presents better prediction accuracy	Enhancing the model's performance requires the inclusion of supplementary input features.

A deep learning model, such as the LSTM, was used to develop a way of predicting fluctuations in path loss [82]. The training and validation data were taken from measurements of path loss in an urban environment. The model was compared to a conventional approach that predicts using the most recent observed median path loss value, utilizing 100 fast-fading data points as input data. In the validation analysis, the measurement campaign was restricted to an urban environment, and the error analysis was limited to the root mean square error. They outperformed the traditional method by more than 1 dB, achieving RMSE prediction accuracy of nearly 2 dB.

The authors in [83] examined two machine learning models, using tabular data and images as two different forms of input to perform path loss predictions in metropolitan locations. They looked at occasions where CNN received just one image and not the other two. By simply creating three duplicates of the same channel, they were able to change the monochrome images into colored ones while still using the same CNN architecture. With an MAE value of 3.07 dB as opposed to the 3.15 dB of the conventional bimodal approaches, the proposed methodology outperformed existing fusion methods in terms of results.

Similarly, a deep learning technique was utilized in [84] to explain the process of path loss based on the path profile in urban propagation situations. Even still, the LoS and NLoS scenarios' measuring campaigns were only applicable to urban settings. Simulation findings demonstrated that the suggested model outperformed traditional models, and the explainable model's accuracy reached 72%.

In [85], image texture techniques were used to enhance the DL model for path loss prediction. Thus, the algorithm produced a new set of features that showed the specified area's built-up profile. However, further experimental data are needed to verify and rate the effectiveness of the suggested model. The model-aided approach provides an improvement of about 1 dB.

In a separate study [86], a methodology involving a 3D-CNN and a 3D-LAMS algorithm was applied to sample and extract three-dimensional spatial data between the transmitter (Tx) and receiver (Rx) for creating a 3D image representation. The measurement campaign is expected to extend its scope beyond urban environments to explore additional factors influencing path loss. Through multiple trial runs with varying dataset sizes, the proposed path loss prediction model demonstrated its optimal performance.

To compare the similarities and differences between the CNN model and the NN model, Kuno et al. [87] devised a CNN model. They made use of the training and verification data supplied during the IEICE's propagation competition. As a result, the CNN model's estimation accuracy declined near the main roadway and the plaza.

Three machine learning models were used in [88] for radio channel modeling in urban vehicle environments. However, the inquiry was only able to simulate LOS and NLOS conditions utilizing the ray tracing-generated data set. Among the chosen models, RF performed best with a low RMSE of 1.80 ns, while the MLP model had the highest RMSE at 11 ns.

Utilizing machine learning methods, Aldossari et al. [31] presented innovative approaches to improve path loss models, addressing the challenge associated with complex channel characteristics and time-consuming measurements. In their study, they successfully reduced the measurement workload necessary for wireless channel modeling through the application of regression techniques.

In [89], data from online sources such as OpenStreetMap and various Geographical Information Systems were collected to construct a machine learning model aimed at predicting cellular coverage in metropolitan regions. This model demonstrated the capability to promptly estimate path loss, even in the absence of training data from the physical measurement campaign. Also, numerous feature engineering strategies were investigated in [90] to enhance the machine learning algorithms' predictive performance. They found that, especially for small datasets, more basic models can be just as effective as more complex ones.

In [91], the author employed the image reflection technique to create a dataset that could be used to test any straightforward machine learning model for indoor prediction. The outcome of the comparative analysis demonstrates that the ANN model outperformed the linear model and provided the dataset with the lowest MSE and MAE values.

A novel path loss model capable of estimating path loss was proposed in [92]. The proposed model is grounded in multidimensional Gaussian process regression (GPR), which predicts local shadow fading to give channels spatial consistency in propagation in indoor environments. To test and validate the suggested model, though, more varied environments must be used.

In [93], the authors conducted path loss prediction at 7 GHz within an urban environment by employing a model-assisted deep learning approach. Their proposed model utilizes a distinct set of input features, encompassing both fundamental and engineered attributes. The numerical results demonstrate that the deep learning model outperforms the chosen empirical models in terms of prediction performance. The proposed approach must be enhanced in the context of an environment with additional obstacles because it is still a hybrid model.

In similar work by [94], a viable alternative to improve path loss prediction with the use of the random forest model was proposed. The test carried out in their work showed that the use of the random forest technique with attributes such as geographical coordinates, distance, azimuth, and antenna gain presented better results than other considered models [95]. Although additional features need to be considered to train and test the model to improve its performance.

6.1. Assessment of Machine Learning Path Loss Models in Outdoor Urban Environments

In [81], among the four machine learning models that were examined for their suitability in path loss prediction at 2.1 GHz, the RF model outperformed the rest of the models with minimum RMSE, MAE, and MAPE values of 4.662 dB, 3.19 dB, and 2.96%, respectively. Similarly, in [88], the RF model outperformed the two other models such as the CNN and MLP at 5.9 GHz, having the minimum RMSE and MAE values of 1.44 dB and 2.19 dB, respectively, followed by the CNN model with an RMSE value of 2.03 dB, as shown in Figure 6.

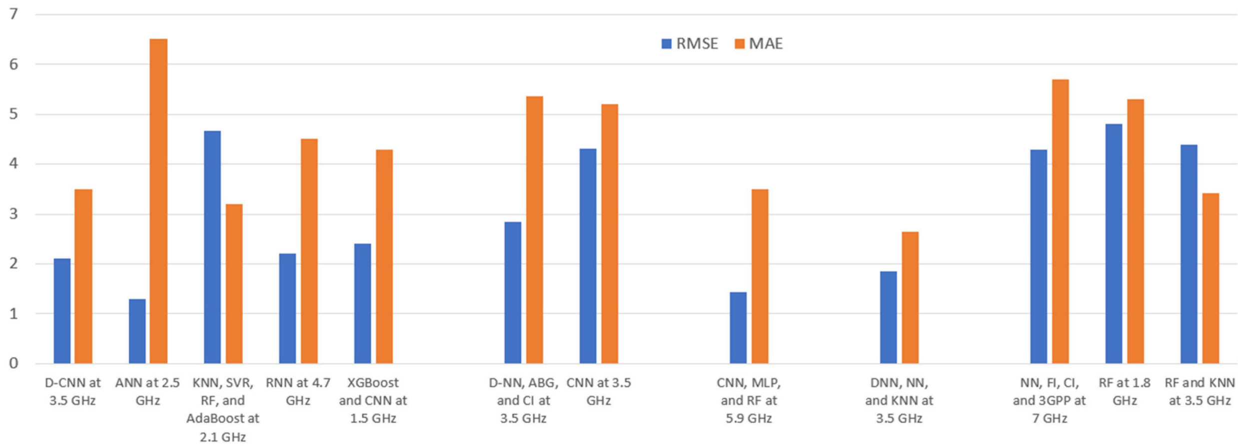

Figure 6. Comparative analysis of models in the mid-band frequency spectrum for outdoor urban environments.

Also, the RF model outperformed the KNN model at 3.5 GHz in [95], with a minimum RMSE value of 3.42 dB. Among the other works that considered a comparison of machine learning models at 3.5 GHz is that of [91], involving the DNN, NN, and K-NN. The DNN model outperformed the rest of the models with the minimum RMSE value. Meanwhile, the supremacy of the machine learning model over empirical models is showcased in [84], where the DNN model outperformed the ABG and CI models at 3.5 GHz with the minimum RMSE value of 4.84 dB, and in [93], where the NN model outperformed the FI and CI empirical models with an RMSE value of 4.3 dB at 7 GHz.

The XGBoost model was not left out when it competed with the CNN model in [83] to show its excellent performance over the CNN model with a minimum RMSE value of 2.4 dB at 1.5 GHz.

6.2. Evaluation of High-Band Machine Learning Path Loss Models in Urban Environments

Several machine learning models were tested for predicting of path loss in urban environments at high-band frequencies in different scenarios. At the same time, some disagreed with the empirical models. For example, the NN model outperformed the empirical models, including the FI, CI, and 3GPP models in [93], which had a minimum RMSE value of 4.5 dB, as shown in Figure 7.

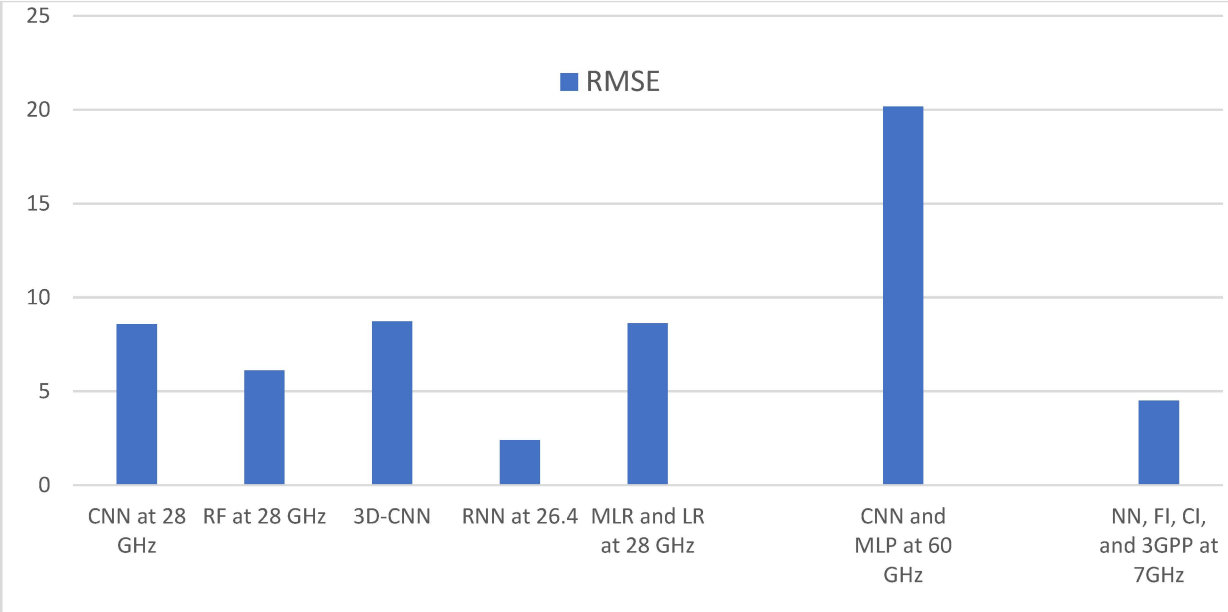

Figure 7. Comparative analysis of models in the high-band frequency spectrum for outdoor urban environments.

Meanwhile, the independent machine learning models performed excellently, like the CNN model with an RMSE value of 8.59 dB at 28 GHz, the RF model with an RMSE value of 6.1 dB at 28 GHz, and the RNN model with an RMSE value of 2.4 dB at 26.4 GHz.

6.3. Evaluation of Indoor Machine Learning Path Loss Models

Several researchers focused on investigating the performance of machine learning models in an industrial environment for both mid-band and high-band frequencies. Two different models have been tested for mid-band frequencies, as in the case of ANN and LR in [91], where ANN outperformed with the minimum MAE value of 5.37 dB at 2.5 GHz, and KNN and GPR in [92], where the proposed GPR outperformed the KNN with the minimum MSE value of 4.25 dB at 2.3 GHz, as shown in Figure 8.

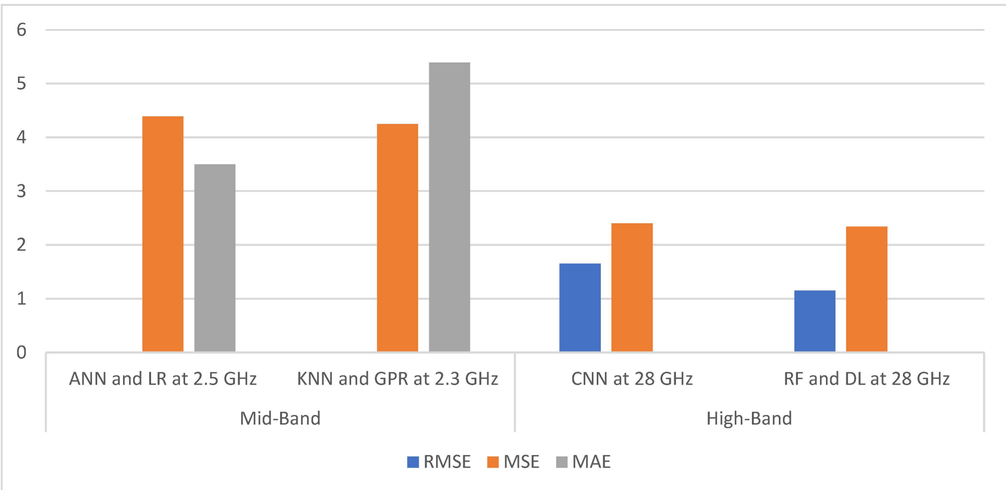

Figure 8. Comparative analysis of models in the mid-band and high-band frequency spectrums for indoor environments.

Similarly, for the high-band scenario, the CNN model performed excellently well at 28 GHz with an RMSE value of 1.65 dB, while in the context of RF and DL models at 28 GHz, the RF model outperformed the DL model, having the lowest RMSE value of 1.15 dB.

7. Open Research Issues

Accurate path loss is central to the success of 5G deployments, a critical factor that directly impacts network planning, optimization, and resource allocation. While considerable research has been devoted to path loss modeling, a comprehensive survey revealed significant research gaps and outlined promising directions for future work in understanding the performance of path loss models across the diverse frequency bands of 5G, including mid-band and high-band channels.

7.1. Research Gaps

In an attempt to present a reliable and stable ML model in [31,75–77,82–85,87–89,91,92] for high-band channels in urban environments, the *k*-NN, MPL, CNN, and SVR models performed similarly across all frequencies under consideration, with the random forest model (RF) delivering the most accurate predictions in [77,81] and the XGBoost model in [83] in an urban environment.

Similar approaches in the deployment of machine learning models to predict path loss in the mid-band channel revealed that the random forest model performed excellently in [88,94,95] in an urban environment, while the neural-network-based models performed similarly in [81,84,86]. However, because every urban environment is made of unique layouts and streets, researchers should think about improving the models' performance in the propagation of mid-band 5G network deployment and future wireless communication networks in distinct scenarios of complex urban environments.

Efforts made by the authors in [42,73] to address the issue of path loss along mid-band channels in urban environments using early empirical models indicate that the COST-231 Hata model outperformed other considered models. On the other hand, current empirical models that were adopted [47,62,68–70] to prove their prediction accuracy along high-band channels in an urban environment showed that the CI, ABG, and FI models provide more accurate estimated path loss models.

i. Dynamic urban environments: Urban environments are highly dynamic, with changes in building layouts, vegetation, and infrastructure occurring frequently. The current empirical models, such as the ABG, CI, FI, and 3GPP, may not be able to account for these dynamic changes adequately, resulting in inaccuracies in path loss predictions. Integrating real-time or dynamic elements into empirical models is a research gap that needs to be addressed. Hence, they need to be improved to fit the worst-case scenario of the urban environment and to make them reliable in any other urban environment. The current empirical models may not adequately capture or account for these interference and multipath effects, leading to inaccurate predictions.
ii. Inadequate integration of machine learning techniques: Machine learning techniques, such as the random forest model and neural networks, have shown promise in improving path loss prediction accuracy across the considered mid-band and high-band frequency spectrums. However, limited research exists on effectively integrating these techniques into empirical models for path loss in the mid-band frequency spectrum in urban environments. Exploring the potential of machine learning-based approaches and their integration into existing models is an important research gap.
iii. Lack of validation in real-world scenarios: Empirical models developed for predicting path loss in mid-band and high-band frequencies in urban and suburban environments may not have been extensively tested and validated in real-world scenarios. The absence of comprehensive field measurement and validation studies can introduce uncertainties and limit the reliability and accuracy of the models.
iv. Inadequate consideration of complex environment: The empirical models that were used did not sufficiently account for factors such as high-rise buildings, vegetation, and

diverse land use patterns, leading to inaccuracies in path loss estimation. Developing models that can accurately capture and incorporate the characteristics of complex urban and suburban environments is a significant research gap.

v. Lack of relevant features on labeled training data: There is a shortage of relevant features on labeled datasets, as in the case of the random forest model that outperformed other chosen models [77,83]. This scarcity of relevant features that greatly impact the prediction poses a significant research gap as it hinders the development and deployment of an accurate model in these scenarios. The result should be modeled with multiple parameters and examined in a commercial environment with more obstructions to accurately determine the stability of the models.

7.2. Future Direction

To obtain a representable empirical model with high performance in path loss prediction, an extensive measurement campaign and experimental data across similar buildings under consideration will be required. The result should be modeled with multiple parameters and examined in a commercial environment with more obstructions to accurately determine the stability of the selected empirical models.

In the context of using machine learning models for path loss prediction at mid-band and high-band frequencies in distinct scenarios, the lack of interpretability of machine learning models can limit their practical usability and acceptance. Addressing this research gap by developing a transparent and explainable model is essential to establishing trust and facilitating effective deployment in real-world scenarios.

In future research, an ensemble supervised machine learning-based path loss model that can predict path loss in distinct urban environments that comprise modern and old buildings that have fewer structure layouts and infrastructure will be used to enhance a trusted empirical model at the mid-band frequency spectrum to develop a hybrid model. This unique urban environment is essential for the path loss model because the construction materials in old buildings present different attenuations as compared to modern buildings, as it was reported in [96] and adapted in [97] that the attenuation in modern buildings is approximately 20–25 dB higher than the attenuation in older structures. This proposed model can be used to support the design of wireless communication networks in any urban environment.

In this case, all the relevant features that describe the environment under consideration, with the adoption of the feature selection technique to further prioritize the most relevant features, will be considered to generate optimal datasets for the training and testing of the machine learning model. An illustration of some of the relevant features is presented in Figure 9.

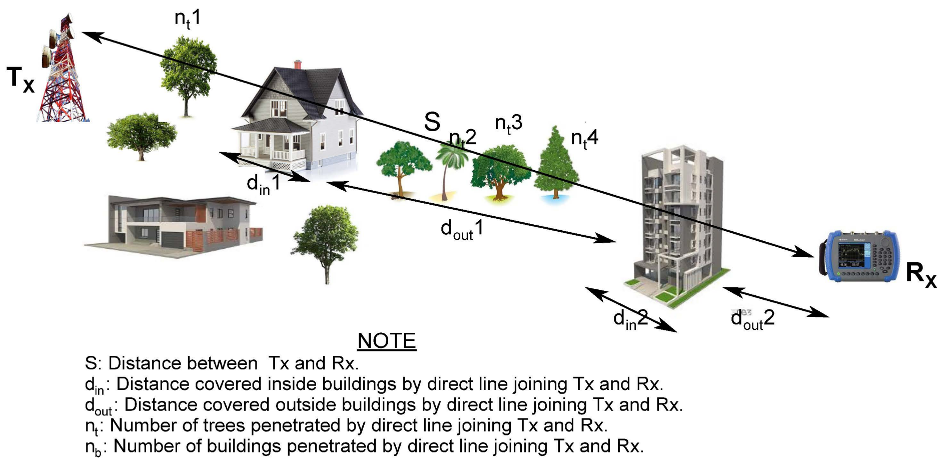

Figure 9. Illustration of some of the training features.

Relevant RF planning software tools, such as PL5 version 5.1, will be used to carry out the 3D ray tracing technique and path profile simulation to generate additional information, as well as that from a measurement campaign for a comprehensive dataset.

The proposed model is anticipated to aid RF engineers in designing effective mid-band and high-band channel modeling for distinct scenarios, and it will be very helpful for 5G/6G research and system implementation.

8. Conclusions

This paper reviewed several approaches for implementing empirical and machine learning models in different scenarios of urban, suburban, rural, and indoor environments to address the issue of high path loss in 5G mobile wireless communication. Some of these models have shown the capability of accurately predicting path loss in an urban, suburban, rural, and indoor environment along the mid-band and high-band frequency channels. These models can aid network planners and researchers in designing, analyzing, and evaluating various wireless technology solutions and optimizing coverage for existing and future deployments.

In general, the analysis of both empirical and machine learning models for path loss prediction across the mid-band and high-band channels in different scenarios reveals the complex and dynamic nature of 5G communication networks, highlighting the need for adaptable and accurate modeling techniques to ensure efficient network planning, deployment, and optimization.

In conclusion, our comprehensive review and analysis delved into the performance of path loss models across mid-band and high-band frequency spectrums, specifically within the context of 5G communication networks. One significant aspect of our investigation focused on the development and evaluation of machine learning models designed to predict path loss under various scenarios. These machine learning models were rigorously compared to conventional empirical models to gauge their predictive capabilities.

Our findings illuminated a compelling trend in favor of machine learning models. They consistently demonstrated superior performance in terms of prediction accuracy and computational efficiency when compared to their empirical counterparts. This marked a significant breakthrough, suggesting that machine learning models have the potential to offer a novel and promising approach for path loss prediction, particularly in high-band frequency channels.

Nonetheless, our analysis is just the initial step in uncovering the full potential of these machine learning models. Substantial further research is warranted to confirm and extend these findings, encompassing a broader spectrum of scenarios, including those within the mid-band frequency range. Moreover, it is essential to explore different propagation conditions to better understand the applicability of machine learning in various real-world contexts.

This review underlines the integral connection between path loss models and channel models, including considerations of slow and fast fading, in wireless communication. Path loss models play a pivotal role in shaping comprehensive channel models by quantifying the attenuation of signals over different frequencies and in diverse environmental scenarios. These models, as showcased in our study, offer critical insights into the complex and dynamic nature of 5G communication networks. By accurately predicting path loss, they form the foundation for understanding the effects of signal fading, both slow and fast, which are fundamental aspects of channel modeling.

Our review emphasizes the emerging significance of machine learning models in enhancing path loss prediction accuracy, particularly in high-band frequency channels, further enriching the sophistication of channel models. As we advance, it becomes clear that bridging the gap between path loss and channel models is essential for the evolution of 5G and future wireless communication networks, enabling more efficient network planning, deployment, and optimization in the face of dynamic propagation conditions.

Future work will focus on tuning an ensemble machine learning model to enhance a stable empirical model with multiple parameters to develop a hybrid path loss model capable of predicting path loss in the worst-case scenarios of the urban environment with more obstructions and irregular layouts of buildings.

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